SYSC4907 - ENGINEERING CAPSTONE PROJECT FINAL REPORT

# ACTIVITY OF DAILY LIVING ASSESSMENT

## STOVE USE


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# 1.INTRODUCTION

Monitoring nutrition has gained widespread interest since it aids in documenting intake for dietary evaluation and health observation [1]. Furthermore, preventing chronic diseases and managing appropriate health activities through patient monitoring are the best ways to lower health facility costs and enhance people's sense of autonomy [2]. Human bodies receive the essential nutrients they need to function properly from the food they consume. The nutrients obtained from our food are converted into energy which is then used for bodily functions ranging from physical to mental. The better we feel, the healthier we eat, which in turn gives us more energy and even clearer thoughts. Individuals who practice healthy eating habits are less likely to experience depression or mood disorders, according to research findings [3]. Some disorders can cause people to forget to eat, thus worsening their state. As an example, a person with dementia may forget to eat or lose their appetite due to their dementia progressing [4]. In some cases, physical restrictions can also constrain a person from eating or cooking.

Awareness, consciousness, behavioral patterns, and physical limitations are factors that have been discovered to influence people's emergency response in case of a fire [5]. The majority of unintended fire-related deaths in Canada occur in residential buildings [6]. Older people are more likely to pass away in a residential fire, as found in prior research [6]. Individuals aged seventy (70) and older accounted for nearly one-third of fatalities caused by unintentional residential fires in Canada, despite representing one-eighth of the population in 2020 [6]. According to the 2017 Canadian Survey on disability, seniors are more likely to have disabilities (such as mobility impairments). These impairments might hinder a person's capability to react to or evacuate from a fire [7]. Leaving the stove unattended while turned on is a major safety issue. Unsupervised cooking equipment was the main cause of home food preparation fires in Ontario, whilst human error (examples: lack of consciousness, getting easily distracted, misunderstanding of hazards), and mishandling of substances burned were responsible for three-quarters and one-half of each British Columbian and Albertan kitchen fires, respectively [8].

The project’s main objective is to create a comprehensive solution that enhances nutrition management on the elderly population as well as cognitively impaired individuals through the use of image processing and image classification. The system monitors stove use, and a web application delivers alerts based on the stove usage and safety. By doing this, the project aims to mitigate potential health issues that could arise from improper nutrition management and stove safety hazards.

## 1.1 MOTIVATION

With advancements in medical and technological fields, the quality of life has significantly improved over the last decade, enabling people to live longer and healthier lives [9]. These advancements have provided seniors with easily accessible mobile applications for tracking fitness, health, nutrition, and heart rate, allowing them to lead more independent lives [10]. Furthermore, health professionals can monitor seniors' health through medical alert systems installed in their smart homes.

However, the COVID-19 pandemic has exposed new challenges that people, especially seniors, face daily [11]. The senior population constitutes 23% of Canada's population and 7% of Ottawa's population [12]. With this growing demographic, it is increasingly important to ensure that aging adults maintain healthy nutrition and are safe from potential hazards in the kitchen.

Growing older presents unique challenges, ranging from limited mobility and cognitive decline to preparing healthy meals [12]. One prominent challenge with cooking is that it involves various hazards to which aging adults can be susceptible [5]. Slower mobility and forgetfulness can put them at risk of fire hazards [5]. Developing healthy and organized cooing habits can significantly improve the quality of life for older adults [2].

Aging inevitably results in changes in a person's cognitive and physical abilities. Individuals may experience memory lapses, difficulty maintaining focus, and a decrease in problem-solving abilities as cognitive decline sets in, which can impact their ability to prepare meals efficiently, posing potential risks in the kitchen. Along with cognitive decline, ageing people may experience physical limitations that limit their mobility, strength, and coordination. These difficulties can make it harder for seniors to perform daily kitchen tasks. As a result, the likelihood of accidents, injuries, and falls may increase, emphasizing the need for a safe and adaptable kitchen environment that meets their needs.

This project focuses on identifying cooking patterns and hazards using a thermal camera. Thermal cameras are preferred over regular cameras in this project due to their ability to detect potential temperature rises in surfaces, areas, or rooms, making them an excellent choice for detecting fire hazards and unsafe stove usage. The chosen thermal camera is low-cost and easily accessible for homeowners to integrate in their kitchens.

The project's purpose is to detect unsafe stove usage using a thermal camera, which will also identify cooking patterns (frying or boiling) and analyze video feeds through image processing. The project focuses on setting up the thermal camera externally to acquire video feed of the stove. The previous team successfully set up the camera and recorded video feeds. Instead of manually analyzing images, the goal is to classify images using machine learning.

Another project focus is identifying cooking patterns, which can help track an individual's health and monitor their nutritional intake. Healthy nutrition is particularly important for aging adults to maintain a healthy life. Recognizing cooking patterns can also help identify unhealthy meals that may be harmful to the individual. This information can assist healthcare professionals in pinpointing any underlying issues or health problems and addressing them in a timely manner. This comprehensive approach aims to support the elderly population in maintaining a safe and healthy environment in the context of cooking and nutrition, ultimately enhancing their overall quality of life.

## 1.2 BACKGROUND

### 1.2.1 RGB VS THERMAL CAMERAS

Our project involves the utilization of thermal cameras for the purpose of data collection and analysis. Unlike RGB cameras, which capture visible light and color information [13], thermal cameras measure infrared radiation emitted by objects [14], allowing them to detect temperature differences. This makes thermal cameras particularly well-suited for analyzing cooking activities, as they can effectively capture the heat generated during cooking processes. While RGB cameras can provide valuable visual information, they may not be as effective in detecting subtle temperature changes or identifying potential hazards in the kitchen.

A relevant study that highlights the differences between RGB and thermal cameras is the Cooktop Sensing project based on a YOLO Object Detection Algorithm [15]. This project used RGB cameras and Deep Learning techniques to detect common kitchen objects and identify interesting situations for users, such as detecting utensils on lit hobs, recognizing boiling, smoking, and oil in kitchenware, and determining good cookware size adjustment. The authors achieved sensor fusion by using a cooker hob with Bluetooth connectivity, allowing external devices to interact with it automatically.

### 1.2.2 SIMILAR PRODUCTS

In a similar system, the study conducted by Ming Ye Yuan, James. R. Green, and Rafik Goubran relied on traditional image processing techniques to monitor stove tops. Their analysis was performed using MATLAB. They used a high-end FLIR model A40 thermal imaging camera worth $7512 [16] for their stove top monitoring system. The system operated in two modes: calibration and monitoring, and temperature thresholds were used to detect human activity and the state of the stove. Their method involved a series of filtering steps, including border filtering and time filtering, to differentiate between human activity and thermal noise. Their camera was mounted on a tripod above the stove top and connected to a laptop computer through a FireWire connection, with all processing done in MATLAB [17].

In contrast, our project takes advantage of machine learning to process the data captured by the more affordable MLX90640 IR array thermal imaging camera, which costs around $394[18]. We have trained a machine learning model to recognize human presence and various stove states based on the thermal data. By utilizing machine learning, our system can adapt and improve its performance over time, potentially leading to better accuracy and more efficient processing compared to traditional image processing techniques.

The primary difference in our approach compared to the study is the use of machine learning to analyze the thermal data and the choice of thermal imaging camera. While the study's system relies on a high-end, expensive camera and predefined temperature thresholds and filtering steps, our project benefits from the adaptability and learning capabilities of the machine learning model, as well as the accessibility and affordability of the MLX90640 thermal imaging camera. This difference in methodology and equipment has the potential to provide more accurate and efficient results in detecting human presence and stove state, ensuring a higher level of kitchen safety for the elderly living independently. Furthermore, our project is enhanced by applying machine learning on differentiating the cooking methods of frying and boiling. By using a more budget-friendly thermal imaging camera, our project has the potential to reach a wider audience and benefit more individuals.

