LeakLink

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***Abstract*—** LeakLink is a user-controlled robotic system that is used for non-destructive inspection of horizontal, metallic, HVAC ducts. Instead of manual inspection, cameras, or pressure drop tests to inspect functionality of HVAC ducts, our system collects the acoustic signature of the duct using ultrasonic sensors paired with a machine-learning model with defect classification to correctly identify corrosion and cracks. LeakLink can navigate ducts as small as 120mm wide while navigating 90° turns and inspecting up to 60m per deployment. LeakLink's system allows for a 90% or greater defect detection accuracy and more than a 25dB signal to noise ratio. LeakLink brings a new angle to HVAC duct inspection by providing an automated, localized precision solution, allowing for safer, and more reliable defect detection in ducts.

***Index Terms*—** Acoustic Emission Sensor, Duct Inspection, HVAC Robotics, Leak Detection, Machine Learning, Non-Destructive Testing, Robotic Localization

I. Introduction

Civil engineers and heating, ventilation, and air conditioning (HVAC) technicians are responsible for maintaining safe and functioning systems in commercial buildings, hospitals, laboratories, and industrial facilities. Ductwork, especially in buildings like hospitals, should routinely be inspected to prevent structural degradation and safety hazards. When it comes to HVAC ducts, undetected corrosion, cracks, and air leaks can lead to worse damage over time, eventually compromising the entire system. Right now, the most common method is manual inspection, where engineers have to crawl into small spaces with minimal vision. There is a growing need for automated inspection methods that are safe, minimally invasive, non-damaging, and operable in confined spaces.

Civil engineers and HVAC technicians face significant challenges when inspecting pressurized ductwork. Manual inspections of disassembled HVAC ducts is time-consuming and require the shutdown of surrounding areas. As a result, these inspections are usually performed only when the defects have reached late stages and have caused irreparable damage. An alternative to this procedure is installing cameras within the ducts for constant monitoring. However, the cameras are unreliable in detecting defects as they rely on visual cues which develop in late-stage deformation. In addition, the cameras themselves require an amount of maintenance and are only accessible when the ducts are disassembled. Another alternative inspection method is manually tapping the duct to excite the material and listening for the acoustic signature. This is time-consuming and requires a highly trained ear, which many technicians may not have.

LeakLink overcomes the restrictions that methods like pressure drop testing, which can only inform you of the presence of a leak without localizing it, and camera-based systems by leveraging acoustic excitation and machine learning to not only detect but localize and classify various early-stage defects. LeakLink can navigate ducts as small as 120mm wide while navigating 90° turns and inspecting up to 60m per deployment. LeakLink's system allows for a 90% or greater defect detection accuracy.

In this paper, the proposed solution is an autonomous robot that maneuvers through HVAC duct systems and detects corrosion and cracks with their locations using the acoustic signature of the ducts. The robot moves through the duct and stabilizes itself at different points within the duct and captures the acoustic response with ultrasonic transmitter and receiver sensors. Then, the acoustic data is processed onboard to detect and log potential defects. By enabling precise, data-driven inspections in areas that were previously inaccessible, LeakLink has the potential to transform how engineers maintain and safeguard critical infrastructure.

II. Use-Case Requirements

Our use-case requirements were designed with the goal of creating a robotic inspection system that makes defect detection in ducts accurate, accessible, and at a lower cost than existing automated solutions. The requirements we have defined for LeakLink ensure that our inspection robot provides reliable technical performance while catering to the existing needs of Civil and HVAC Engineers. We divided our use-case requirements into five key sections as described below. It is important to note that LeakLink should have an overall cost of under $600 to manufacture.

A. Operational Environment Requirements

This project focuses on galvanized steel HVAC duct systems because they are the most common systems amongst residential, corporate, and industrial buildings and are heavily standardized for the convenience of civil engineers and architects. Since the robot must operate within a duct system, the robot must execute non-destructive inspection and navigate a low visibility environment. As such, there are strict size and weight requirements based on the smallest standard sizes and load capabilities of HVAC ducts. The robot must be less than 15 pounds and less than 12 inches in width.

B. Mobility and Traversal Requirements

The speed of the robot must be 0.1 to 0.2 m/s based on standard speeds of robots with the size requirements stated previously. In addition, in order for the robot to collect the acoustic signatures of ducts, the motor vibrations must not interfere with the collection process. Therefore, the robot must operate at a minimum speed. The speed of the robot must be 0.1 to 0.2 m/s based on standard speeds of robots with the size requirements stated previously. In addition, in order for the robot to collect the acoustic signatures of ducts, the motor noise must not interfere with the collection process. Therefore, the robot must operate at a minimum speed. The robot must be able to traverse 60 meters or more during inspection as well as make 90° turns in order to follow the duct. HVAC duct systems may be longer than 60 meters, however, they have access points every 30 to 50 meters. Therefore, in an ideal scenario, the user can insert the robot into the duct via one of the access points, the robot can inspect the duct section and make its way to the next access point, at which the robot can be retrieved.

C. Power and Runtime Requirements

The robot must have a battery life of at least one hour based on the speed and inspection range. In addition, the acoustic signal processing and machine learning (ML) model classification will run on board the robot, so the robot must have enough battery to collect, process, and classify the data. Overall, the system should sustain continuous operation during the one-hour inspection period without performance degradation. The power should support high-frequency acoustic sampling and onboard interference.

D. Defect Detection Requirements

In terms of the classification, the minimum internal surface corrosion area that the robot should detect is 75 cm². The minimum crack length that the robot should detect is 4 mm. These measurements are based on the early-stage detection measurements of corrosion and cracks. The robot must be able to detect defects in the early stage so that the system can prevent irreparable damage. The system must be able to detect these defects in the early stage with 90% accuracy. The acoustic sampling window should exceed 100ms to account for material ring-down time, and the sampling density should be at least one tap every 10cm. This accuracy is based on current ML models that focus on using acoustic emissions for structural health monitoring, although these models have not specifically targeted HVAC duct systems. The target localization accuracy is 5 cm positional error, which is based on the early-stage defect measurements described above as well as the current capabilities of using acoustic emissions to detect defects.

