Novel Automated CO Forecasting, Dead-Zone Detection, and Ventilation System for Homes

Grant Proposal

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Author Note

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Executive Summary

In the modern household, around 2.1 billion people worldwide cook using open fires or inefficient stoves fueled by harmful chemicals, with over 3.2 million people per year dying due to air pollution (WHO, 2025), carbon monoxide (CO) poisoning being one of the deadliest (EIA, 2024). In the body, CO binds to hemoglobin, inducing hypoxia, lack of oxygen, which can kill a person within a matter of minutes. Currently, around 400 people die a year due to CO poisoning with around 100,000 emergency visits per year (CDC, 2025). Current electrochemical sensors, despite being economical, are affected severely by environmental sensitivities such as hydrogen gas and carbon dioxide, while lacking advanced forecasting capabilities. Additionally, current residential ventilation systems tend to contain leftover pollutants, consume high amounts of energy, and aren't suited for autonomous poisonous gas filtration, with the current residential ventilation fan module costing upwards to $300; Additionally, advanced and autonomous filtration capabilities are exclusive to only commercial or industrial fans. The goal of this project is to design a novel, dual-mode carbon monoxide dead-zone detection and ventilation system that not only detects dead-zones, areas with little circulation but high levels of CO, and forecasts future CO levels for users to install detectors in those areas, but also smartly informs the user where carbon monoxide might be building up for further action.

Keywords: carbon monoxide, ventilation, dead-zone, detection, filtration

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Carbon Monoxide (CO) is a poisonous, tasteless, and odorless gas that is created through the incomplete combustion of fuel-burning appliances, making it commonplace (Mississippi State Department of Health, 2025). Current electrochemical detectors are cheap; however, since every electrochemical detector is designed to react to a specific gas, other gases such as H_2 (hydride) or CO_2 may trigger a reaction with sensor electrodes, causing more cross interference, which ultimately results in false positives (Safety Online, 2024). However, about 60% of households in the United States utilize natural gasses in their everyday lives, with an overall gas consumption rate of 12.4 billion cubic feet per day (United States Energy Information Administration, 2024). Since natural gases such as H_2 play a role in the significant number of false positives for carbon monoxide sensors, the number of false positives in the US for electrochemical carbon monoxide sensors makes them unreliable for accurate detection. Additional environmental sensitivities, such as humidity, also greatly increase the number of false positives for current CO detectors. Therefore, these environmental sensitivities can limit the areas detectors can be placed in. For example, CO detectors are generally avoided from being placed in environments with high humidity, such as bathrooms in homes and near windows where sunlight can directly affect electrochemical sensors' sensitivity and operation over time (HomeSmiles, 2024). This is why it is important to integrate additional information about the surroundings—humidity levels, temperature, concentration of inhibiting gases---to receive accurate readings from carbon monoxide detectors. This method is called multisensor data-fusion technology, which was historically combined with machine learning to output accurate environmental readings for purposes such as environmental temperatures, CO concentrations, and household appliance status (Tsanousa, 2022).

Current Issues with Residential Ventilation Systems

Current ventilation systems lack the capability to properly filter out carbon monoxide. Current products in the market, such as the Humidex (GVS-SD2-HDEX) have carbon monoxide sensors built into the fan to accurately detect carbon monoxide in the garages of homes. However, it lacks an exhaust system to completely filter carbon monoxide from a user's home; instead, it just blows CO away in hopes of increasing circulation to reduce CO emissions.

Another commonly used ventilation fan module is the QuietCool Classic Advanced Whole House Fan. Even though it covers whole-house ventilation needs, it lacks autonomy when making decisions on whether to increase fan speed due to differences in temperature and humidity. It must be changed manually, which lacks efficiency and is significantly more error prone. It is also very expensive, yet smaller than a user would expect, making it the least valuable option.

Even though these two systems lack features like autonomy or sophisticated exhaust systems, there is one feature that is predominantly lacking in both current detection systems: dead-zone detection. Dead-zones are areas within a user's environment where air circulation is low, and carbon monoxide levels are high. This allows for less oxygen in those areas and more carbon monoxide build-up, which can lead to more hazardous outcomes.