Both systems share the common goal of enhancing kitchen safety for the elderly and promoting independent living. The primary differences between the two systems are the cost and type of thermal imaging camera used, the approach to data analysis, and the implementation of additional features such as a database and app in our project. The study's system relies on a high-end, expensive camera and traditional image processing techniques, while our project utilizes a more affordable and accessible camera, with machine learning at its core.

In addition to the differences in camera and data analysis, our project also employs a database to store relevant information and an accompanying app to provide a user-friendly interface for monitoring and interacting with the system. These added features further enhance the usability and functionality of our solution, making it a more comprehensive and accessible option for promoting kitchen safety and independent living among the elderly population.

### 1.2.3 USER INTERFACE AND VISUALIZATION

A user-friendly interface and visualization tools are essential components of the system, enabling users to interact with the collected data and monitor the cooking activities. The interface can provide the user with visualizations of the extracted features and machine learning model predictions. This can help users and caregivers better understand the cooking patterns and identify potential hazards, allowing for timely interventions and adjustments to ensure a safe and healthy cooking environment.

### 1.2.4 DATABASE SYSTEM

The database system employed in this project serves as a central repository for storing and managing the collected data, including raw video footage, extracted features, and machine learning models. The database is designed to support efficient data retrieval and storage, allowing users to access and visualize the data through a user-friendly web application. By implementing a robust database system, the project aims to facilitate seamless integration of data from various sources and enable efficient data analysis and management.

### 1.2.5 THE IMPACT OF COGNITIVE IMPAIRMENT ON KITCHEN SAFETY AND NUTRITION

Ageing, dementia, and cognitive impairment are important aspects to consider when developing this project because they can have a substantial impact on a person's ability to properly use and navigate their kitchen environment. This is especially true when utilising stovetops. For people with dementia, it's essential to maintain independence and live in a familiar setting because doing so can greatly improve their quality of life [19].

People of all ages can experience cognitive impairment, a loss in thinking or memory that is mostly brought on by ageing [20]. A loss in memory and cognitive performance can be brought on by dementia, a prevalent type of cognitive impairment [21]. Addressing the particular demands and difficulties this demographic face becomes more crucial as the world's population ages [22] and cognitive impairment and dementia are predicted to become more common [23].

Cognitive impairment, dementia, and aging can significantly affect an individual's appetite [24], making it even more challenging to maintain proper nutrition. Different types of dementia may impact appetite differently, but overall, these conditions tend to disrupt a person's eating habits in various ways.

For instance, frontotemporal dementia, a behavioral variant, may cause individuals to crave sweeter foods in larger volumes [25]. In contrast, people with Lewy body dementia and Parkinson's disease may experience a loss of smell and taste [26], which can lead to a diminished appetite. In Alzheimer's disease, the appetite may not change significantly until the disease is very advanced [27]. However, the cognitive impairment itself can make preparing and eating meals more difficult, resulting in poor nutrition.

The challenges faced by individuals with cognitive impairments include not only the planning and preparation of meals but also the ability to safely use kitchen appliances, including stoves [28]. As mentioned earlier, the inability to handle appliances carefully increases the risk of accidents in the kitchen, such as fire hazards when using stovetops.

Along with safety issues, it's critical to take care of the dietary requirements and shifting appetites of people with cognitive disabilities [29]. Giving these people assistance and suggestions to maintain a nutritious diet will improve their general well-being and quality of life.

In light of this, our research intends to create a stove monitoring and safety solution that is inexpensive, flexible, and effective that considers the requirements and difficulties experienced by people with dementia, cognitive impairments, and ageing populations. By attending to these issues, we may contribute to making the environment for persons who are vulnerable safer and more supportive, hence lowering accidents and enhancing general wellbeing. Cooking can help dementia sufferers keep their fine motor skills and stimulate their minds, both of which are crucial for daily living.

Innovative stove monitoring and safety solutions can play a vital role in helping dementia patients maintain their independence while minimizing the risks associated with cooking. These solutions should be affordable, adaptable, and user-friendly to cater to the unique needs and challenges faced by dementia patients and their caregivers, ultimately creating a safer and more supportive home environment.

## 1.3 PROBLEM STATEMENT

When it comes to regular cooking tasks, such as utilising stovetops, elderly people and those with cognitive impairments face higher hazards and problems [28]. Accidents, such as fires, are more likely under these circumstances, and ensuring regular meal consumption is vital for overall wellness. Current options for monitoring stove usage and resolving safety problems are frequently insufficient, overpriced, or inflexible, one example is iGuard stove which automatically shuts off the stove, however, it is overpriced [30].

The issue with current stove monitoring systems and safety solutions is that they often fail to meet the needs of consumers due to their limitations, high costs, or lack of adaptability. For instance, the iGuard Stove is an automatic shut-off device designed to improve stove safety. However, its high price point which is around $659 [31] and limited additional features can make it an impractical option for many households [30].

The issue at hand is the development of an effective, user-friendly, and easily available system that can monitor stove usage, classify culinary activities, and warn caretakers or contacts of any unsafe circumstances that have occurred. This approach should provide a dependable and adaptive safety net for older people and those with cognitive impairments during their everyday culinary activities.

## 1.4 PROPOSED SOLUTION

The objective of this project is to create an analytics system through image processing and classification to use a thermal camera to identify the stove use of aging adults. The analytics system takes images from the video feed and classifies stove use into three main categories: ON/OFF, Safe/Unsafe, and Boiling/Frying of an egg. With the classifications regarding the state of the stove, the type of cooking method being used to cook an egg and the safety status of the cooking process, the classification will be integrated to a web application to alert the caretakers, and family members when the stove use is determined to be unsafe.

## 1.5 ACCOMPLISHMENTS

The team has successfully completed various milestones during the project. The gathering of thermal data using the Seek Thermal CW-AAA Compact-All-Purpose Thermal Imaging Camera for Android USB-C, the creation of a comprehensive feature extraction procedure, and the use of machine learning algorithms to classify cooking are among these achievements. In addition, the team created a user-friendly web application to improve user engagement, as well as an efficient database system for storing and managing the acquired data. Furthermore, the investigation of data resampling approaches, notably the employment of the Synthetic Minority Over-sampling Technique (SMOTE), resulted in a more balanced dataset and better machine learning model performance. These accomplishments are to be discussed in greater depth in the following sections of the report.

## 1.6 OVERVIEW OF THE REPORT

This report presents the development and implementation process of a solution designed to analyze cooking activities to promote safety and wellness, as captured through video feeds from the Seek Thermal CW-AAA Compact-All-Purpose Thermal Imaging Camera for Android USB-C. The focus of the report lies in discussing the various aspects of the project, including machine learning techniques, database management, data collection and curation and web application development.

This report delves into the various stages of development, starting with the acquisition of thermal data and continuing through the feature extraction process. Additionally, the investigation of machine learning techniques for classifying cooking activities is discussed, as well as the implementation of an efficient database system for storing and managing the collected data. The development of a user-friendly web application to facilitate data visualization and user interaction is also covered. Furthermore, the report highlights the exploration of data resampling methods, particularly the use of Synthetic Minority Over-sampling Technique (SMOTE), to create a more balanced dataset and improve the performance of the machine learning model.

# 2. THE ENGINEERING PROJECT

## 2.1 HEALTH AND SAFETY

As real data collection is a fundamental component in this project, ensuring personal safety while collecting data during cooking processes for safe and unsafe, on and off, and boiling and frying conditions is crucial. Adhering to safety protocols and maintaining awareness of potential hazards is essential in preventing accidents and ensuring a safe working environment.

To guarantee safety, several factors should be considered when gathering data. To prevent harm or overheating, the thermal camera must be properly positioned, keeping it at a safe distance from heat sources and cooking equipment [32]. The camera should also be firmly mounted to avoid collapsing or being knocked over, and the field of vision should catch the pertinent cooking area while minimizing interference from other heat sources or items.

