MULT 25-610 Smart Buildings-Sustainability and Efficiency

Project Proposal

Prepared for

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Siemens

By

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Under the supervision of

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Executive Summary

The primary objective of this capstone project is to leverage operational data from laboratory HVAC systems in the VCU College of Engineering to implement a predictive maintenance (PdM) model for stakeholders, Siemens and the VCU building operations team. The sponsor of this capstone project, Siemens, provides the Internet of Things (IoT) network that implements building automation systems around the VCU campus.

The project goals that address the sponsor's needs are to access and process Siemens historical, laboratory HVAC data, perform data mining and profiling, construct a machine learning model, test and validate the PdM model, optimize model performance, and visualize key findings.

The design objective is to implement a predictive maintenance model that predicts potential failures in HVAC systems. The model implementation should improve upon a baseline accuracy, indicating that the model's knowledge discovery is valid and useful. The design will be achievable within the available data collection and computational resources, leveraging current machine learning techniques like classification algorithms and time-series analysis. The design will realistically provide predictions within a timeframe that allows for preventive action, generating anomaly alerts two weeks before a potential malfunction or failure is likely to occur. The design will be implemented, tested, and deployed within a 6-month timeline, with iterative model improvements over 2-week sprints.

High Level Overview of Timeline:

1. **Data Collection and Preprocessing**: Complete by January 2024
2. **Model Training and Cross-Validation**: Complete by First Half of February 2025
3. **Model Iterative Fine-tuning and System Validation**: Complete by Second Half of February 2025
4. **Final Optimization and Prototype Delivery**: Complete by March 2025
5. **Final Report and Presentation Preparation**: Complete by March 2025

More granular information about upcoming two-week sprints is described in detail in Section C.2.

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Section A. Problem Statement

The primary objective of this capstone project is to leverage operational data from laboratory HVAC systems in the VCU College of Engineering to implement a predictive maintenance (PdM) model for facility maintenance and management. The sponsor of this capstone project, Siemens, is a technology company focused on building automation systems, software, healthcare, industrial automation, and energy. In this project's scope, Siemens provides the Internet of Things (IoT) network that implements building automation systems around the VCU campus. The project stakeholders are Siemens and the VCU building operations team.

The current approach to building operations is a reactive maintenance model, which involves allowing systems or, more minutely, subsystems to malfunction and only intervening to repair them after the issue arises. This break-fix cycle is expensive and disruptive due to spontaneous out-of-budget repair expenses needed for sudden machine failures and subsequent unplanned machine downtime [1]. By implementing a PdM model, we aim to improve the reliability of laboratory HVAC systems, reducing the risk of sudden machine failures and the associated costs and disruptions.

The application of PdM modeling in building operations also supports efforts towards sustainability. By proactively identifying emerging failures in HVAC systems, energy consumption, waste, and a building's carbon footprint are reduced. PdM fosters a safe environment for building occupants. Addressing laboratory HVAC system failures proactively decreases the likelihood of hazardous situations that affect occupants' safety. Proper ventilation, heating, and cooling in a laboratory allows for tight air quality control, protecting occupants' health and preventing outdoor air contamination [2].

In the PdM project life cycle, data pre-processing and data mining are used to construct descriptive or predictive (machine learning) models. These models discover knowledge from systems data to predict anomalies and the state of health of equipment [3]. Knowledge-based or data-driven approaches to PdM vary based on business objectives and resource availability. Knowledge-based approaches rely on the knowledge of experts in the domain where predictive maintenance is applied. Thus, rule-based, case-based, and fuzzy algorithms are utilized in knowledge-based PdM models and can suffer from low accuracy when applied to complex data. Data-driven PdM models use machine learning and data analytics on historical system datasets to predict system health and detect anomalies in real-time data [4].

Figure 1. Workflow of predictive maintenance [3]

Remaining Useful Life (RUL) PdM models estimate the lifespan of a machine in building subsystems based on historical, run-to-failure data periods. By analyzing the operational performance of machine components near the end of their lifespan, based on historical work orders, RUL models provide knowledge of when building operators can anticipate equipment failures and implement necessary maintenance. Kang et al. used the principal component analysis feature selection, grid search parameter optimization, and a multi-layer perceptron (MLP) machine learning algorithm to implement an RUL model. The MLP model outperformed implementations of random forest and support vector regression algorithms for the machine learning component of the RUL models [5].