III. Architecture and/or Principle of Operation

As the minimum viable product (MVP) for our project, LeakLink should be able to maneuver through HVAC ducts, capture the acoustic signal with an acoustic emission (AE) sensor, classify the structural defect using an onboard machine learning model, and make contact with the duct using a solenoid tapper to notify the user that a defect was found. Throughout the inspection process, LeakLink will follow a repeated cycle of moving, stopping in 10cm increments, stabilizing, recording the acoustic signals, and processing the data in the machine learning model, eventually outputting the type of defect on the monitor to the user and tapping the walls of the duct at the defect location.

The raw acoustic data is a waveform of voltage values over time. From this waveform, we will collect the peak-to peak, RMS, and statistical features such as standard deviation and kurtosis. Then, we will use the fast Fourier Transform to obtain the frequency domain data. From this, we will obtain the angular frequency, mean frequency, mean frequency power, and frequency window. The embedded control system allows for real-time interaction between mobility of the robot, acoustic sensing, and computation. A Teensy microcontroller will handle motor control, and solenoid actuation. A Jetson Orin Nano will be the high level controller of the system and will perform high-level signal processing and machine learning. Our system integrates embedded systems, signal processing, machine learning, and system level software.

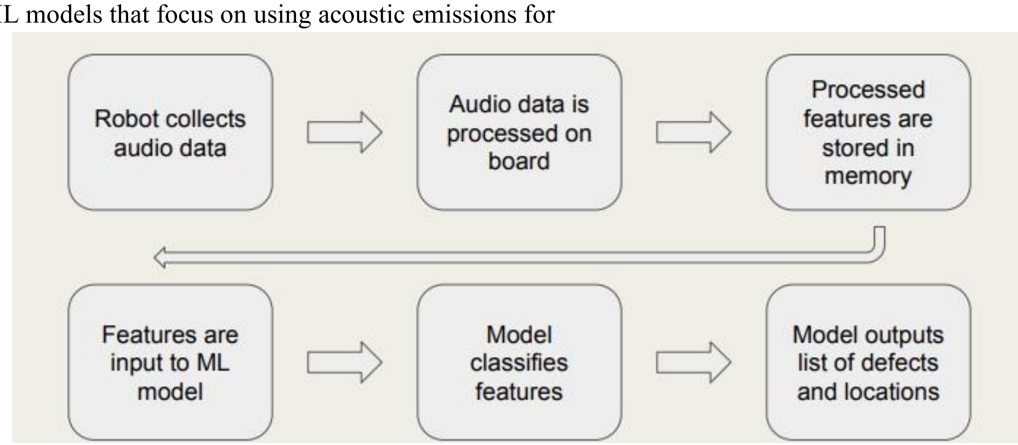

Figure 1. Full model functionality of LeakLink Robot

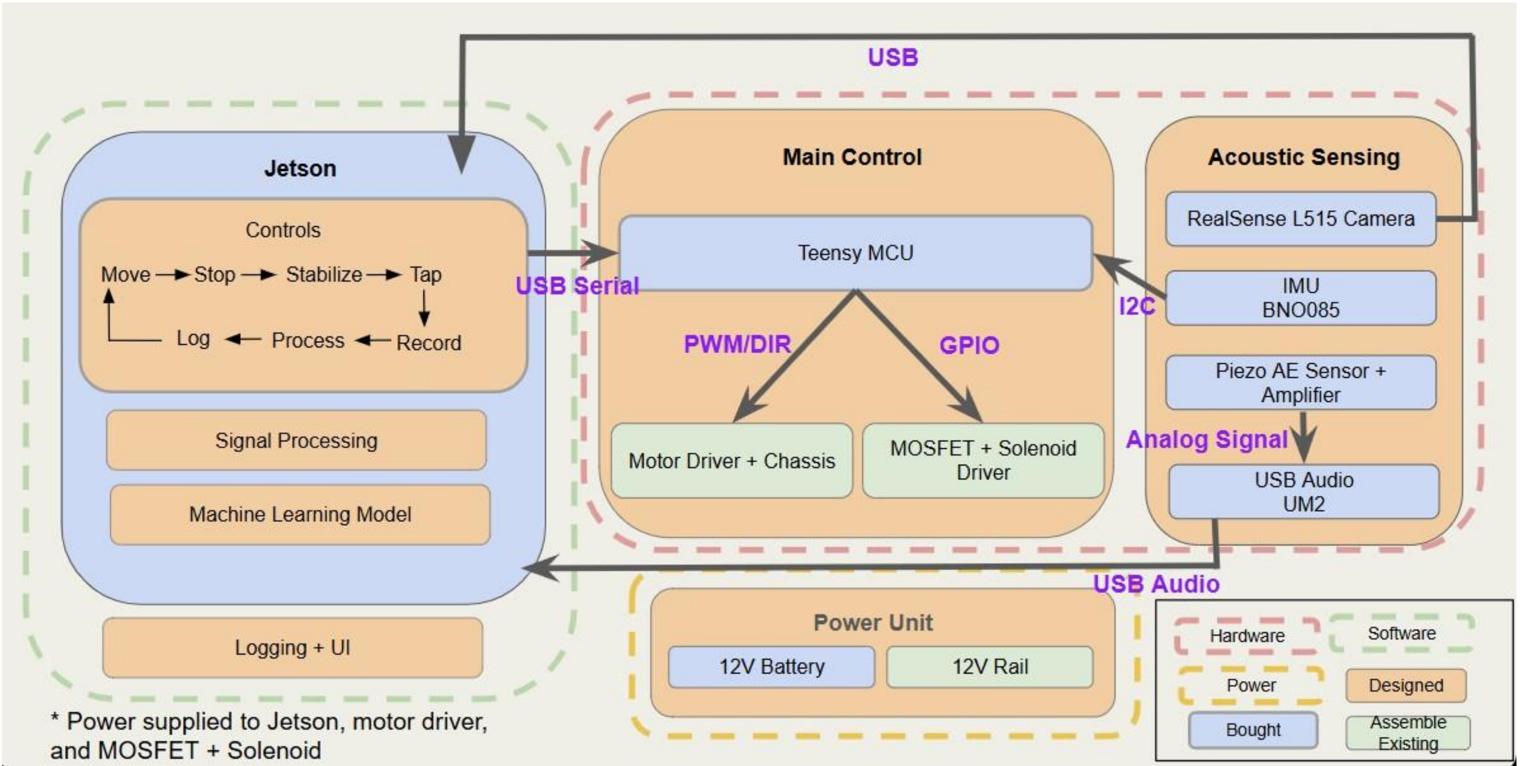

Figure 2. Full system and hardware architecture plan

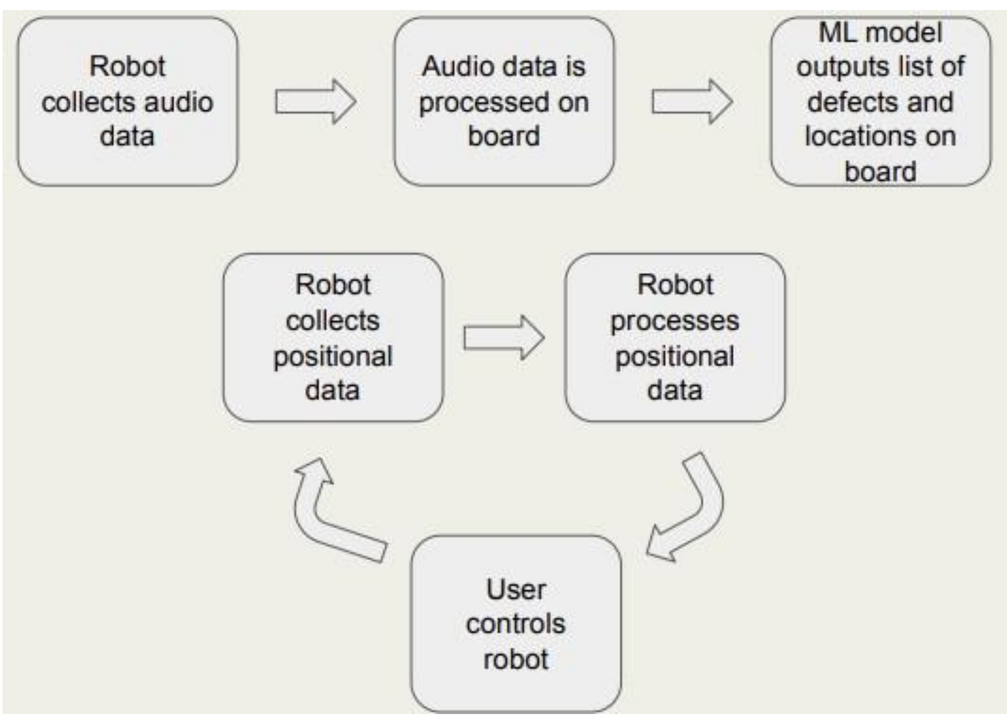

Figure 3. Diagram showcasing user interaction with system and learning model pipeline

IV. Design Requirements

LeakLink should operate inside HVAC ducts while navigating horizontal distances with turns and perform defect detection without causing damage to the duct system. Here, we translate those requirements into design specifications across various subsystems. We have split our design requirements into five main sections as shown below.

A. Mechanical Specifications and Duct Navigation

Our robotic system should be able to operate inside ducts and be retieved through access points or the entry point. Overall, the robot mass should be less than 15 pounds to ensure the robot can navigate through the ducts without causing structural damage. The robot's maximum width should be under 12 inches to fit in standard ducts, allowing for 90 degree turns. The robot should also be designed in such a way that all of its components don't cause damage to the HVAC ducts.

B. Mobility, Navigation, and Turn Performance

Our robotic system should traverse 60m sections of a HVAC duct and navigate 90 degree turns while ensuring acoustic signal measurements are accurate. The robot must maintain a speed within 0.1-0.2 m/s in straight ducts to correctly collect data and allow for precision sampling of data. While collecting acoustic data, the wheels of the robot and speed should be 0 m/s. We will be enforcing a policy where the robot stops before collecting acoustic emission data. This ensures little noise interference when collecting data. The robot should also be able to turn at 90-degree angles with a turn success rate exceeding 90% and a final heading error within +/- 10 degrees. The robot should also traverse 60-meter distances, consistent with standard HVAC duct access points distance metrics. The mobility and navigation requirements are important because acoustic emission signatures are sensitive to outer noise and vibrations so the robot must be as still as possible during data collection.