A laptop is consistently used when gathering data to display and store the data recorded by the thermal camera. Placing the laptop on a stable surface, such as a countertop, away from heat sources and possible sources of spills or accidents. Ensuring that the laptop does not add to the clutter or cause obstacles in the cooking workplace.

It is critical to remain attentive and observant during the data acquisition process, especially when collecting unsafe data. When a stove is deliberately left on for an extended period with nothing on it, there is a danger of forgetting that the stove is on, and data collection is occurring. To avoid possible accidents or harm caused by an unattended stove, it is critical to stay concentrated and aware of the ongoing data gathering. Setting reminders or timers, as well as averting distractions, can aid to keep awareness and guarantee a secure and effective data gathering process.

While cooking, follow set safety procedures such as using a working smoke detector and maintaining a fire extinguisher nearby [33]. This reduces the possibility of injury or property loss because of cooking-related accidents. When gathering data, it is critical to be cautious around high temperatures. Furthermore, keeping a clean workplace and being conscious of one's surroundings can help prevent accidents while collecting data.

During the project, the team prioritized COVID safety precautions to ensure the well-being of all members involved. To facilitate communication and collaboration, regular meetings were held with Dr. Bruce Wallace via Zoom on a weekly basis. Additionally, the team members met with each other once a week via Microsoft Teams. This allowed everyone to stay connected and up to date on the project's progress without risking in-person contact. Moreover, to minimize the risk of exposure, data collection was carried out individually by team members at their respective homes.

## 2.2 ENGINEERING PROFESSIONALISM

The project under consideration had the attribute of Engineering Professionalism integrated into its various aspects. Throughout the project, the team members displayed a sense of collaboration and worked collectively to bring the project to its end goal. Critical thinking and effective communication were employed to bring about a successful outcome. The team's ethical standards were also noteworthy as we demonstrated honesty, respect, and integrity towards each other.

To document the project's various aspects, the team submitted reports in a timely manner. These reports, such as the proposal and progress report, were crucial in documenting the engineering design choices made throughout the project and the challenges that the team encountered. The reports conformed to the IEEE formatting and referencing guidelines, which further highlights the team's professionalism in approaching the project.

## 2.3 PROJECT MANAGEMENT

Effective project management is a crucial aspect of any project, as it encompasses the process of planning, organizing, and coordinating activities aimed at accomplishing specific objectives within a defined timeframe. A well-executed project management plan ensures that the project is completed within budget and on schedule while adhering to strict health and safety standards. Some of the core components of project management include identifying and managing risks, establishing project milestones, and delegating tasks to team members. This was done easily with the help of Gantt Charts which can be seen in FigureFigure 1 and Figure 2 below. Moreover, efficient communication and collaboration among team members play a pivotal role in the success of the project.

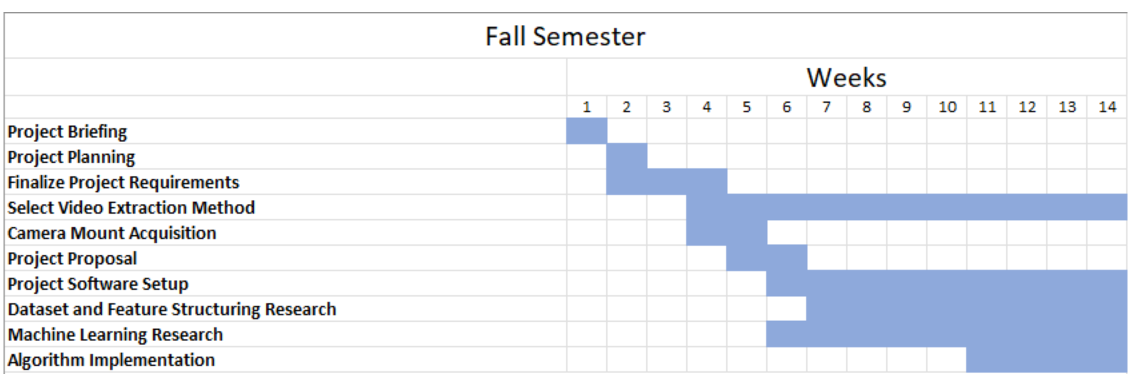


**Figure 1: Gantt Chart Showing Project Progression in the Fall Semester**

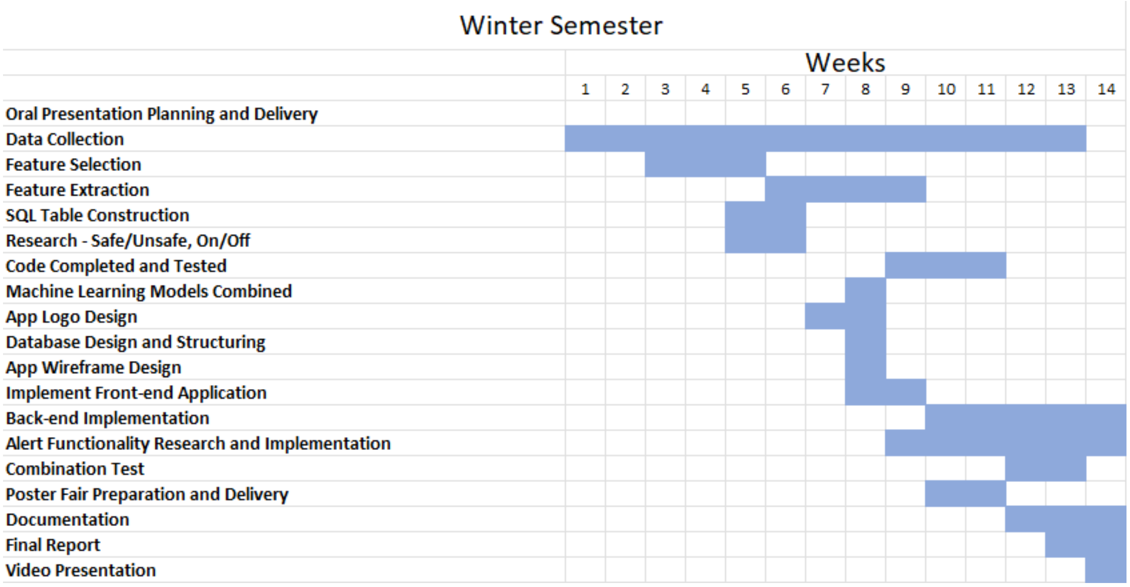


**Figure 2: Gantt Chart showing Project Progression in the Winter Semester**

## 2.3.1 PROJECT GITHUB

Two GitHub repository were created for this project, which are the repository for project and the repository for the application. Individual branches are used in the repositories, which allow us to delete and modify unnecessary code without the fear of corrupting the work that has been already done. Pushes to the main branch will only be done after testing that the new changes on the branch work as expected and will not cause any unexpected damage.

The GitHub repository for this project can be found here. This repository has been sectioned into two directories: "MachineLearning" and "ThermalSoftware". Figure 3 below shows the repository of the project with its machine learning code and code for thermal image processing.