Normal Behavior Models (NBM) establish a "normal" operation baseline for building sub-systems. By mining historical, healthy system data to construct a machine learning-based NBM model, anomalies in real-time data that indicate potential malfunctions or failures can be flagged by the model and reviewed by building operators. Chesterman et al. used linear interpolation for missing values imputation, sensor signal filtering, and an elastic net regression (ENR) machine learning algorithm to implement an NBM model. Chesterman et al. found the ENR model outperformed a more complex machine learning model, support vector regression. The ENR underperformed when compared to lighter machine learning models, multi-layer perceptron and gradient boosting machines. However, the study found that elastic net regression suffered less model degradation from extreme changes in data compared to the lighter models [6]. By detecting deviations from normal behavior early, building operators can implement necessary maintenance before the problem worsens.

Section B. Engineering Design Requirements

The Engineering Design Requirements for this project were derived by carefully analyzing Siemens' specific needs, industry benchmarks, and existing smart building systems. The design objectives focus on creating an efficient, predictive maintenance system that integrates seamlessly with Siemens' infrastructure while optimizing system performance and reducing downtime. Each requirement, such as cost, safety, usability, and scalability, was researched and aligned with relevant codes and standards to ensure a robust and compliant solution. These requirements will be revisited periodically to ensure that the design stays aligned with the project's goals.

B.1 Project Goals (Client Needs)

The purpose of this project is to develop a comprehensive predictive maintenance system that leverages Siemens' data and machine learning technologies to enhance the management of smart building systems. The client, Siemens, requires an efficient solution that can harness large volumes of operational data from building systems to predict equipment failures, optimize energy use, and improve overall system reliability. The goals of this project focus on extracting actionable insights from this data and delivering them in a user-friendly manner that enhances decision-making and performance monitoring.

The overall goals of the project include:

1. **Access and Process Siemens Data**: Collect, manage, and analyze operational data from Siemens' smart building systems.
2. **Understand and Recognize Patterns in Data**: Use advanced data analysis techniques to detect patterns and trends in the data that correlate with mechanical faults and system inefficiencies.
3. **Develop a Machine Learning Model**: Implement a machine learning model that accurately predicts mechanical failures in key systems like HVAC, pumps, and compressors based on the patterns identified in the data.
4. **Testing and Validation of the Model**: Conduct thorough testing and validation to ensure the model improves on the initial benchmarks.
5. **Optimize System Performance**: Provide insights and recommendations to optimize the operational efficiency of building systems, focusing on reducing energy consumption and extending equipment lifespans.
6. **Data Visualization**: Create a visualization dashboard to display system performance, failure predictions, and energy optimization insights, enabling building managers to make informed, proactive decisions.

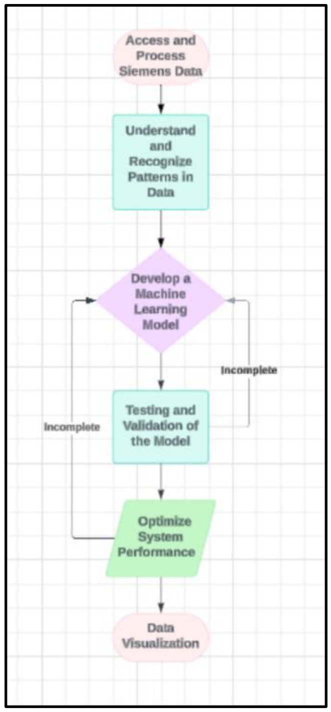


Figure 2. Project Goals Flowchart

In summary, this project aims to provide Siemens with a robust predictive maintenance system that utilizes machine learning to analyze operational data from smart building systems. The primary goal is to predict mechanical failures, optimize energy efficiency, and enhance system reliability. By leveraging advanced data analysis techniques, a machine learning model will be developed, tested, and validated to accurately forecast equipment issues. The project will also include a data visualization dashboard, enabling building managers to make informed decisions and ensure the smooth operation of critical systems.

B.2 Design Objectives

Below are the design objectives following the S.M.A.R.T guidelines.

Specific

- The design will predict potential failures in HVAC units using historical data related to the units' operational parameters, maintenance history, and environmental factors.

Measurable

- The design will achieve a failure prediction accuracy that meets or improves upon the accuracy of a baseline model or metric.