C. Acoustic Excitation and Timing

Our robot must stabilize itself and collect reliable audio data to detect and classify defects. The robot should collect a 200-point voltage waveform every 10cm of travel through the duct to meet the required sampling density. The time to stabilize the robot must be greater or equal to 15 seconds based on observations made during the testing phase. All these requirements must be consistent to allow for specific recording alignment. The sampling rate of our system must be greater than or equal to 80 kHz which accounts for the Nyquist frequency, ensuring that we can correctly detect frequencies below 40 kHz without aliasing. The signal to noise ratio should be greater than 25dB and the amplifier must provide sufficient gain to lift AE signals.

D. Defect Detection and Classification Performance

LeakLink should detect a corrosion with internal surface area of greater than or equal to 75 cm^2. The system should also detect cracks with a minimum length of 4mm. The onboard classifier and machine learning model should achieve at least 90% accuracy, and the system should seek to limit false negatives for safety-critical defects. The system should report a defective location with no more than 5cm absolute position error and it should maintain this during its one hour of operation timing. The absolute location error is especially important since HVAC technicians operating the robot should then be able to successfully find the defect and correct it.

E. Power and Runtime

Our robot should operate long enough to cover our inspection range of 120m while powering our entire mechanical embedded system, acoustic sensing, and machine learning model. The full system should operate for at least an hour. The power subsystem, because of this requirement, should provide power rails for the motors and the solenoid. The battery will be a 19V battery. The onboard compute platform should support real time feature extraction and classification. A 19V battery will allow for sufficient division of power across all the parts of our robot while satisfying runtime requirements.

V. Design Trade Studies

Our design trade studies explore the three main areas in our project: Hardware, Signals and Systems, and Software.

A. Piezoelectric Transducer

A piezoelectric transducer can function in both transmit and receive modes, converting electrical pulses into ultrasonic mechanical waves and returning echoes back into electrical signals. In an active implementation, the system drives the piezo element with a high voltage, then uses a receiver to receive the acoustic echo. This approach enables precise defect localization and thickness measurement but requires careful analog front-end design, impedance matching, and protection circuitry to separate transmit and receive paths. In a passive acoustic emission configuration, the piezo element acts only as a receiver, listening for stress-induced ultrasonic emissions generated naturally by crack propagation or corrosion. This reduces excitation hardware complexity and power consumption but depends heavily on signal amplification and noise filtering, since HVAC environments can introduce mechanical and airflow noise. After careful experimentation with both approaches, we decided to use the active approach. The amount of power consumed by the active approach is minimal compared to the added precision of classification we reached.