The goal of this project is to improve upon current detectors and ventilation systems by taking a dual approach to minimize false positives in detection and dead-zones. Specifically, this project will implement carbon monoxide concentrations, humidity, temperature, and pressure data to output accurate readings and help the user decide what the best course of action in that current moment is, then communicates to a secondary system that will effectively guide and filter air out of the user's environment. This technology, if implemented in small-scale residential environments, could serve as a cost-friendly, eco-friendly, and effective alternative to existing CO detection and ventilation systems, providing safer air for a cheaper cost.

Engineering Aims

Given these gaps in current systems, this proposal's objective is to reduce current and prevent future carbon monoxide from false positive detections and dead-zones through a handheld detector and ventilation system. Our long-term goal is to implement a dual handheld detector and ventilation system into more residential environments, where the central hypothesis of this proposal is that carbon monoxide false-positives and dead-zones will be reduced by a significant amount worldwide. The rationale is that with more household appliances emitting natural gases such as carbon monoxide, it is crucial that an autonomous, carbon monoxide dead-zone detection and ventilation system is implemented to not only inform, but to protect the user. The work we propose here will reduce carbon monoxide build-ups and dead-zones in residential environments while informing users of future carbon monoxide build-ups, reducing the risk of carbon monoxide poisoning. To achieve these goals, this project was divided into 3 specific aims.

Specific Aim 1: CO-Level Forecasting

The ability to accurately forecast future CO levels in the environment is important because of the advantages of an early-warning system for user action. For example, a user may be completely unaware of a CO leak due to its undetectability; however, this feature will allow the handheld detector can effectively forecast future levels of CO based on that point in time and using additional environmental data such as temperature, pressure and humidity, the model can further validate the CO predictions, leading to more accurate time-series forecasting.

Specific Aim 2: Accurate Dead-Zone Detection

The ability to detect dead zones within a user's environment is crucial because dead zones serve as significant indicators of rising carbon monoxide levels. Along with temperature, humidity, and pressure data, ventilation conditions will also be monitored, as the airflow of the current environment greatly affects the circulation (Vandervort, 2025). This ultimately determines the magnitude of dead zones.

Specific Aim 3: Optimization of Ventilation Fan Module Design

Optimizing a ventilation system layout before building the fan module is crucial for analyzing CO dead zones. Visualizing airflow patterns can significantly determine not only where the fan module should be placed but also informs design choices for the fan module. For example, analyzing different fan layouts can determine how different designs affect velocity fields, pressure distributions, and mixing patterns, ensuring complete room coverage.

The expected outcome of this work must be implemented in real homes with little effort to decrease the likelihood of carbon monoxide dead-zones and help forecast future carbon monoxide levels to prevent carbon monoxide poisoning.

Project Goals and Methodology

Relevance of Project:

The relevance of this project is that many people around the US die from CO poisoning, with homes lacking accurate, active and autonomous CO detection and interventional protocols. Current households feature static detectors and manual ventilation systems often prone to inaccuracies, increasing the likelihood of CO poisoning.

Innovative Features:

While there exist residential electrochemical detectors, those are built-in wall plug-ins and don't effectively monitor whole-house CO levels. Additionally, they don't effectively forecast future levels of

CO to inform the user ahead of time and suggest what to do. There is also a lack of autonomous interventional systems using automated ventilation that effectively filters CO from the environment while directly communicating data with the handheld detector. This system fills both of those gaps, with a handheld detector that forecasts future CO levels using environmental data and current CO levels, while sending that data to a ventilation system that activates ventilation.

Methodology

This project uses an app on the user’s phone as the main control hub for automated carbon monoxide handheld detection and ventilation system, featuring gauges to display each of the 4 important metrics: carbon monoxide concentrations in parts per million (ppm), humidity in %, pressure in hPa, and temperature in degrees Celsius. The mobile app will receive data from two main sources: the handheld CO detector and the ventilation fan module attached to the ceiling of a user’s home. After receiving the data, The sensors on the handheld detector and the ventilation fan module were initially calibrated with industry-grade sensors by recording the value of 4 key metrics from those sensors and values from the detector, in which an exponential relationship was derived to ensure consistency between sensor readings and real-life conditions.