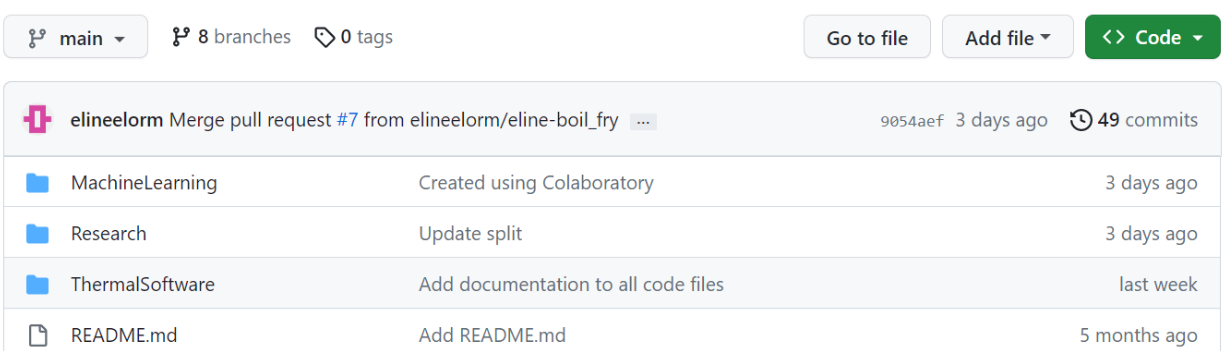


**Figure 3: Screenshot of Project GitHub Repository**

In addition, the repository for the application can be found [here](). The repository includes the application code with the firebase dependencies. The public directory is the setup code for React and the *"src"* directory is where the content of the application has been added. Files in the root directory are mainly configuration files and files that contain dependencies. Figure 4 below shows the repository of the application.

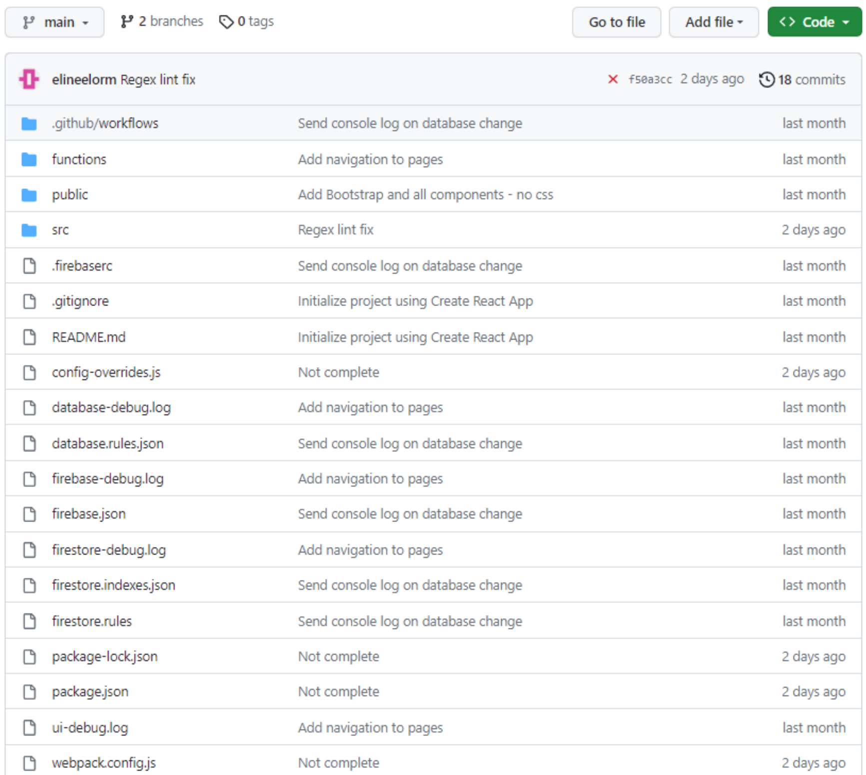


**Figure 4: Screenshot of Web Application GitHub Repository**

## 2.3.2 WEEKLY MEETING

Regular weekly meetings were integral to our communication within the group, as they ensured that we kept each other informed about project progress and allowed us to constantly reassess and reorganize tasks as necessary. These meetings were conducted using Microsoft Teams, a professional communication platform.

Furthermore, we held weekly meetings with Professor Wallace to provide updates on our progress and to seek his input on any issues we encountered during the week. These meetings were conducted on Zoom and occasionally in person and were a vital part of our project management approach.

### 2.3.3 TASK MANAGEMENT

At the beginning of the project, duties were distributed and supervised using Trello. However, as the project progressed, upcoming tasks were determined based on the progress, and new deadlines and milestones were set. These new milestones are deadlines were reviewed weekly during team meetings, where team membered reported on their advancement and strategized on how to proceed. This allowed everyone to work quickly as we were always aware of the parts of the projects that had dependencies. It also helped us steer the project back on track as it was easier to detect when we were falling behind.

### 2.3.4 DATA COLLECTION MANAGEMENT

Data collection is an essential component of this project since thermal videos are being recorded and used to develop machine learning algorithms. To facilitate the process of manual data labelling, an Excel document was used to keep track of the number of collected data and their features. Two versions of Excel have been utilized to manage the data collection.

Version 1 of the Excel document consists of separate tables for each type of video with an extra column added next to the table for comments of the recorded video. The second row of the table records the total video counts and the number of videos recorded by each person. However, version 1 was quickly abandoned after a few days due to its confusing layout and scattered data on the same Excel sheet.

| | A | B | C | D | E | F | G | H | I | J | K | L | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | Types | Hanan | Comments | Jaime | Comments | In total | Comments | | Types | Hanan | Comments | Jaime |
| 2 | Total | Frying | 0 | | 5 | | 5 | | Total | Boiling | 0 | | |
| 3 | | | | | 2023.02.25-23.29.00 [Fry Egg].mp4 | | | | | | | | 2023. |
| 4 | | | | | 2023.02.26-18.56.48 [Fry Egg].mp4 | | | | | | | | 2023. |
| 5 | | | | | 2023.02.27-20.38.22 [Fry Egg].mp4 | | | | | | | | 2023. |
| 6 | | | | | 2023.02.28-21.11.56 [Fry Egg].mp4 | | | | | | | | |
| 7 | | | | | 2023.03.01-13.05.56 [Fry egg].mp4 | | | | | | | | |
| 8 | | | | | | | | | | | | | |
| 9 | | | | | | | | | | | | | |
| 10 | | Types | Hanan | Comments | Jaime | Comments | In total | Comments | | Types | Hanan | Comments | Jaime |
| 11 | Total | Unsafe | 2 | | 2 | | 4 | | Total | Safe | 0 | | |
| 12 | | Stove On for 2mins+ | 2023.02.26-22.31.48 [On].mp4 | | 2023.02.27-22.56.04 [On].mp4 | Might be too short | | | | | | | 2023. |
| 13 | | | 2023.03.01-13.01.29 [On].mp4 | | 2023.03.01-19.52.12 [On].mp4 | The temp is a little low | | | | | | | 2023. |

Figure 5: Version 1 of Data Collection Management

Version 2 of the Excel document was then created. It listed all types of videos in the same table. The additional column for comments on version 1 of the Excel document was not added in version 2 as it was deemed unnecessary. The total video counts of different types, states and safety of each person who recorded them were calculated using Excel functions at the top of the list of video data. The table that displays the total video counts allows us to determine whether the video data was balanced or not.

| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 7 | | | Videos | Types | | | | | | | | |
| 8 | | | Total | Boil | Fry | On | Off(No heat) | Off(Cooling) | Safe | Unsafe(Stove On) | Unsafe(A little water boil off) | Unsafe(Pan with nothing) |
| 9 | | Hanan | 24 | 3 | 2 | 19 | 5 | 0 | 10 | 7 | 4 | 3 |
| 10 | | Jaime | 101 | 15 | 18 | 66 | 21 | 14 | 68 | 9 | 7 | 17 |
| 11 | | Total | 125 | 18 | 20 | 85 | 26 | 14 | 78 | 16 | 11 | 20 |
| 12 | | | | | | | | | | | | |
| 13 | | | | Total Boil vs Fry | | Total ON vs Off | | Total Off | Total Safe vs Unsafe | | Total Unsafe | |
| 14 | | | | 38 | | 125 | | 40 | 125 | | 47 | |
| 15 | | | | | | | | | | | | |
| 16 | | | | Type | | | | | | | | |
| 17 | id in csv | Student | Video | Boil | Fry | On | Off(No heat) | Off(Cooling) | Safe | Unsafe(Stove On) | Unsafe(A little water boil off) | Unsafe(Pan with nothing) |
| 18 | 1 | Jaime | 2023.02.25-21.31.26 [Boil Egg].mp4 | J | | J | | | J | | | |
| 19 | 2 | Jaime | 2023.02.25-23.29.00 [Fry Egg].mp4 | | J | J | | | J | | | |
| 20 | 3 | Jaime | 2023.02.26-18.56.48 [Fry Egg].mp4 | | J | J | | | J | | | |
| 21 | 4 | Jaime | 2023.02.27-19.37.27 [Boil Egg].mp4 | J | | J | | | J | | | |
| 22 | 5 | Jaime | 2023.02.27-20.38.22 [Fry Egg].mp4 | | J | J | | | J | | | |
| 23 | 6 | Jaime | 2023.02.28-19.44.40 [Boil Egg].mp4 | J | | J | | | J | | | |
| 24 | 7 | Jaime | 2023.02.28-21.11.56 [Fry Egg].mp4 | | J | J | | | J | | | |
| 25 | 8 | Jaime | 2023.02.26-18.44.28 [Off].mp4 | | | | J | | J | | | |
| 26 | 9 | Jaime | 2023.02.26-20.44.29 [Off].mp4 | | | | J | | J | | | |
| 27 | 10 | Jaime | 2023.02.26-20.56.59 [Off].mp4 | | | | J | | J | | | |
| 28 | 11 | Jaime | 2023.02.26-21.13.01 [Off].mp4 | | | | J | | J | | | |
| 29 | 12 | Jaime | 2023.02.26-21.33.07 [Off].mp4 | | | | J | | J | | | |
| 30 | 13 | Jaime | 2023.02.26-21.40.37 [Off].mp4 | | | | J | | J | | | |
| 31 | 14 | Jaime | 2023.02.26-22.01.10 [Off].mp4 | | | | J | | J | | | |
| 32 | 15 | Hanan | 2023.02.26-22.31.48 [On].mp4 | | | H | | | | H | | |
| 33 | 16 | Jaime | 2023.02.27-22.11.24[Off].mp4 | | | | J | | J | | | |
| 34 | 17 | Jaime | 2023.02.27-22.56.04 [On].mp4 | | | J | | | | J | | |

Figure 6: Version 2 of Data Collection Management

Version 2 of the Excel document proved to be easier to manage and provided more information than version 1. Further details on the usage of thermal video data collection can be found in Section 8 of this report.

To conclude, the use of Excel has enhanced the process of manual data labelling by facilitating the management of data collection for the machine learning algorithms.

## 2.4 JUSTIFICATION OF SUITABILITY FOR DEGREE PROGRAM

Menna Abdelhadi is a fourth-year Biomedical Electrical Engineering student at Carleton University. During her school years, she has learned the foundation of imperative programming from SYSC 2006 which taught her to code in C programming. She also learned to code in C++ from ECOR 2606, Numerical Methods. She has extensive knowledge in MATLAB modeling and Simulink from SYSC 3610, Systems modeling and control. She took SYSC 4405 to strengthen her knowledge in digital signal processing techniques to better analyze images and signals. She self-taught the basics of Python and Java via online courses, such as Coursera. These opportunities have provided her with the necessary skillset needed to undertake the challenges of this project. She now has the opportunity to implement her knowledge and her programming experience in collecting thermal data and to contribute to implementing test coverage. This project will provide her with a solid understanding of Machine Learning and Image processing.

Hanan Alshatti is a fourth-year Electrical Engineering student at Carleton University. As a fourth-year electrical engineering student, she has gained knowledge of coding in python from ECOR1051, MATLAB modeling of advanced devices from ELEC4700, foundations of imperative programming from SYSC 2006 and object-oriented software development from SYSC 2004. For the third-year project, her knowledge of python coding was implemented during her third-year project to read data acquired from an MLX90640 thermal camera in which the maximum pixel value from six arrays is taken to compute an individual's temperature. She is currently taking SYSC 4405 to strengthen her knowledge in digital signal processing to better analyze images and signals. From her knowledge, she will undertake the task of classifying a certain cooking method from another.

Eline Elorm Nuviadenu is a proficient fourth-year Computer Systems Engineering student with extensive experience in Full Stack Development. She has participated in various programs such as Google's Software Program Sprint and worked as a software lead for Carleton's Electric Self Driving Car club. Her primary interests lie in User Interface and Experience, Web, and Embedded development. During her study at Carleton University, Eline has acquired a wealth of programming skills, including C, Python, and Java. She accomplished this through participating in Carleton's Students as Partners Program and contributing to the creation and curation of content for a C programming course for non-programming graduate students. She also completed courses such as Data Structures and Algorithms, Object-Oriented Programming, Software Architecture, and a Computer Systems project course. Her knowledge, gained from self-study and the aforementioned courses equipped her with the essential skills to research and work on the classification of images from a thermal camera, as well as the design and integration of various application functionalities. These skills demonstrate her proficiency and strength in both the theory and practice of systems development, which is important in the technological world of today.

Hiu Sum Jaime Yue is a fourth-year Computer Systems Engineering student. In her school years in the Computer System Engineering program, she has gained a solid foundation in Python, Java, and C. During the SYSC 3010 project, she has the chance to create an app using Android studio with Java. The app was designed to show data and control the robot using Firebase, which is a database. But more importantly, it will send an alert notification to the user if the robot senses fire. Other than Firebase, she also has experience using MySQL, which is a relational database. With her prior experience with databases, her focus on this project was the back-end design of the project. This project relates to her program as this project demonstrates her proficiency in practical application of database concepts that are fundamental concepts in her program.

## 2.5 INDIVIDUAL CONTRIBUTIONS

Everyone in the team has contributed to different components throughout this project. The components were then integrated together to create a final product that met the requirements outlined in the project proposal. Table 1 and Table 2 describe how the components were split between team members and also in the context of this report.

### 2.5.1 PROJECT CONTRIBUTIONS

As mentioned in Section 2.3.1, two GitHub repositories were used in this project. The Project GitHub and the repository for the web application are called Capstone_ADLA_StoveOvenUse and The-OG respectively.

Each member has written code and pushed to GitHub. Table 1 shows the project coding contributions and contains the links to the files of our GitHub repositories.

**Table 1: Contributions to Features and New Functionalities**

| Code in GitHub | Team Member |
|---|---|
| Capstone_ADLA_StoveOvenUse<br>- Machine Learning/Training/OnOff.ipynb<br>- Research/OnOffTrainTest.ipynb (edited) | Menna Abdelhadi |
| Capstone_ADLA_StoveOvenUse<br>- Research/SafeUnsafe_FindBestAlgorithm.ipynb (edited)<br>- Research/SMOTE.ipynb<br>- Research/SafeUnsafeImbalancedataset.ipynb<br>- MachineLearning/Training/safeandunsafe_traintest_smotedata.ipynb | Hanan Alshatti |
| Capstone_ADLA_StoveOvenUse<br>- MachineLearning/classification.py<br>- MachineLearning/database.py<br>- MachineLearning/main.py<br>- MachineLearning/Training/Boil_Fry_LR.ipynb<br>- Research/FindingBestAlgoritm(BF).ipynb<br>- ThermalSoftware/Project/frame_data.py (edited)<br>- ThermalSoftware/Project/thermalImageProcessing2023.py (edited)<br>The-OG<br>- src/Pages/<br>- src/components/<br>- src/images/ | Eline-Elorm Nuviadenu |

| | |
|---|---|
| - src/App.css<br>- src/App.js<br>- src/firebase.js<br>- src/index.js<br>- src/public/firebase-messaging-sw.js<br>- functions/index.js | |
| Capstone_ADLA_StoveOvenUse<br>- ThermalSoftware/names.py<br>- ThermalSoftware/screen_recorder.py (edited)<br>- ThermalSoftware/testModels.py<br>- ThermalSoftware/Project/checkDuration.py<br>- ThermalSoftware/Project/cooking_thermal_2023.db<br>- ThermalSoftware/Project/database2023.py (edited)<br>- ThermalSoftware/Project/thermalImageProcessing2023.py (edited)<br>- ThermalSoftware/Project/Models/frame_data.py (edited)<br>- ThermalSoftware/Project/Models/testdata.py<br>- ThermalSoftware/Project/Models/testdataWithId.py<br>- ThermalSoftware/Test Data/<br>The-OG<br>- src/Pages/Home.js<br>- src/Pages/Login.js<br>- src/Pages/Signup.js<br>- utils/ | Hiu Sum Jaime Yue |

### 2.5.2 REPORT CONTRIBUTIONS

The report has 15 chapters in total. Each member has been assigned tasks that they are responsible for. Table 2 provides a clear breakdown of each member's contributions.