B. Microphone vs. Acoustic Emission (AE) Sensor

Microphones will pick up additional noise, so we have opted for an AE sensor. Since AE sensors operate in ranges greater than 20kHz, the AE sensors will filter a lot of the surrounding noise that may be in the duct. Below, in (2), we define signal to noise ratio (SNR). Our SNR requirement is that it should be greater than 25dB. An AE sensor satisfies our requirements whilst ensuring little noise for signal integrity.

$$SNR = 10\log10(P_{signal} \div P_{noise}) \quad (2)$$

C. Microphone vs. Acoustic Emission (AE) Sensor

At first, the design for the acoustic data collection was to use a solenoid tapper to excite the wall of the ducts. In this design, a microphone mounted on the robot would collect each impulse response. However, these responses would be short and extremely vulnerable to being corrupted by noise within the ducts. Therefore, we decided to look into academic research on collecting acoustic signatures for structural health monitoring. From this literature review, we quickly realized that all of the studies use acoustic emission (AE) sensors.

An AE sensor is a transducer, typically using a piezoelectric element, that detects high-frequency, inaudible ultrasonic waves generated by structural, localized stress changes within materials, such as corrosion and crack growth. These sensors convert transient mechanical energy into electrical signals, serving as a key non-destructive testing tool to monitor structural integrity and detect failures before they occur in real-time. The acoustic emission data collected by these sensors offer more meaningful information on defect detection.

From the response, we would be able to extract more features than we would from a single audial impulse. These sensors are also less vulnerable to corruption via noise than a microphone attempting to record the sound of a tap. Hence, we began looking into different AE sensors to use. To begin the search for an AE sensor, we referred to the academic studies using acoustic signatures for structural health monitoring. The sensors used in these studies are extremely precise, however, they are also extremely expensive and fragile. These sensors would not have been able to be mounted on a moving robot to collect data in a duct. Therefore, we had to turn to cheaper, more robust AE sensors. We were able to find a piezoelectric ultrasonic transducer on Amazon that was within our price range and robust.

D. Software

The two primary classification architectures we considered were a Convolutional Neural Network-based model and a Support Vector Machine-based model. CNNs are commonly used in acoustic emission analysis because they can automatically learn hierarchical feature representations directly from raw time-series signals or time–frequency representations such as spectrograms. In structural health monitoring applications, CNNs have demonstrated strong performance in identifying crack growth and corrosion progression due to their ability to capture localized temporal and spectral patterns. However, CNNs require larger labeled datasets to achieve reliable generalization. Given that we will be making our own dataset and thus may have dataset size constraints, we chose to begin with an SVM-based system. SVMs perform well on smaller, structured feature sets and allow us to explicitly control feature engineering in both the time and frequency domains. Additionally, SVMs are easier to tune, faster to train, and more computationally efficient for onboard inference.

In designing the user interface for civil engineers, we initially considered developing a real-time spatial mapping visualization that would display detected defects along the HVAC duct layout. While this approach could provide an overview of inspection results, it introduces additional complexity in localization accuracy, mapping calibration, and visualization infrastructure. Instead, we decided to implement a more direct and reliable feedback mechanism: whenever corrosion or a crack is detected, the robot will pause and perform a distinct tap sequence to notify the civil engineer immediately. This auditory alert system provides intuitive, real-time confirmation of defect detection without requiring continuous screen monitoring. This user interaction will create an actionable notification method that aligns with traditional manual HVAC engineer inspection practices.

Below, in table I, is a summary of design tradeoff choices made where hardware is concerned. We eventually landed on using Jetson Nano for onboard ML processing capabilities.

TABLE I. HARDWARE TRADEOFFS

Component	***Advantages***	***Disadvantages***
Simple passive AE Sensor	Simple electronics and low power	Less control over how much excitation is generated
Microphone	Easy to implement and collect direct audio data	Generates noisy data
STM32 Architecture	Low power Simple Real-time Control Low Cost	Limited RAM Cannot easily run FFT Cannot do advanced ML on board Cannot have real time logging
Jetson Nano Architecture	Can run FFT Can support ML onboard Easier to debug	Needs higher power Costs more

VI. System Implementation

A. Acoustic Sensing Subsystem

Acoustic emission (AE) sensors are commonly used as a passive structural health monitoring (SHM) approach. These sensors detect elastic waves generated by damages in structural components, such as corrosion and cracks. In this project, a piezoelectric AE sensor is used because it fulfills the use-case requirements of non-destructive detection of early-stage defects and remains within the budget limitations. The sensor used in this project detects up to 40 kHz, therefore this sensor is paired with a pre-amplifier.

We used transmitter and receiver ultrasonic to output an ultrasonic wave and collect the echo of the wave bouncing back from the galvanized steel duct. This amplified analog signal will be digitized by an ADS1220 and transmitted to the Jetson for processing in the machine learning system.

B. Solenoid Tapper Localization Subsystem

The solenoid tapper is driven with a N-channel MOSFET and the GPIO trigger from the Teensy MCU. The solenoid tapper is attached to the chassis so that it taps against the duct wall, but it will also make sure that the tapping is dampened to make sure it does not cause any structural damage. The solenoid tapper will be instructed to tap the duct if the classification model states that a defect is present.

C. Robot Mobility Subsystem

The robot moves using a wheeled chassis with a motor driver that is controlled by the Teensy MCU which is controlled by the Jetson. The Teensy MCU will make sure that the motors on the chassis move the robot forward, stop before tapping, and will control the motors to make 90 degree turns. The motors are attached to a chassis which contains the Jetson nano and all other system components.

D. Embedded Subsystem

The embedded subsystem essentially contains a Teensy 4.0 MCU and the NVIDIA Jetson Orin Nano. The Teensy MCU is what drives the motors and the solenoid actuator. The MCU we are using interfaces with the Jetson through USB serial communication. On our NVIDIA Jetson Orin Nano, we deal with the acoustic signals, feature extraction as well as the machine learning, data logging, and the overall user interface.

E. Power Subsystem

The robot is powered by a 12V ($LifePO_4$) battery which allows for enough energy to power the robot for 1 hour. We will regulate the power distribution ensuring that 12V are given to the motors and solenoid and that 19V are provided for the Jetson. We will use 5V and 3.3V rails for the MCU and the sensors we use in our system.