Development of Handheld Detector

To effectively build a handheld detector, a data collection rig was first built using an MQ7 CO Arduino sensor, along with a BME280 that records humidity, temperature, and pressure. This data was then recorded and stored on an SD card. Environmental data was collected from multiple rooms, such as the kitchen, living room, bedrooms, bathrooms, and under conditions such as when cooking with flames so the detector recognizes increased CO level readings from cooking on a gas stove vs actual gas leak to accurately differentiate from false positive CO level readings. The detector will then be placed in different areas, such as near stoves and manually validated by placing a lighter near the detector and testing its sensitivity to validate forecasting. To validate dead-zone detection, this study will assume that since CO dead-zones are areas where CO build-ups are high, CO concentrations are going to remain at a constant level that, according to the OSHA, is around 1200 ppm (USEPA, 2025). However, various environmental factors such as humidity, temperature, and pressure will vary using an environmental chamber to simulate variation. Non-dead zone data will be collected at the researcher’s house to simulate baseline levels.

Development of Ventilation System

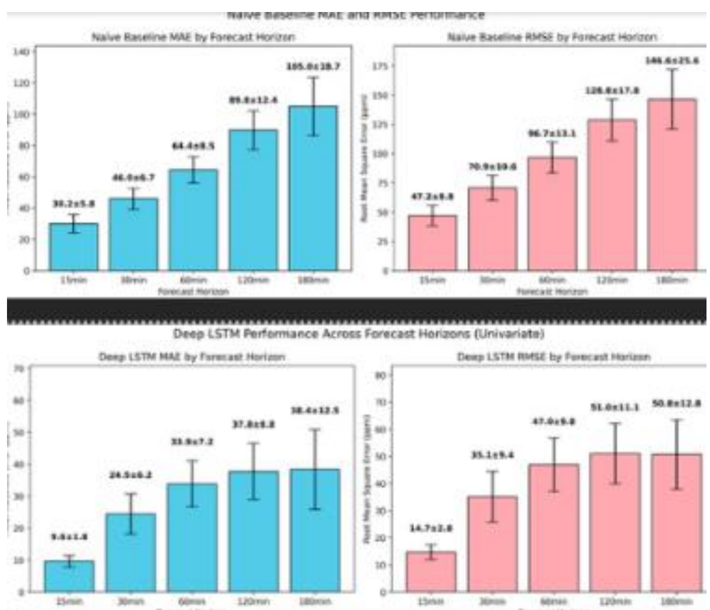
The ventilation system consists of models of ventilation fan modules that respond to real-time data transmitted from the handheld CO detector. To guide its design, the fluid flow of CO will be simulated using ANSYS fluent, accounting for its turbulent nature. Initial simulations will employ a simpler CFD model such as the k-epsilon turbulence model, a model that accounts for the kinetic energy and dissipation rate of CO. The model will have a little number of varied parameters such as number of windows opened, number of inlets and outlets, a starting CO concentration of 400 ppm, and will later account for other factors such as atmospheric pressure, inlet velocities and the CO density accounting for slight buoyancy. Ventilation effectiveness will be quantified using the AEE, or Average Exchange Effectiveness, which is defined as the global mean age of air divided by the local mean age of air at standardized occupants’ breathing zones. After data collection, different designs will be evaluated based on simulation data, and one design will be chosen and iterated extensively.

Specific Aim #1: Accurate CO level Forecasting

The first aim of this project was to build a handheld detector that accurately detects dead zones within a user’s environment while also accurately forecasting future carbon monoxide levels in the user's environment to immediately report valuable feedback to the user about their current environment. For combined dead-zone detection and CO level forecasting, our approach is to use the CO ppm from the MQ-7 Arduino CO sensor; and temperature (C), pressure (hPa), and humidity (%) data from a BME280 to transmit via BLE (Bluetooth Low Energy) to an LSTM (Long Short-Term Memory) model on a user's app. That LSTM model will then be used as a multi-task model responsible for not only detecting dead-zones but also forecasting CO levels in the future for further action from the user.

Justification and Feasibility:

This method can help increase the user's awareness of CO levels and the presence of dead-zones within their environment because of the use of Long-Short Term Memory (LSTM) models instead of regular decision-tree logic. LSTMs, compared to a base LOCF (Last Observation Carried Forward) model, a simple LSTM model resulted in a MAE (mean absolute error) reduction of 8.9%, 1.5%, 7.7% and 7.1% for 15, 60, 120 and 180 minutes after starting CO_2 conditions (Mountzouris et al. 2025).