Achievable

- The design will be achievable within the available data collection and computational resources, leveraging current machine learning techniques like classification algorithms and time-series analysis.

Realistic

- The design will realistically provide predictions within a timeframe that allows for preventive action, generating anomaly alerts two weeks before a potential malfunction or failure is likely to occur.

Time-bound

- The design will be implemented, tested, and deployed within a 6-month timeline, with iterative model improvements over 2-week sprints.

B.3 Design Specifications and Constraints

The goal of this project is to develop a **predictive maintenance system** that leverages operational data from Siemens' building control systems to anticipate mechanical failures in critical systems such as HVAC, pumps, and compressors. This project focuses on identifying potential system breakdowns before they occur, allowing for timely interventions and reducing unplanned downtime.

Prediction Accuracy

- **Specification**: The predictive model must achieve an anomaly prediction accuracy that improves upon the anomaly prediction of a baseline model/metric.
- **Objective**: Ensure the system reliably predicts anomalies in equipment operations, providing actionable insights for preventive maintenance through predictive data mining.
- **Measurable Criteria**: The predictive model will be validated through usage of appropriate testing datasets to confirm that the model can accurately make anomaly predictions.

Data Collection and Processing

- **Specification**: The system must collect and process real-time data from **at least 1** critical building system (HVAC, pumps, compressors) with a data refresh rate of **1 week**.
- **Objective**: Provide continuous monitoring of system performance to detect and predict mechanical failures.
- **Measurable Criteria**: The system’s data refresh rate and real-time monitoring capabilities will be tested to ensure compliance with the specified time frame.

Integration with Siemens Building Control Systems

- **Specification**: The predictive maintenance system must integrate seamlessly with Siemens' existing building control systems, utilizing operational data from at least one sensor installed in the Engineering Research Building without requiring additional hardware infrastructure.
- **Objective**: Leverage existing data streams from Siemens infrastructure to implement the predictive maintenance model.
- **Measurable Criteria**: Integration tests will confirm that the system can access and process data directly from Siemens' control systems without disruptions.

Budgetary Constraint

- **Specification**: The total project cost, including software and any necessary infrastructure upgrades, must not exceed $1,000, unless more funding is received.
- **Objective**: Ensure the project remains cost-effective while meeting all functional requirements.
- **Measurable Criteria**: All expenditures will be tracked, and the final project costs must remain within the $1,000 limit.

Testing and Validation

- **Specification**: The system must undergo **extensive testing and validation** using historical operational data to confirm its predictive accuracy.
- **Objective**: Ensure the system's predictive model is reliable before live deployment.
- **Measurable Criteria**: The system will be tested against historical data to verify its prediction accuracy, and it must achieve a before moving to real-time deployment.

Scalability

- **Specification**: The system must be designed to scale across multiple subsystems within a single building without requiring significant changes in architecture.
- **Objective**: Ensure the predictive maintenance model can expand to cover more systems in the future.
- **Measurable Criteria**: The system architecture will be reviewed to ensure scalability and tested on additional systems for performance consistency.

Real-Time Alerts

- **Specification**: The system must generate **preventative alerts on a weekly basis** for building operators when performance metrics deviate beyond acceptable thresholds.
- **Objective**: Provide timely notifications for preventive action before failure occurs.
- **Measurable Criteria**: The system's alert system will be tested to ensure that alerts are generated immediately when thresholds are exceeded.

B.4 Codes and Standards

For the development of a predictive maintenance system using machine learning, the following codes and standards are critical to ensure data security, system interoperability, and electrical safety:

1. **IEEE 802.3 (Ethernet Standards)** – **Networking Protocols**: Defines the standards for wired Ethernet networks, ensuring that data transmission between building control systems and the predictive maintenance model is reliable and fast.
    - **Relevance**: Ensures seamless communication and integration between sensors, building control systems, and the machine learning platform.
2. **ISO/IEC 27001 (Information Security Management)** – **Data Security**: Specifies requirements for establishing, implementing, maintaining, and improving an information security management system.
    - **Relevance**: Critical for ensuring that data gathered and processed by the predictive maintenance system is secure and protected from unauthorized access or breaches.
3. **NIST SP 800-53 (Security and Privacy Controls for Information Systems)** – **Data Integrity**: Provides a catalog of security and privacy controls for federal information systems, including cloud-based data storage.
    - **Relevance**: Ensures that data processed by the machine learning algorithms is stored and handled securely, especially if cloud-based resources are used.
4. **Project Haystack (Data Tagging Standard for Building Automation) – Data Tagging and Organization**
    - **Relevance**: Project Haystack offers an open standard for tagging and organizing data generated by building automation systems like HVAC. This ensures that data collected from Siemens' systems can be structured in a way that enhances pattern recognition and machine learning, making it easier to identify trends and anomalies.
5. **ASHRAE 135 (BACnet – A Data Communication Protocol for Building Automation and Control Networks)** – **System Interoperability**
    - **Relevance**: This standard is critical for ensuring that different control systems, such as HVAC, lighting, and metering, can communicate seamlessly using the BACnet protocol. Integrating your predictive maintenance system with Siemens' building control infrastructure will rely on this standard to ensure data is shared effectively between subsystems.
6. **ANSI/ASSP Z9.5-2022 (Laboratory Ventilation)** – **Ventilation Safety for Laboratories**
    - **Relevance**: This standard establishes the minimum requirements for laboratory ventilation systems, focusing on controlling air contaminants and ensuring safe airflow within lab spaces. If your predictive maintenance system will include HVAC systems for laboratory spaces, this standard is crucial to ensure compliance with proper ventilation and air quality management.
7. **AIHA Laboratory Ventilation Standard (Z9.5)** – **Airflow and Safety in Labs**

- **Relevance**: This standard outlines best practices for airflow and contaminant control in laboratory environments. If your predictive maintenance system includes HVAC systems in labs, compliance with this standard ensures proper ventilation, air quality, and safety. It specifically addresses fume hoods and exposure control devices, which are key to maintaining safe lab environments.

Section C. Scope of Work

Key Objectives

- Design and implement a machine learning model to predict potential HVAC unit failures.
- Set a baseline for our preliminary ML model
- Ensure model precision and build upon baseline numbers.
- Provide failure/maintenance predictions of two weeks prior to the occurrence.
- Deploy the model within 6 months, two-week sprint cycles. As progress is made on the project, the plan for the upcoming month will be updated on a 2-week sprint basis.

Boundaries

- Time**:** The project will be completed within a 6-month period.
- Budget**:** The project must stay within the allotted budget (exact amount defined to be $1000).
- Resources**:** The team will have access to data from Siemens, computational resources for training the model, and guidance from the faculty advisor.

Development Methodology

The **Agile** methodology will be followed, with 2-week sprints to allow for iterative development, frequent feedback from stakeholders, and adjustments to the model as needed. Regular communication with the project sponsor and faculty advisor will ensure the project stays on track.

C.1 Deliverables

Deliverables

- Preliminary design report
- A functional ML model capable of predicting HVAC failures with an improved accuracy based on our initial baselines.The trained predictive maintenance models will be given to Siemens in the form of Python code.
- Documentation detailing the training and testing datasets, preprocessing steps, data splitting methodologies, model architecture, and testing procedures.
- Fall poster and presentation

- A simple website that displays our graphs/model.
- Final report including a summary of the project, results, and future recommendations.
- A drive holding all the data used (post-processed testing and training datasets, database implementation of data and related schemas)
- Capstone EXPO poster and presentation
- This should all culminate in a minimum viable product.

- **Out of Scope:**
    - HVAC system hardware modifications.
    - Long-term maintenance of the model post-deployment.
    - Ongoing data collection and retraining after the initial deployment phase (stop after minimum viable product)
    - Limitation of data domain (data is collected from only one lab)

Risks/Obstacles

- **Engineering the model**: It is the team's first time constructing a machine learning model; thus, obstacles will arise as the project progresses. The team may take more time in some areas during development so the defined sprint schedules will be iterated upon as needed.
- **Data availability issues**: If sufficient historical data is not available, the timeline may shift to accommodate additional data collection.
- **Model performance**: If the model does not meet performance criteria, the team will explore alternative algorithms and techniques within the timeline.
- **Scope creep**: Any new requests or changes to the project scope will need formal approval from both the faculty advisor and project sponsor.