F. Systems

The signals captured by the AE sensor were 200-point voltage waveforms that needed to be processed into different features to input into the SVM classification model. The features were initially chosen based on a literature review of papers using AE signals for SHM. For instance, the peak-to-peak amplitude is the distance between positive and negative peaks of the signal. High peak-to-peak can indicate corrosion and a significant jump or “peak” in the signal can indicate the presence of a crack. In addition to the peak-to-peak amplitude, the chosen time domain features include the max peak value and root-means-square (RMS) energy level. The standard deviation, skewness, and kurtosis were selected as statistical analysis features. Kurtosis of a signal measures the "tailedness" of its distribution, helping to identify peaks and transients. This can indicate the presence of corrosion by measuring the "peakedness" or impulsiveness of vibration signals (May et al., 2021). In addition, since small cracks produce impulsive, non-periodic impacts, they cause sharp, sporadic spikes in vibration data, significantly increasing the kurtosis value even when the overall RMS energy level remains low (Quick, Denecke, & Schmidt, 2025).

However, many features were added or removed during the data collection process as we became aware of our distinct acoustic data. For example, the spike count was added as a feature since the count differed between healthy duct data and corroded duct data. Although peak-to-peak values were used as a feature in academic studies, there was not enough of an overall difference between the peak-to-peak values of defect and healthy acoustic data, therefore, we removed this feature so as not to confuse the ML model.

G. Software

The software subsystem is built around three main goals: detecting defects, determining their locations, and clearly communicating those results to the civil engineer. To detect defects, we frame the problem as a supervised classification task. After the robot comes to a complete stop and stabilizes itself, the acoustic emission signal is recorded and first processed to improve signal quality. This includes bias correction to center the waveform around zero and denoising techniques to reduce electrical interference and environmental disturbances inside the duct. Once the signal is cleaned, we extract meaningful features from both the time domain and the frequency domain. Time-domain features such as RMS energy, skewness, and kurtosis help capture the intensity and impulsiveness of the response. These features are combined into a structured feature vector and passed into a multi-class Support Vector Machine classifier trained on labeled examples of healthy ducts, corrosion, and cracks from our custom-built dataset. Because the model runs onboard the robot, it then generates a prediction immediately after each tap, enabling near real-time defect identification during inspection.

Finally, the user interface is designed to present results in a way that is intuitive and actionable. Instead of overwhelming the civil engineer with raw waveform plots or technical signal metrics, the system translates complex acoustic analysis into clear defect labels and associated positions. In addition to on-screen feedback, we incorporate a tapping-based alert mechanism: whenever corrosion or a crack is detected, the robot pauses and performs a distinct tap sequence. This provides immediate confirmation of a defect without requiring constant visual monitoring. By combining automated classification, spatial tagging, and straightforward feedback, the software subsystem supports a more efficient, data-driven inspection process while keeping the user experience simple and practical.

VII. Test, Verification and Validation

A. *Tests for Machine Learning Model Accuracy*

The baseline design specification for the classification subsystem is a multi-class Support Vector Machine (SVM) trained to distinguish between two classes: no defect and defect. We used to have three classes and separated between corrosion and crack, but because corrosions and cracks usually exist within the same area, they are not differentiable. This has no effect on our ability to meet our user requirements, since the user only needs to know that a defect is present to decide which ducts to replace. To verify that the model satisfies the quantitative requirement of at least 85% classification performance, we conducted structured validation using supervised evaluation techniques. The collected acoustic emission dataset was divided into training, validation, and testing splits, and five-fold cross-validation was performed to assess generalization across different duct segments. Performance was measured using precision, recall, overall accuracy, and confusion matrix analysis. The subsystem is verified since precision and recall both exceed 85%.

```
Classification report:
              precision    recall  f1-score   support

      no (0)       0.89      0.89      0.89         9
     yes (1)       0.89      0.89      0.89         9

    accuracy                           0.89        18
   macro avg       0.89      0.89      0.89        18
weighted avg       0.89      0.89      0.89        18

Train CV accuracy : 0.930
Test accuracy     : 0.889
```

Figure 4. Classification report of trained SVM

The Receiver Operating Characteristic (ROC) curve demonstrates strong classification performance for the defect detection subsystem, with an Area Under the Curve (AUC) of 0.96. This indicates a high degree of separability between defect and no-defect classes, meaning the model can reliably distinguish between the two across a range of decision thresholds. The curve rises steeply toward the upper-left corner, showing that high true positive rates can be achieved while maintaining relatively low false positive rates. This behavior is particularly important for the application, as it suggests the system can effectively identify defects without excessively flagging healthy duct segments. While the step-like shape of the curve reflects the limited size of the dataset, the overall trend supports that the classifier meets and exceeds the required performance threshold, reinforcing its suitability for deployment in real-world HVAC inspection scenarios.

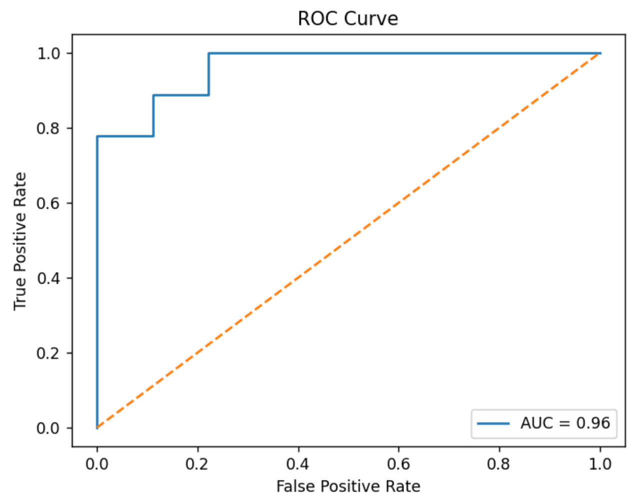

Figure 5. ROC Curve

Because inference is performed onboard the NVIDIA Jetson Orin Nano, real-time performance testing was required. We benchmarked total processing latency, including feature extraction and model inference time. The complete pipeline from solenoid tap to classification output executed within 500 milliseconds to maintain inspection speed requirements. Additionally, localization validation was performed by comparing predicted defect positions to ground truth measurements. The system is able to detect defects on board the robot with 85% accuracy, which was measured by repeatedly running the robot through the duct system and tabulating the results. We completed this test 20 times and the robot was successful 17 out of 20 times.