**Table 2: Contributions to Final Report**

| Tasks | Responsible |
| --- | --- |
| 1.1 Motivation<br>1.2 Background<br>2.2 Engineering Professionalism<br>2.4 Justification of Suitability for Degree Program<br>9.2 ON/OFF<br>9.4 SMOTE<br>14 Conclusion<br>15 Reflections | Menna Abdelhadi |
| 1. Introduction<br>1.1 Motivation<br>1.2 Background<br>1.4 Accomplishments<br>1.5 Overview of the report<br>2.1 Health and safety<br>2.4 Justification of Suitability for Degree Program<br>6.3 Future additions for Thermal Video Collection<br>9.3 Safe/Unsafe<br>9.4 SMOTE<br>9.6 Future additions for classification | Hanan Alshatti |
| 2.3 Project Management<br>2.4 Justification of Suitability for Degree Program<br>7.1 Feature Extraction<br>9 Machine Learning Using Binary Classification<br>9.1 Frying/Boiling of an Egg<br>9.5 Combinational Algorithm<br>9.6 Future Additions for Classification<br>11 The Old-Guard Application ("The-OG")<br>12 Sequence diagram<br>13 Testing | Eline-Elorm Nuviadenu |

| | |
|---|---|
| 2.3.1 Project GitHub<br>2.3.4 Data Collection Management<br>2.4 Justification of Suitability for Degree Program<br>4 Overview<br>5 Apparatus Setup<br>6 Thermal Video Collection<br>7 Thermal Cooking Database<br>8 Data Collection<br>10 Firebase Structure<br>13.1 Database (Under 13 Testing) | Hiu Sum Jaime Yue |
| Requirements<br>Production of the Presentation Video for the project | All |

# 3. PROJECT REQUIREMENTS

The project requirements were slightly changed since the project proposal was written. The project proposal is included in Appendix A.

**Table 3: Project Functional and Non-Functional Requirements**

| | |
|---|---|
| **Functional Requirements** | The system shall be able to distinguish between boiling an egg and frying an egg, between a stove that is off and a stove that is on, and between the cooking process is safe and unsafe.<br>The database shall hold information relating to the stove use.<br>The application shall be able to send an alert if the stove is unsafe.<br>The application shall be able to present the information of the cooking process, including the state, type, and safety of the cooking process to the user. |
| **Non-Functional Requirements** | When the stove is on with nothing on top of it for 4 minutes, the user is alerted.<br>When the stove is on with only a pan on for 4 minutes, the user is alerted.<br>The system shall be able to detect and send an alert if the stove is turned on and a pot with water inside has been completely steamed off within 4 minutes. |

# 4. OVERVIEW

## 4.1 DEPLOYMENT DIAGRAM

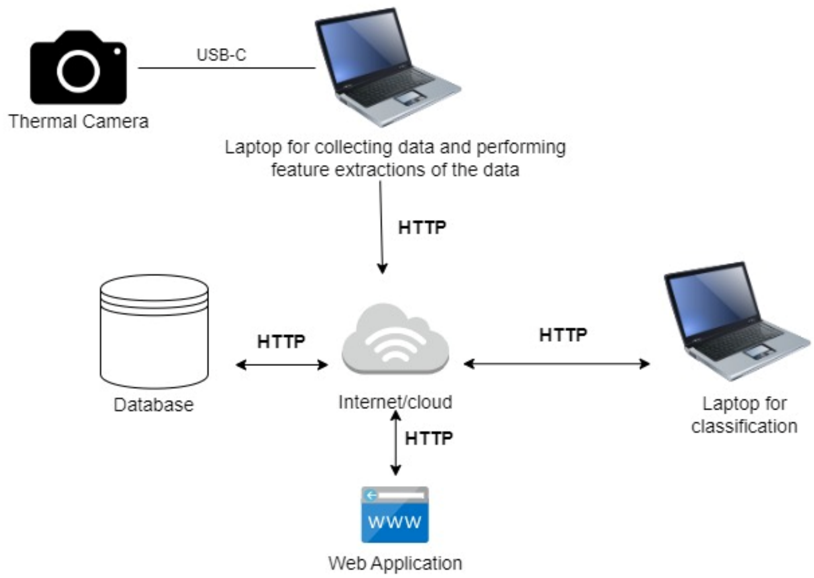


**Figure 7: Deployment Diagram Showing System Communications**

Figure 7 above, shows the general deployment design for this project. The laptop for collecting the data and performing feature extractions of the data, the laptop for classifying the data, the database and the web application communicate using the Internet. On the physical layer of the system, the laptop for collecting data and performing the feature extractions of the data is connected to a thermal camera using a USB-C cord. This camera will be used to collect the thermal data, after performing feature extractions, the datasets will be sent to the cloud. The laptop responsible for the classification retrieves the thermal data from the cloud, execute the code, and return the output to the cloud to be placed into the database. The web application communicates with the database, sending and receiving messages as necessary.

## 4.2 SPECIAL COMPONENTS AND FACILITIES

The main component needed in this project is a Seek Thermal camera. The team used Seek Thermal CW-AAA Compact-All-Purpose Thermal Imaging Camera for Android USB-C. The Seek thermal camera that the team used costs around $400 on Amazon [34]. To collect data of the stove, a USB-C extension cord was used to connect the thermal camera to the computer of the user. A USB-C extension cord costs around $10 to $20 on Amazon [35]. Furthermore, the placement of the thermal camera can make an impact on collecting the data from the video feed. Therefore, a tripod mount or a webcam stand is required to clamp onto an object near the stove for proper data collection. In the case of special facilities required, the only facility that is needed for this project is a stove to collect data while cooking.

## 5. APPARATUS SETUP

This section highlights how our team set up the apparatus to get the thermal videos using the Seek thermal camera.

To get useful thermal videos for this project, which successfully collects the thermal data of the pan and the food, the Seek thermal camera had to be positioned at a suitable recording angle. We carefully selected a clamp to set up the thermal camera according to the environment around the stove which we used for recording thermal videos. We purchased a clamp for $34.99 on Amazon to hold the Seek thermal camera so our team can record the thermal video from a proper recording angle [36].

Learning from the experience of the previous team, a good recording angle is right on top of the stove, instead of away from the stove. Hence, we set up the Seek thermal camera to the clamp, and the clamp was then mounted on the handle of the stove. We also used some elastic bands and cardboard to keep the thermal camera in place. Figure 8 demonstrates this setup. To get varying data, another setup was done to record data from a metal stovetop. In this setup, the camera was placed on top of the box with some wires to keep it in place and safe from falling. This setup can be seen in Figure 9.