C.2 Milestones

This project follows a structured approach where key milestones represent major phases necessary to ensure the successful delivery of the predictive maintenance model for HVAC systems. These milestones include critical tasks such as data collection, computational model development, and testing procedures. The project timeline is broken into 2-3 week increments, with each milestone focusing on specific activities like data preprocessing, model training, optimization, and validation. As the project progresses, adjustments may be made based on findings from earlier phases, consistent with an Agile development approach. The timeline takes into account the time needed for data processing, development of the machine learning model, testing, and preparing final reports and presentations. The completion dates of each milestone are carefully planned to keep the project on track, ensuring the final deliverables are completed within the allocated time frame. Regular reviews with the faculty advisor and project sponsor will ensure that any necessary changes to the project scope or timeline are documented and agreed upon.

6. **Data Collection and Preprocessing**: Complete by January 2024
7. **Model Training and Cross-Validation**: Complete by First Half of February 2025
8. **Model Iterative Fine-tuning and System Validation**: Complete by Second Half of February 2025
9. **Final Optimization and Prototype Delivery**: Complete by March 2025
10. **Final Report and Presentation Preparation**: Complete by March 2025

Timeline & Milestones

Disclaimer: There will be 2 two-week sprints for each month, which will be specified based on ongoing substantive progress and/or potential setbacks. Currently, only October and November have a defined sprint schedule.

- **October-January: Data Collection, Preprocessing, Profiling**
    - Gather data on HVAC system operational parameters, including airflow rates, pressure differentials, heat transfer efficiencies, and mechanical wear in components such as fans, compressors, and heat exchangers.
    - Analyze mechanical failure modes and degradation patterns over time (e.g., wear and tear on bearings, belt slippage, or coil fouling).
    - Gather historical data on HVAC operational parameters, maintenance records, and environmental factors
    - Clean and preprocess data, imputation of missing or incorrect values, handle imbalanced classes, feature selection, feature engineering
        - Sprint Schedule for October
            - 14th-31th:
                - Evaluate and finalize the source lab and historical time-frame for data collection
                    - Collect historical data from Siemens team
                - Choose database technologies for data storage and develop data schema for configuration of database
                - Initialize data preprocessing and profiling
                    - Examine data formats, feature naming conventions, data types and intervals, potential missing values
                    - Perform data distribution analysis on numerical and symbolic features.
                - Inspect mechanical systems in the lab, to verify their operational condition and suitability for the data collection timeframe
        - Sprint Schedule for November
            - 1st-15th:
                - Continue data preprocessing and profiling