B. *Tests for HVAC Operability*

During system-level testing we will focus on making sure the fully integrated robot can actually operate in real HVAC environments. We begin by verifying the physical constraints of the system. The assembled robot was measured to ensure it fits within the 12-inch width and height limits and remains under 6 pounds, allowing it to safely travel through standard ductwork. The actual dimensions of the robot are 5.8-inch width, 6.8-inch depth and 5.5-inch height. The actual weight of the robot is 5 pounds. We also tested turning capability by driving the robot through a 90-degree duct elbow. The robot was able to complete turns within 10 degrees of a true 90-degree rotation and achieve at least 85% reliability when performing these turns. This ensured that the robot can realistically navigate duct layouts without getting misaligned or stuck.

To validate runtime and inspection coverage, we operated the robot continuously at its designed speed of 0.1 to 0.2 meters per second using a fully charged 12V LiFePO4 battery. During this test, we confirmed that the robot can travel at least 60 meters and operate for at least one hour without shutting down. At the same time, we logged power consumption from the motors, microcontroller, and onboard processor to verify that our battery capacity calculations were accurate. Sampling density is another critical requirement, so we tested whether the robot consistently performs one tap every 10 centimeters during traversal.

Finally, we tested safety and recovery mechanisms. By simulating microcontroller freezes and communication loss, we can verify that the watchdog timer properly resets the system and that the robot defaults to a safe extraction protocol by reversing toward its entry point. These tests help ensure that the robot is not only accurate and efficient, but also reliable and safe in real-world operating conditions.

Category	Test Performed	Requirement	Measured Result
Physical Constraints	Robot dimensions and weight verification	≤ 12 in (W,H), ≤ 6 lb	5.8 × 6.8 × 5.5 in, 5.0 lb
Navigation	90° duct elbow traversal	Accurate turning	±10° of 90°, ≥ 85% reliability
Runtime	Continuous operation at nominal speed	≥ 1 hour runtime	≥ 1 hour achieved
Coverage	Distance traveled and sampling rate	≥ 60 m, 1 tap / 10 cm	≥ 60 m, consistent 10 cm sampling
Power Validation	Power logging during operation	Mat[illegible]attery estimates	Matches expected consumption
Safety & Recovery	Fault simulation (freeze, comm loss)	Safe recovery behavior	Watchdog reset + reverse to entry confirmed

Table 2: HVAC Operability Results

VIII. Project Management

This section describes our project schedule, team member responsibilities, bill of materials with budget and risk mitigation plans for our LeakLink Inspection Robot.

A. Schedule

The project schedule follows a structured, phased development process aligned with the updated Gantt chart. The first phase focuses on hardware acquisition and assembly, including integrating the acoustic emission sensor, solenoid tapper, embedded controllers, and power distribution system. Once hardware components are assembled, the second phase prioritizes embedded controls implementation. This includes motor PWM control, solenoid triggering, and establishing USB serial communication between the microcontroller and onboard computing platform. The third phase centers on data collection and model development. During this stage, supervised acoustic emission data will be collected from healthy and artificially damaged duct segments. Signal preprocessing, feature extraction, and SVM training will be conducted iteratively to optimize classification performance. The final phase consists of full system integration and validation. The trained model will be deployed onboard, and the complete robot will undergo performance, accuracy, and stress testing to ensure all quantitative requirements are met. This phased structure reduces integration risk by validating each subsystem prior to final deployment.

B. Team Member Responsibilities

Our team responsibilities are structured around each member's strengths, allowing us to move efficiently while building a highly integrated and forward-looking system. Adithi will lead hardware integration, ensuring all physical components are properly connected, validated, and ready for system-level operation. Adithi will also lead embedded systems development alongside Mahati, focusing on motor control logic, solenoid driver implementation, and ensuring that all real-time control constraints are satisfied to guarantee precise and reliable movement, stabilization, and tapping actions within the confined duct environment. Rayann will lead acoustic signal processing, extracting meaningful time and frequency-domain features from raw audio data captured during inspection.

Mahati will also lead the machine learning subsystem alongside Rayann, developing the preprocessing pipeline, training and optimizing the SVM classifier, deploying the trained model onto the embedded platform, and designing experimental validation procedures to measure system performance.

C. Bill of Materials and Budget

Our table of bill of materials as well as the budget can be found at the end of this document in Figure 4.

D. TechSpark Use Plan

TechSpark facilities supported mechanical fabrication and hardware prototyping. The facility will be used for precision cutting to simulate cracks, milling partial wall notches, 3D printing sensor mounts and chassis brackets, soldering electrical connections, and performing mechanical adjustments during integration.

B. Risk Mitigation Plans

Several risks have been identified and addressed proactively. If classification accuracy falls below 85%, mitigation strategies include expanding the dataset, tuning SVM hyperparameters, or evaluating alternative models such as Random Forest classifiers or lightweight neural networks. Environmental noise interference will be mitigated through improved signal shielding, refined denoising filters, and maintaining a minimum signal-to-noise ratio threshold of 25 dB. If battery capacity proves insufficient, power optimization techniques or higher-capacity battery solutions will be considered.

Mechanical risks, such as the robot becoming lodged inside a duct, are mitigated through watchdog timers and a programmed reverse-extraction protocol. Sensor fragility is addressed through protective mounting and vibration isolation. Special attention is given to minimizing false negatives, as undetected defects pose greater long-term infrastructure risk than false positives. The system is therefore tuned conservatively to favor detection sensitivity while maintaining acceptable precision.

IX. Ethical Issues

LeakLink may fail in several critical ways, most notably through false positives (detecting defects that do not exist) and false negatives (failing to detect defects that are present). Additional failure modes include mobility limitations and sensing inaccuracies, both of which could impair the system's effectiveness in real-world environments.

False positive detections could lead HVAC technicians to spend unnecessary time disassembling ductwork or recommending costly replacements that are not needed, resulting in avoidable economic burdens for system owners. Conversely, false negatives pose more serious risks, as undetected defects may lead to poor air quality, reduced ventilation efficiency, or even structural degradation within the duct system. These issues could adversely affect occupants, particularly individuals with respiratory conditions, and may increase the risk of harm in cases of material failure.