Graphs from Mountzouris et al. (2025). Graphs above showcase how LSTM resulted in an MAE (mean-absolute error) of 8.9%

Summary of Preliminary Data.

Below is a graph of the comparisons of different time-series forecasting models evaluated on an environmental dataset collected by me and how each model performs in different categories which are each weighted differently according to preliminary engineering requirements.

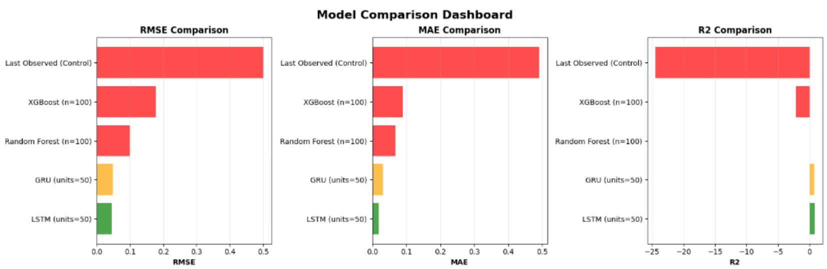


Figure was created by researcher. Graphs above compare the performances of different time-series forecasting models, with red bars representing poor performance while green bars represent the opposite when trying to forecast future CO levels on the same data. LSTMs outperformed all other models compared.

Some models that were evaluated include the LOP (Last Observed Prediction) model that outputs the last seen value as the predicted value, serving as a control. Green bars served as indicators of good performance while red bars served as indicators of poor performance. As the LSTM outperforms every model in this test, showcasing the reason why this model was moved forward with in the study.

Expected Outcomes

The overall outcome of this aim is positive, as past studies and current preliminary data show that LSTMs are the best model for this specific use case. This knowledge can be used to advocate for the use of LSTMs in the forecasting of poisonous gases within a user's environment.

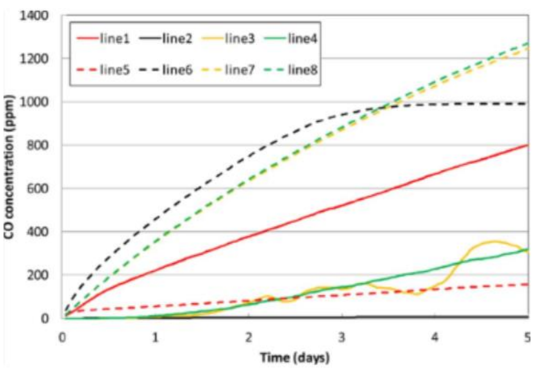
Potential Pitfalls and Alternative Strategies.

Some potential pitfalls of this aim are that the prediction can be impacted by outdoor environmental conditions such as whether a window is open or not, affecting circulation, and therefore affecting future CO levels. To account for this, a wind sensor will be incorporated in the next aim to adjust minor inconsistencies to make the model as accurate as possible.

Specific Aim #2: Accurate Dead-Zone Detection

The second aim of this project was to incorporate dead-zone detection into both the handheld detector and ventilation module to effectively ventilate those dead-zones while alerting the user to place more CO detectors. This can be achieved through the use of environmental sensors that detect carbon monoxide levels, temperature, pressure, humidity, and altitude while also incorporating data from computational fluid dynamics simulations.

Justification and Feasibility.

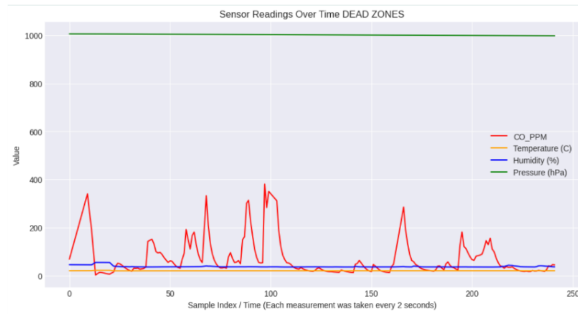


Graph by Yuan et al. (2014). Shows one of the 5 different sampling locations where they detected the early formation of dead zones. Graph displays the increase in CO levels as days pass, with different lines representing the different sampling locations.

Detecting dead zones within a person's home can be crucial data for automatic ventilation systems to target vulnerable circulation in weak spots. In a prior study conducted by Yuan et al., they used data derived from computational fluid dynamic models while actively validating that data with CO gas sensors and other environmental sensors like temperature and pressure sensors. The graph to the right shows one of the 5 different sampling locations where they detected the early formation of dead zones. This graph showcases the increase in CO levels as days pass, with the different lines representing the different sampling locations taken within that sampling location (Yuan et al., 2014).