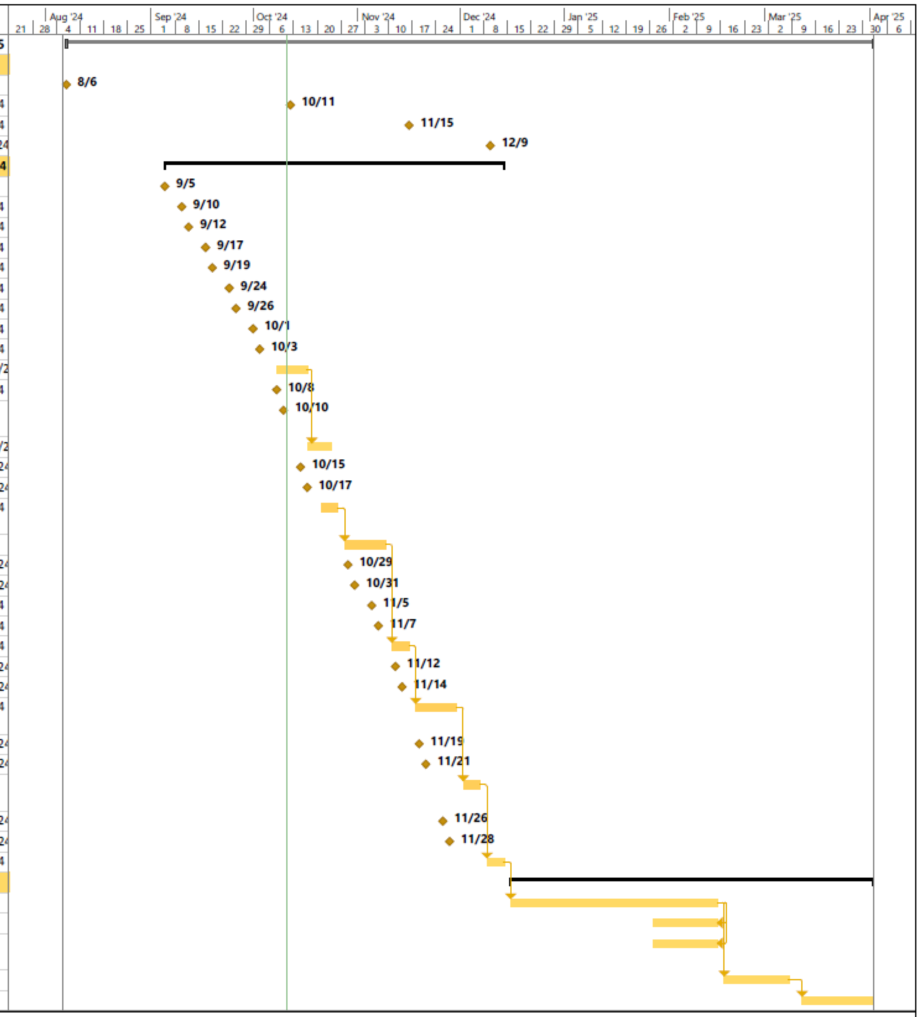
                - Implement correlation and significance tests and data preparation techniques to remove noise from dataset
                - Investigate if the objects and features in the raw dataset are valid, useful, high-enough quality for anomaly detection modeling
            - Compare historical data and recent weekly batch data for data consistency
            - Validate mechanical data features like pressure drops, airflow, and motor RPM. Identify and address inconsistencies that could affect predictive modeling for mechanical failure.
        - 16th-30th:
            - Continue data preprocessing and profiling
                - Evaluate metrics to flag and exclude anomalies from testing dataset for modeling purposes
                - Evaluate and address potential class imbalances through addition of new computed objects, class oversampling/undersampling
                - Select preliminary data mining and machine learning algorithms for model training
- **January-February: Model Training, Cross-Validation Testing, Iterative Fine-Tuning**
    - Include mechanical-specific metrics in the machine learning models, such as motor operating efficiency, vibration levels, and temperature gradients.
    - Ensure the model takes into account mechanical wear and tear patterns, predicting failures of parts such as belts, bearings, and heat exchangers
    - Develop initial ML models (such as logistic regression, decision trees, random forests, clustering, neural networks)
    - Train the models on the preprocessed dataset and evaluate model performance on test dataset through cross-validation and comparisons to baseline
- **March: Model Optimization, Model Deployment**
    - Fine-tune the model by adjusting hyperparameters and combining multiple learning algorithms if necessary
    - Deploy the model and training/testing datasets as a deliverable in a cloud workspace

C.3 Resources

The completion of this project will require various essential resources. Siemens will provide weekly data sets and a large historical data set, both of which will be pre-processed, mined, and analyzed to develop a training dataset for model development in Python. Libraries such as NumPy, Pandas, scikit-learn, Tensorflow, and Pytorch will be utilized for modeling. Additionally, the team is gathering construction documents to analyze the mechanical components currently installed, ensuring the model aligns with the real-world system. Meetings with Siemens will further aid in the integration of data and the decision-making process regarding the cloud data solution, which will be finalized based on cost considerations. Cloud service providers such as AWS and Azure will be utilized for large-scale data processing and model training. GitHub will manage version control and team collaboration. These resources ensure efficient progress toward the project’s deliverables.