**Figure 8: Apparatus Setup on Glass Stovetop**

**Figure 9: Apparatus Setup on Metal Stovetop**

With the thermal camera positioned at an appropriate angle, Figure 10 displays a screenshot of a thermal video that was captured using the Seek thermal camera. It depicts the process of frying an egg and serves as an example of the thermal data that our team aimed to obtain. In contrast, Figure 11 shows the RGB (red, green, and blue) view, which is how human eyes perceive the frying egg process.

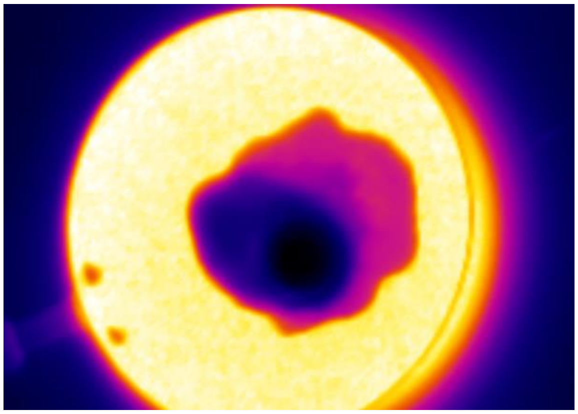

Figure 10: Thermal Image when Frying an Egg

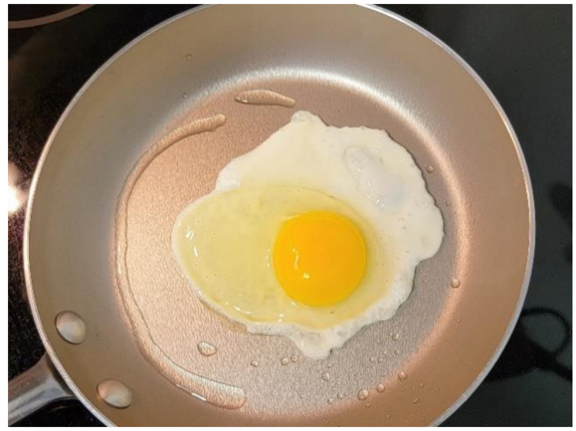

Figure 11: RGB Image when Frying an Egg

## 6. THERMAL VIDEO COLLECTION

Regarding the collection of thermal videos, the code developed by the previous team was used as the foundation of our work. The code was modified to meet the objectives of this project. Section 6.1 outlines the procedures for thermal video collection. Section 6.2 highlights some of the challenges encountered during the process of collecting thermal videos.

### 6.1 APPLICATIONS FOR THERMAL VIDEO COLLECTION

With machine learning being utilized in this project, the acquisition of datasets is crucial. To record thermal videos, the previous team has suggested our team to use the SeekOFix application by frenkinet [37] and a screen recorder application [38]. Figure 12: Interface Used By Previous Team displays the interfaces of theses applications, where the SeekOFix application covers the whole screen.

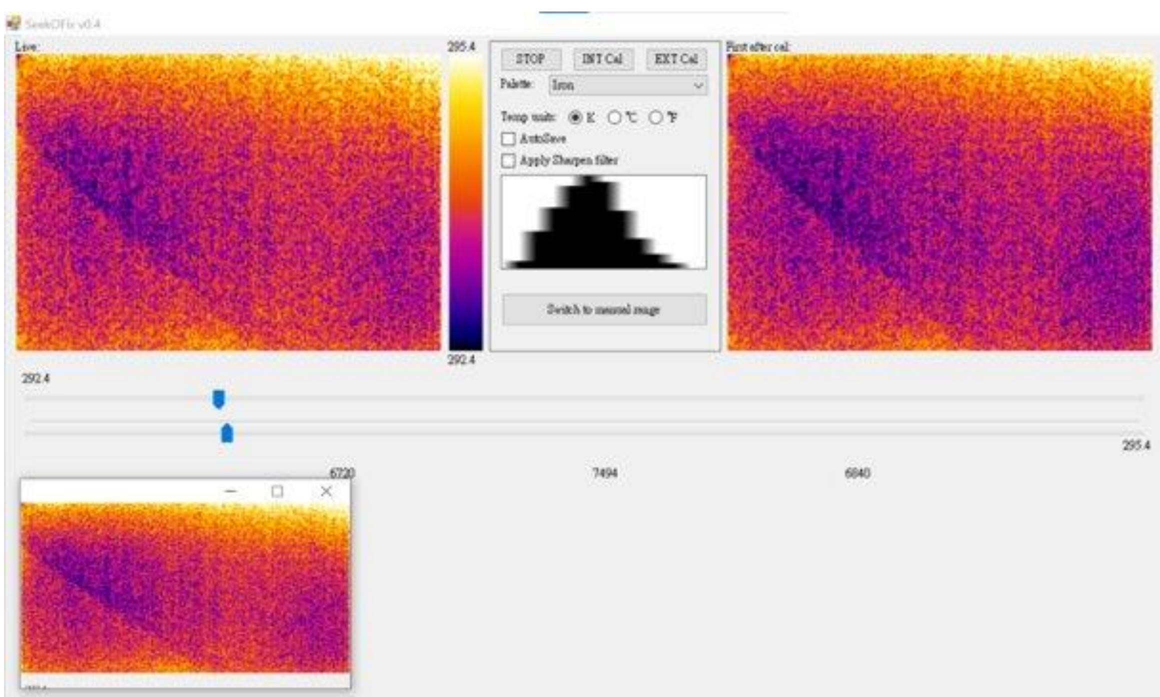


**Figure 12: Interface Used By Previous Team**

Our team focuses on using two primary functions of the SeekOFix application, which are getting the temperature unit to °C (degree Celsius) and switching to manual range from dynamic range to obtain a fixed range of the color palette. The top and bottom range sliders under the live screens can be used to change the range of the color palette, which is displayed on the right side of the live screen. The previous team had set up the top range slider and the bottom range slider, which is the minimum temperature of the color palette as -50 °C and the maximum temperature of the color palette as 350 °C, to extract features with the fixed color palette in their code.

To record thermal videos using the SeekOFix application, a screen recorder is required since the SeekOFix application does not have a built-in video recorder. The application at the bottom left corner of Figure 12 is the screen recorder application that was created by the previous team. However, there is a rule for the screen recorder application to function with the SeekOFix application, which requires the SeekOFix application to be running before the screen recorder application is launched. It is best to avoid opening other applications while recording as the screen recorder does not fixate on the SeekOFix application. If other applications are opened at the position where the screen recorder has set the dimensions of the live screen of the SeekOFix application, they may appear in the thermal video recording. It is also important to note that the set dimensions of the live screen of the SeekOFix application in the screen recorder code might need to be adjusted based on the screen dimensions of the computer to obtain the correct position of the live screen.

When the recording is completed, press “q” on the keyboard to end the recording. The recording will be stored in the Test Data Folder. To ensure that the thermal video in the Test Data folder can be passed into the databaseClient application properly, a label must be added at the end of the thermal video filename, such as changing “2023.04.01-13.12.58” to “2023.04.01-13.12.58 [Boil Egg]”. Once the thermal video recording is stopped, it can be passed into the databaseClient application to extract features and write the dataset to the database. More information on extracting features and writing from the dataset to database is provided in Section 8.

## 6.2 CHALLENGES FOR IMAGE PROCESSING

At the beginning of this project, our team was indecisive between two sets of code, the code from the previous team and the code from a research student that worked with Professor Wallace to start the project. Our team faced quite several problems in making this decision, but eventually, we decided to move forward with the code of the previous team. The decision was made based on the fact that our team can build on their code and avoid repeating what had already been done.

Between the two sets of code, they both have their advantages and disadvantages to pick from to start our part of the project.

### 6.2.1 CODE FROM PREVIOUS TEAM

The previous team provided us the link to their GitHub repository and their final report. However, we found that there were only vague instructions on how the entire process of collecting the data works. The lack of clarity in the instructions made it difficult for our team to determine which code to use and the order in which to run the code. Although the results from the previous team would be useful for continuing the project, the extra time required to understand the code and determine the order of running the code made our team hesitant.