Summary of Preliminary Data.

The graph on the right was dead-zone data collected by the researcher by collecting dangerously fluctuating levels of carbon monoxide, pressure, temperature, and humidity. According to the graph, CO levels fluctuate intensely between 0 to 400 ppm, with a slight drop in pressure of about 10-20 hPa. The fluctuation in carbon monoxide levels serves as a significant indicator of poor air circulation, indicating dead zones. The decrease in pressure serves as an additional indicator, since pressure drops in this context correlate with brief intrusions of airflow.



This graph shows CO concentrations (red) maintaining a dangerous baseline around 1000 ppm with periodic spikes in dead-zone conditions, while pressure (green) shows correlated drops. Temperature and humidity remain stable. This validates using multiple sensors to detect dead-zones and supports automated ventilation intervention.

Expected Outcomes

The expected outcome of this procedure is to gather accurate, real-world data to train the LSTM model on, achieving a high dead-zone detection accuracy.

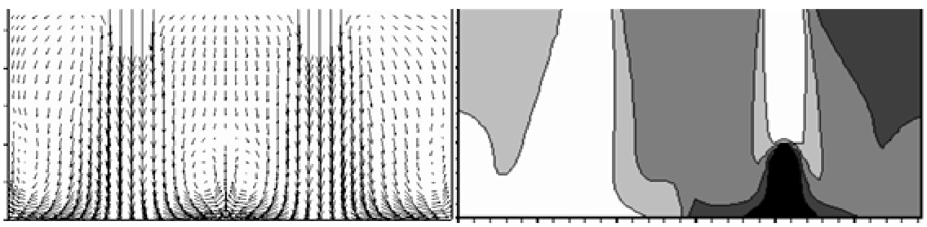
Potential Pitfalls and Alternative Strategies.

Some potential pitfalls that might be encountered in this process include additional environmental sensitivities such as open windows or outlets that affect airflow within a room. To avoid this, data will always be collected within a closed room with no air pockets for air to escape through.

Specific Aim #3: Optimization of Ventilation Module Designs

Another engineering aim is the optimization of the ventilation fan module design. The goal of this part of the project is to come up with 3 designs and validate them using computational fluid dynamic simulations using ANSYS, a fluid dynamic modelling software. The three designs share some similarities, with the degrees of freedom differing between each design. For example, the three designs are modules equipped with fans that tilt side-to-side, up and down, and both side-to-side and up-and-down. First, residential floorplans will be manufactured in space claim (3D CAD software embedded into ANSYS) with a varying number of inlets (areas where gas enters the house) and outlets (openings where gas exits the house). The AEE, or air exchange effectiveness, will be calculated through ANSYS, with a higher AEE correlating to better air circulation.

Justification and Feasibility.



(a) Velocity vector distribution (b) Contaminant concentration distribution
Fig. 7. The airflow and contaminant distribution in a section through the two diffusers in a cleanroom obtained by using a RANS model (Zhang and Chen 2007)

The k-epsilon turbulence model is appropriate for residential applications, as Chen's study demonstrated strong correlation ($R^2 > 0.85$) between CFD predictions and experimental ventilation measurements (Chen, 2009). The figure to the right showcases the velocity vector and contaminant concentration distribution modeled using a RANS (Reynolds-Averaged Number) model, more specifically the k-epsilon model. In graph b, darker regions represent regions with lower air velocities, indicating how more dead zones are created in lower air velocity regions.

Preliminary Data and Expected Outcomes

It is expected that there will be results that showcase the AEE, or Average Exchange Effectiveness, of the three different fan module designs and then the design with the highest AEE will be chosen to move forward with when designing the automatic ventilation system.