Appendix 1: Project Timeline

ID	Task Name	Duration	Start	Finish
0	**Senior Design Project**	**170 days**	**Tue 8/6/24**	**Tue 4/1/25**
1	**Milestones**			
2	Team Contract	0 days	Tue 8/6/24	Tue 8/6/24
3	Project Proposal	0 days	Fri 10/11/24	Fri 10/11/24
4	Fall Poster Due	0 days	Fri 11/15/24	Fri 11/15/24
5	Preliminary Design Report Due	0 days	Mon 12/9/24	Mon 12/9/24
6	**Fall Semester**	**72 days**	**Thu 9/5/24**	**Fri 12/13/24**
7	Weekly Faculty Meeting	0 days	Thu 9/5/24	Thu 9/5/24
8	Weekly Student Meeting	0 days	Tue 9/10/24	Tue 9/10/24
9	Siemens Navigator Training	0 days	Thu 9/12/24	Thu 9/12/24
10	Weekly Student Meeting	0 days	Tue 9/17/24	Tue 9/17/24
11	Weekly Faculty Meeting	0 days	Thu 9/19/24	Thu 9/19/24
12	Weekly Student Meeting	0 days	Tue 9/24/24	Tue 9/24/24
13	Weekly Faculty Meeting	0 days	Thu 9/26/24	Thu 9/26/24
14	Weekly Student Meeting	0 days	Tue 10/1/24	Tue 10/1/24
15	Meeting with VCU Maintenance	0 days	Thu 10/3/24	Thu 10/3/24
16	Analyze Construction Drawings	7 days	Tue 10/8/24	Wed 10/16/2
17	Weekly Student Meeting	0 days	Tue 10/8/24	Tue 10/8/24
18	Meeting with Siemens Predictive Maintenance	0 days	Thu 10/10/24	Thu 10/10/24
19	Analyze HVAC Manuals	5 days	Thu 10/17/2	Wed 10/23/2
20	Weekly Student Meeting	0 days	Tue 10/15/2	Tue 10/15/2
21	Weekly Faculty Meeting	0 days	Thu 10/17/2	Thu 10/17/2
22	Initialize Data Preprocessing and Profiling	5 days	Mon 10/21/24	Fri 10/25/24
23	Continue Data Preprocessing	10 days	Mon 10/28/2	Fri 11/8/24
24	Weekly Student Meeting	0 days	Tue 10/29/2	Tue 10/29/2
25	Weekly Faculty Meeting	0 days	Thu 10/31/2	Thu 10/31/2
26	Weekly Student Meeting	0 days	Tue 11/5/24	Tue 11/5/24
27	Weekly Faculty Meeting	0 days	Thu 11/7/24	Thu 11/7/24
28	Validate Mehcanical Data	5 days	Mon 11/11/2	Fri 11/15/24
29	Weekly Student Meeting	0 days	Tue 11/12/2	Tue 11/12/2
30	Weekly Faculty Meeting	0 days	Thu 11/14/2	Thu 11/14/2
31	Continue Data Preprocessing and Profiling	10 days	Mon 11/18/24	Fri 11/29/24
32	Weekly Student Meeting	0 days	Tue 11/19/2	Tue 11/19/2
33	Weekly Faculty Meeting	0 days	Thu 11/21/2	Thu 11/21/2
34	Identify and Adress Mechanical Inconsistenceis	5 days	Mon 12/2/24	Fri 12/6/24
35	Weekly Student Meeting	0 days	Tue 11/26/2	Tue 11/26/2
36	Weekly Faculty Meeting	0 days	Thu 11/28/2	Thu 11/28/2
37	Prepare Initial Prototype	5 days	Mon 12/9/24	Fri 12/13/24
38	**Spring Semester**	**77 days**	**Mon 12/16/2**	**Tue 4/1/25**
39	Develop Initial ML Model	45 days	Mon 12/16/2	Fri 2/14/25
40	Train the Model	15 days	Mon 1/27/25	Fri 2/14/25
41	Ensure Model Takes into account Mechanical Wear &	15 days	Mon 1/27/25	Fri 2/14/25
42	Fine Tune Model	15 days	Mon 2/17/25	Fri 3/7/25
43	Deploy the Model	15 days	Wed 3/12/25	Tue 4/1/25



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Appendix 2: Team Contract (i.e. Team Organization)

Step 1: Get to Know One Another. Gather Basic Information.

Team Member Name	***Strengths each member bring to the group***	***Other Info***	***Contact Info***
Grant Forest-Collins	Analytical thinking, problem-solving, strong leadership skills, and project management experience	Experienced in mechanical engineering and project management, skilled in using software tools like AutoCAD and MATLAB, familiar with Lean Construction and OSHA safety standards. Involved in various extracurricular activities, including leadership roles in Omega Psi Phi Fraternity and The National Society of Black Engineers	forestcollgc@vcu.edu
Esha Sharma	Logical reasoning/problem-solving skills, research skills, strong skills/knowledge of software architecture and tools, effective at communication	Experienced in fundamental computer science, especially machine learning (pytorch, tensorflow), data science and NLP (sentiment analysis), fluent in Java, C, Python, SQL	esharma@vcu.edu
Daniel Gubay	Analytical thinking, problem-solving, Strong knowledge of high-level software concepts, ability to learn new coding languages	Strong in automation using tools like Ansible and Terraform. Experienced in fundamental computer science concepts.	gubaydd@vcu.edu
Jaime Gerardo Juarez	Creative design abilities, effective communication skills, hands-on experience with SolidWorks, and strong teamwork	Experienced in AutoCAD and managing construction projects. Active in SHPE, helping with leadership, networking, and community activities.	gerardojuajs@vcu.edu