Mobility or sensing failures could further reduce system reliability and may prompt technicians to seek manufacturer support or reimbursement. However, a broader concern with autonomous or semi-autonomous systems is the potential for user overreliance. If HVAC technicians begin to place undue trust in LeakLink's outputs without sufficient verification, system errors may go unnoticed, compounding their impact over time.

Such risks highlight the importance of maintaining human oversight. While LeakLink is designed to assist rather than replace HVAC technicians, accountability in the event of system failure may be complex. Responsibility may reasonably be shared between the system manufacturer and the technician operating the device. Establishing clear expectations for system use, along with emphasizing the necessity of human validation, is essential to ensuring safe and effective deployment.

X. Related Work

Structural Health Monitoring and AE sensing has been widely studied in civil and mechanical engineering applications. There are several studies from Oxford University as well as NASA which utilize AE sensors to detect cracks in structures such as bridges and pipes. In the context of HVAC systems, most approaches do rely on manual inspection or cameras so till date, there has not been a lot of robotic systems that utilize AE sensors. However, there have been robotic systems that utilize cameras for defect detection. LeakLink is different because it is a robot designed specifically for HVAC applications while using AE sensors and real time machine learning, something, as far as our research leads us to believe, that has not been done before.

XI. Summary

LeakLink is ultimately a user-controlled inspection robot designed for defect detections, specifically corrosions and cracks in galvanized metallic HVAC duct systems. The system integrates acoustic emission sensing, onboard signal processing, and machine learning and classification methods, as well as robotic localization to provide an alternate defect detection mechanism when compared to original methods. The primary impact is to civil and HVAC engineers as it will lower the risk involved with inspection, and provide a cost-effective, time-efficient, and reliable solution to enhance infrastructure safety. Some challenges we faced were ensuring a sufficient SNR in HVAC environments and achieving realistic and reliable localization, however with our embedded system design, LeakLink will prove to be a scalable solution for modern HVAC structural health monitoring.

A. *Future Work*

Future work for LeakLink will focus on improving system robustness, expanding operational capabilities, and enhancing the accuracy and generalizability of defect detection. While the current system demonstrates strong performance, several opportunities remain to further refine both the hardware and software components.

On the hardware side, future iterations could improve mobility and adaptability to more complex duct geometries. Although the current design supports ducts as small as 120 mm in width and can navigate 90° turns, additional work is needed to handle vertical transitions, irregular cross-sections, and obstacles such as dampers or debris. Enhancing locomotion mechanisms and incorporating adaptive suspension or modular configurations could allow LeakLink to operate in a wider range of HVAC systems. Battery life and power efficiency may also be optimized to extend inspection range beyond the current 60 m per deployment.

From a sensing perspective, integrating complementary modalities could significantly improve reliability. While ultrasonic acoustic sensing provides strong performance, combining it with additional techniques—such as vibration analysis, thermal sensing, or visual inspection—could enable sensor fusion approaches that reduce false positives and false negatives. Improving sensor placement and shielding may also further increase the signal-to-noise ratio beyond the current 25 dB threshold.

On the software side, future work will focus on enhancing the machine learning model's performance and adaptability. Expanding the training dataset to include a broader variety of duct materials, defect types, and environmental conditions will improve model generalization. Additionally, exploring more advanced architectures and real-time inference optimization could increase classification accuracy beyond the current 90% while maintaining efficiency for onboard processing. Incorporating continuous learning or update mechanisms may allow the system to improve over time based on field data.

Another important direction is the development of more intuitive user interfaces and decision-support tools for HVAC technicians. Providing clear visualizations, confidence metrics, and actionable recommendations could help users interpret system outputs more effectively and reduce the risk of overreliance on automated decisions. Integration with maintenance records and building management systems could further enhance the practical utility of LeakLink in real-world workflows.

Finally, future work should address validation and deployment at scale. Conducting extensive field testing across diverse environments will be essential to verify performance under real operating conditions. Consideration of regulatory standards, safety certifications, and cost optimization will also be necessary for commercialization. Through these improvements, LeakLink can evolve into a more versatile, reliable, and widely deployable solution for HVAC duct inspection.

B. *Lessons Learned*

Beginning the project early proved essential, particularly for a hardware-focused effort where component procurement, assembly, and iterative debugging require significant time. Additionally, we found that system integration posed greater challenges than the design of individual subsystems, emphasizing the importance of planning for compatibility and interaction between components.

Through the implementation process, we strengthened our intuition in machine learning and computer vision by applying theoretical concepts within a practical, real-world system. We also enhanced our ability to efficiently research and understand unfamiliar topics, an important skill in rapidly evolving technical domains.

Furthermore, the project reinforced the importance of effective time management, clear communication, and strong collaboration within a team setting. Iterative design emerged as a critical approach, allowing us to refine and improve our system incrementally.

Ultimately, one of the most significant lessons learned is that successful engineering outcomes are rarely the result of a single breakthrough; rather, they are achieved through the accumulation of many small, continuous improvements.

Glossary of Acronyms

AE – Acoustic Emission
FFT – Fast Fourier Transform
HVAC – Heating, Ventilation, and Air Conditioning
I2C – Inter-Integrated Circuit
LiDAR – Light Detection and Ranging
MCU – Microcontroller Unit
ML – Machine Learning
PWM – Pulse Width Modulation
SNR – Signal to Noise Ratio

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Additional Figures

Item	Supplier	Cost
Jetson Orin Nano	Inventory	$0
Microphone	Inventory	$0
Camera with LiDar	Inventory	$0
Robot Car Chassis - Black Gladiator-Tracked Chassis	MOUSER Electronics	$25
Motor Driver	SparkFun	$14.50
Teensy 4.1 Development Board	MicroCenter	$31.50
Adafruit 9 DOF Orientation IMU Fusion	Microcenter	$12.99
12V 4.5Ah LiFePO4 Battery	Bioenno Power	$79.99
Solenoid	SparkFun	$20
AE Sensor	Ebay	$30
Circuit Kit	SparkFun	$20