Resources/Equipment

[Table of resources + pricing]

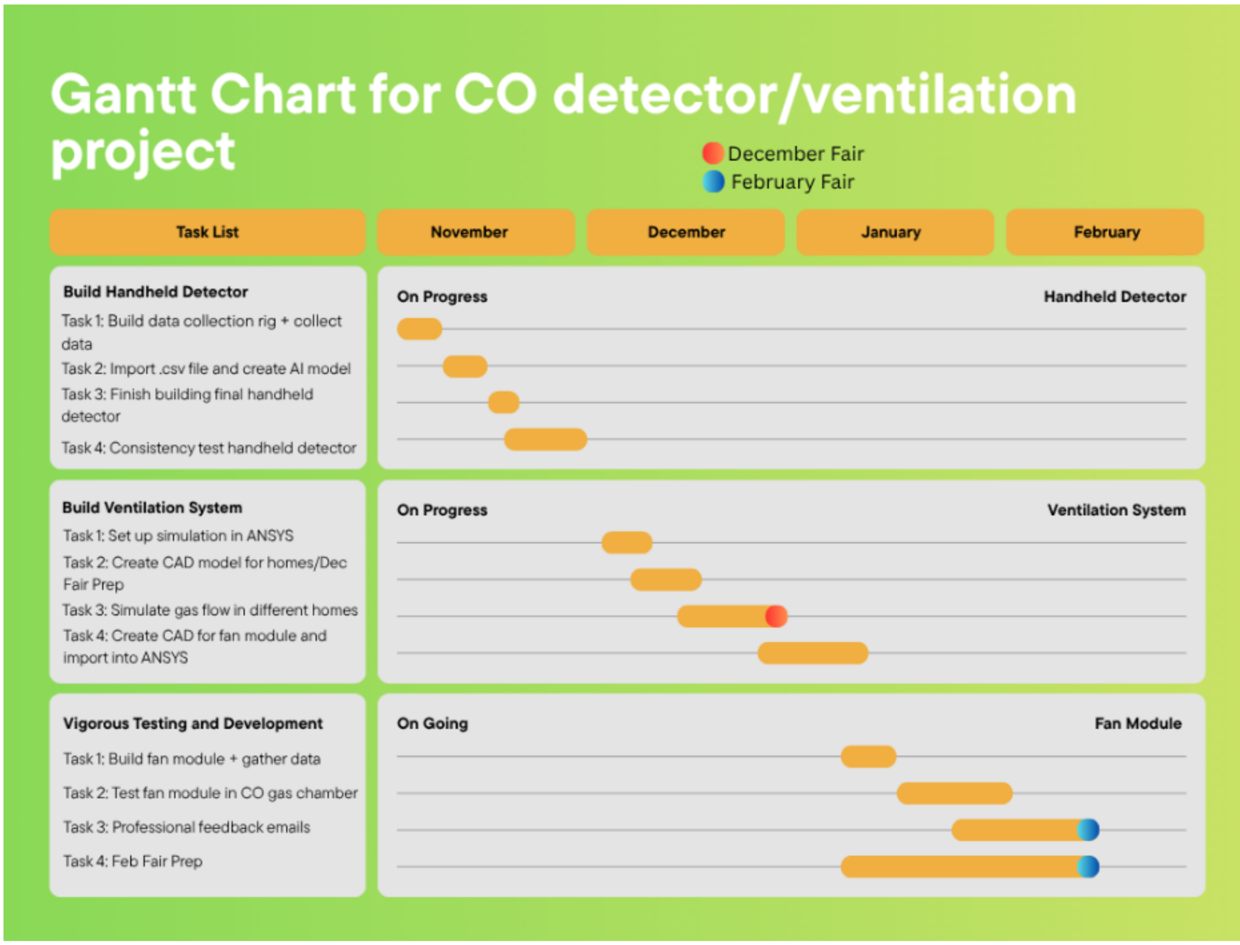
Ethical Considerations

Timeline

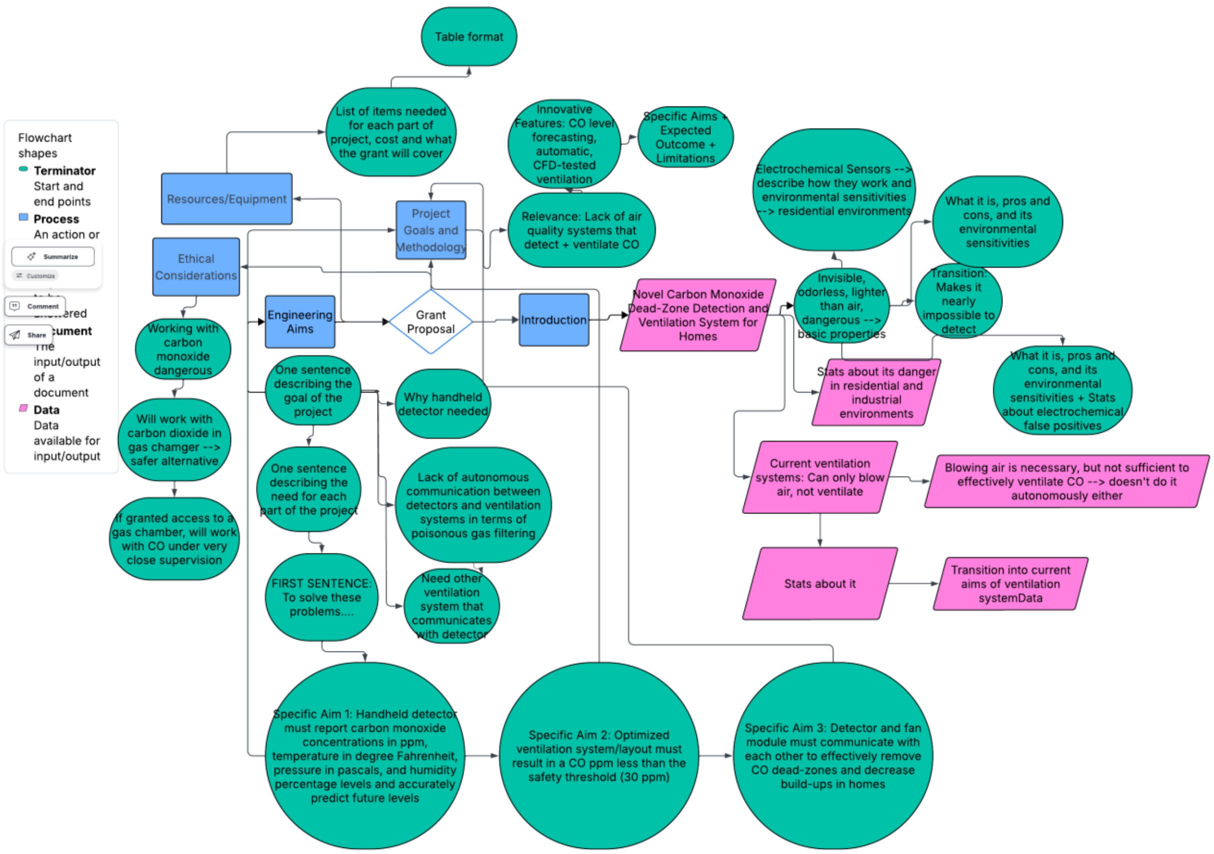
Tasks to Achieve	Date
Create a data collection device to collect data for ML model for dead-zone detection	End-October to Early-November
Finish collecting data for dead-zone detection ML model	November 4th – November 13th
Create a bare bones handheld CO detector without the software (just outputs values) with CAD	November 13th to November 20th
Engineer LSTM model prototype and bare bones app through blynk software for detector	November 20th – November 25th
Implement software into detector and test rigorously --> test for consistency	November 25th to End of November
Start creating models of houses in onshape and learn ANSYS	End of November to Early December 5th
Set up ANSYS CFD modelling environment for project-specific work. Finalize poster	December 5th to December 8th
Develop bare bones, basic simulation of inner residential environment with one configuration for December fair --> also data analysis that will be done for the house --> must have. Start to practice presenting	December 8th to December 10th
Continue to practice presenting elevator pitches	December 10th to December 15th
December Fair	December 15th
Continue developing more Onshape CAD models and introducing more parameters into ANSYS CFD model while still testing handheld detector	December 15th to January 15th
Conduct data analysis on which configuration produces the least amount of CO after a certain amount of seconds	January 15th to January 20th
Start building mini-Arduino fan prototype with 5V cooling fan and Arduino microcontroller	January 20th to End of January/Early February
Finalize Arduino fan prototype and test it while making poster board with documented findings	February 5th to February 8th
Finalize poster and rigorously practice presentation for Feb fair	February 8th to February 14th

FEB FAIR	February 15th
Will add more if I advanced further to more science fairs	

Section VII: Appendix



Approximate, linear timeline of project progress in a Gantt chart format. (Venigalla, 25)



Mindmap that outlines the structure of grant proposal

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