Other Stakeholders	***Notes***	***Contact Info***
Daniel Cranston	CS Faculty Advisor	dcranston@vcu.edu
Joao Soares	MNE Faculty Advisor	jsoares@vcu.edu
Siemens, Kenneth Cossaboon		kenneth.cossaboon@siemens.com

Step 2: Team Culture. Clarify the Group's Purpose and Culture Goals.

Culture Goals	***Actions***	***Warning Signs***
Foster open communication and respect	Encourage team members to share their ideas and feedback freely in meetings and discussions. Use Discord/texting and in-person meetings to communicate	Team members becoming quiet or hesitant to share their thoughts Lack of responses to emails, messages Lack of attendance of meetings
Promote accountability and reliability	Set clear expectations and deadlines for tasks; follow up regularly on progress.	Missed deadlines and lack of updates on assigned tasks.
Encourage collaboration and teamwork Recognize and appreciate contributions	Plan regular check-ins and collaborative sessions to work together on tasks and projects Acknowledge individual efforts and successes in group meetings and via group communication.	Team members working in isolation without seeking input from others. Feelings of being undervalued or unnoticed within the team.

Step 3: Time Commitments, Meeting Structure, and Communication

Meeting Participants	***Frequency Dates and Times / Locations***	***Meeting Goals Responsible Party***
Students Only - Esha Sharma, Grant Forest-Collins, Daniel Gubay, Jaime Gerardo Juarez	As Needed, On Discord Voice Channel	Update group on day-to-day challenges and accomplishments (Esha will record these for the weekly progress reports and meetings with advisor)
Students Only	Every Tuesday at 5 pm in Engineering West Hall/ERB	Actively work on project (Esha will document these meetings by committing to Github with detailed commit messages, etc, then post on Discord and update Capstone Report)
Students + Faculty advisor - Esha Sharma, Grant Forest-Collins, Daniel Gubay, Jaime Gerardo Juarez, Daniel Cranston, Joao Soares	Every Thursday at 10 am-11am in conference room ERB4310	Update faculty advisor and get answers to our questions (Esha will scribe)
Kenneth Cossaboon, Byron Burns, Students, Faculty Advisor	Monthly meetings on Thursday at 10 am in conference room ERB4310	Update project sponsor and make sure the team is on the right track (Esha will scribe; Daniel will present prototype so far)

Step 4: Determine Individual Roles and Responsibilities

Team Member	***Role(s)***	***Responsibilities***
Esha Sharma	Group communication /Scribe	✔ Keep a detailed record of meeting notes and share with group ✔ Record notes for weekly progress reports and meetings with advisor ✔ Write detailed commit messages for Github, etc, then post on Discord and update Capstone Report
Daniel Gubay	Test Engineer	✔ oversees experimental design test plans, procedures, and data analysis ✔ establishes test protocols and schedules ✔ leads presentation of experimental findings and resulting recommendations.

Grant Forest-Collins	PM	Manages all tasks; develops overall schedule for project; writes agendas and runs meetings; reviews and monitors individual action items; creates an environment where team members are respected, take risks and feel safe expressing their ideas. Required: On Edusourced, under the Team tab, make sure that this student is assigned the Project Manager role. This is required so that Capstone program staff can easily identify a single contact person, especially for items like Purchasing and Receiving project supplies.
Jaime Gerardo Juarez	Financial Manager	✔ Handle all team purchase requests ✔ Monitor and track teams budget ✔ Ensure spending stays within allowed amount ✔ Assist in decision making for new acquisition ✔ Support team as needed

Step 5: Agree to the above team contract

Team Member: Esha Sharma *Signature: Esha Sharma*

Team Member: Daniel Gubay *Signature: Daniel Gubay*

Team Member: Grant Forest-Collins *Signature: Grant Forest-Collins*

Team Member: Jaime Gerardo Juarez *Signature: Jaime S Gerardo Juarez*

References

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