Figure 4. Bill of Materials

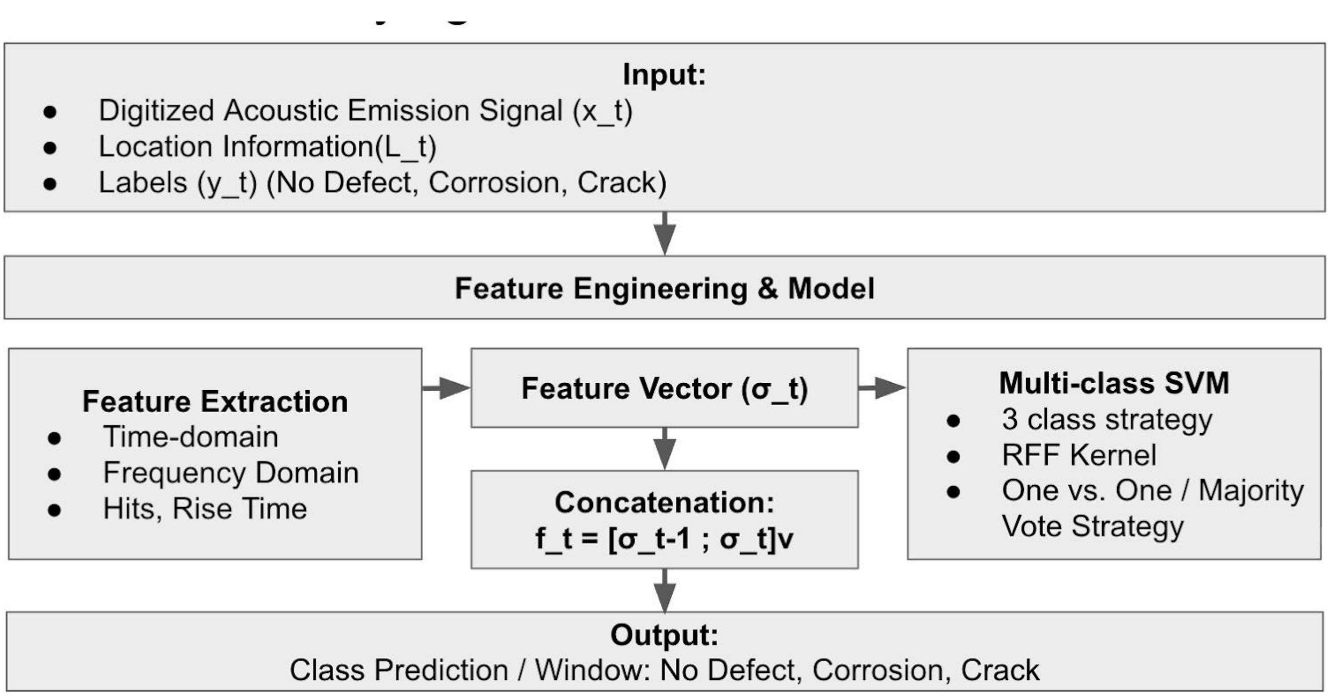

Figure 5. ML Model Diagram

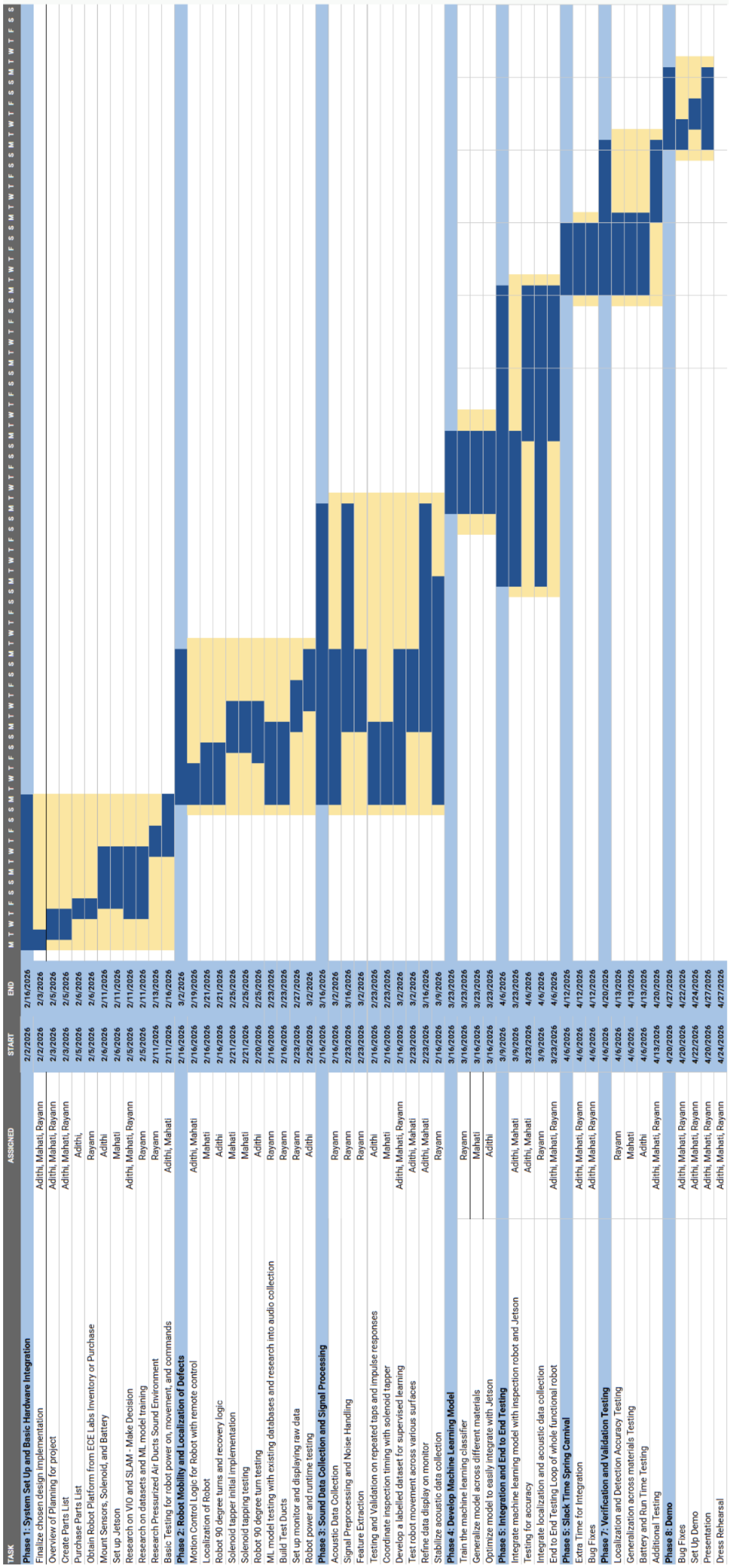

Figure 6. Gantt Chart for Project Timeline