### 6.2.2 CODE FOR RECORDING FROM SEEK THERMAL CAMERA

New code for getting thermal videos was given to us by a research student who works with Professor Wallace. We successfully setup the new code for recording the thermal videos from the Seek thermal camera. Unfortunately, another problem arose which was extracting the thermal data from the thermal video. The author of the new code sent our team a reference code from a GitHub gist to follow, but this reference code was complicated and contained a great amount of unrelated code that our team would need to remove after going through the code. Fully understanding the reference code in order to utilize what was needed was time consuming and challenging. There was no way to confirm if the code would work or not.

### 6.2.3 COMPARISON OF THE TWO SETS OF CODE

After many discussions, our team has decided to continue working on the code of the previous team, despite the additional time required to understand the progress of the code. The ability to easily access to one of the students who was on the previous group made our progress smoother. Although the new code for recording thermal video was useful, using it would have significantly increased our workload by requiring us to replicate what the previous team had already accomplished.

### 6.2.4 CHALLENGES AFTER SETTLED TO USE THE CODE FROM THE PREVIOUS TEAM

Technical issues arose as our team attempted to set up the code from the previous team and the SeekOFix application. Thermal video collection started after the technical issues being resolved, but there was a misunderstanding about how to properly set up the SeekOFix application before recording the video. Dynamic range of the color palette was used instead of manual range with -50 °C to 350 °C. Unfortunately, those thermal video recorded with dynamic range color palettes were deemed unsuitable for use in this project and disregarded.

## 6.3 FUTURE ADDITIONS FOR THERMAL VIDEO COLLECTION

In the future, it might be beneficial for project teams to explore real-time analysis. Being able to do real-time thermal data analysis would allow for analysis of thermal data in real-time and provide valuable insights for the project. In our approach, thermal videos were recorded, data was extracted and stored into a database. The data was then fed through the machine learning model. However, the current approach only captures what has already occurred and does not provide real-time analysis. For example, in the case of safe and unsafe, even if the algorithm classified it was unsafe, the unsafe situation was happened while recording the thermal video but not real-time. Our team discussed the possibility of implementing real-time analysis with Professor Wallace after successfully setting up of the thermal recording applications, we recognized that this would require changes to the software used for recording thermal videos. Given the time constraints of the project, we decided to focus more on the machine learning aspect of the project instead.

Furthermore, in this project, data has been collected exclusively from glass top and metal top stoves. While these stoves are common and widely used, it is important to consider that there are other types of stoves that may have distinct characteristics and usage patterns. In future iterations of the project, it would be beneficial to expand the scope of data collection to include a wider variety of stoves.

## 7. THERMAL COOKING DATABASE

After recording thermal videos, our team proceeded to the next step of the project, which involves extracting features from the thermal videos and writing dataset into the database. This step is important as it forms the foundation for the machine learning part of the project.

### 7.1 FEATURE EXTRACTION

The former team developed a code that utilized edge detection to differentiate between the pan and food sections in a thermal image and obtain their respective temperatures. This code was modified and utilized to generate six distinct features, which consisted of the average pan temperature, the highest and lowest pan temperatures, as well as the average, highest, and lowest food temperatures.

Our team also made changes to the sample rate of feature extraction, which differed from the approach of the previous team. Our team aimed to extract 20 equally spaced frames from each video. To explain more, our team developed a code that takes in the length of the video and divides by 19 to generate 20 equally spaced frames. From each of these frames, our functions extract 7 elements.

This approach of utilizing 20 equally spaced frames instead of extracting all the frames from the thermal videos reduces the computational resources required for data processing. With the total of the extracted features from the 20 frames, we have 140 elements. Additionally, it made a more manageable dataset that can be easily analyzed in the machine learning part of the project.

### 7.2 EDITED DATABASE SCHEMA: ANALYSIS TABLE

The analysis table created by the previous team serves as a base of what features to extract for each frame. It includes 7 elements, namely elapsed time, average pan temperature, area of the pan, number of food elements, food temperature in an array, food area in an array and the classification the previous team obtained using threshold.

Our team used machine learning for classification purposes. Hence, our team made some changes to the elements of the analysis table.

The updated version of analysis table also consists of 7 elements, which are elapsed time, average pan temperature, highest pan temperature, lowest pan temperature, average pan temperature, highest food temperature and lowest food temperature. The changes of elements obtained was to provide a more comprehensive understanding of the temperature range and variability during the cooking process.

## 7.3 NEW DATABASE SCHEMA

### 7.3.1 VERSION 1: TESTDATA

Version 1 of the new database schema is called TestData. There are a total of 143 elements, including 20 frames of 7 elements, which are 140 elements and an additional 3 elements that are for the state of the stove, type of egg being cooked and safety status of the stove. Figure 13 below displays the testdata table.

Table: testdata

| | state | type | safety | time_elapsed_1 | avg_pan_temp_1 | highest_pan_temp_1 | lowest_pan_temp_1 | avg_food_temp_1 | highest_food_temp_1 | lowes |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 0 | 5.05805298249186 | 5.05805298249186 | 5.05805298249186 | 5.05805298249186 | 5.05805298249186 | 5.0 |
| 2 | 1 | 1 | 0 | 0 | 6.97068252134044 | 6.97068252134044 | 6.97068252134044 | 6.97068252134044 | 6.97068252134044 | 6.9 |
| 3 | 1 | 1 | 0 | 0 | 4.2239768242949 | 4.2239768242949 | 4.2239768242949 | 4.2239768242949 | 4.2239768242949 | 4. |
| 4 | 1 | 0 | 0 | 0 | 14.6540988471901 | 14.6540988471901 | 14.6540988471901 | 14.6540988471901 | 14.6540988471901 | 14. |

**Figure 13: SQLite Table with TestData Model**

### 7.3.2 VERSION 2: TESTDATAWITHID

Version 2 of the new database schema is called TestDataWithId. There are in total of 145 elements. Version 2 is very similar to version 1, but version 2 includes the data Id and stove Id. The additional elements allow the classification code to save the id of the stove along with the classification and display on the web application.

Table: testdataWithId

| | id | stoveId | state | type | safety | time_elapsed_1 | avg_pan_temp_1 | highest_pan_temp_1 | lowest_pan_temp_1 | avg_food_temp_1 | highest_food |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 0 | 0 | 0 | 5.05805298249186 | 5.05805298249186 | 5.05805298249186 | 5.05805298249186 | 5.058052 |
| 2 | 2 | 1 | 1 | 1 | 0 | 0 | 6.97068252134044 | 6.97068252134044 | 6.97068252134044 | 6.97068252134044 | 6.970682 |
| 3 | 3 | 1 | 1 | 1 | 0 | 0 | 4.2239768242949 | 4.2239768242949 | 4.2239768242949 | 4.2239768242949 | 4.22397 |
| 4 | 4 | 1 | 1 | 0 | 0 | 0 | 14.6540988471901 | 14.6540988471901 | 14.6540988471901 | 14.6540988471901 | 14.65409 |

**Figure 14: SQLite Table with TestDataWithId Model**

## 7.4 DATA PREPARATION FOR CLASSIFICATION

After the thermal video pass through the databaseClient application, dataset will have the default values for state, type, and safety, which are all set to 0. To properly train the binary classifier, manual data labelling is performed based on the label that was added to the filename of the thermal video. The state of stove is labelled as 0 if the stove is off and 1 if the stove is on. The type of cooking method for an egg is labelled as 0 if it is boiling and 1 if it is frying. The safety of the stove is labelled as 0 if safe and 1 if unsafe. Our team has recorded 7 types of thermal video that can fit into these 6 situations. Section 8 describes the types of videos correspond to each situation.

With the testdataWithId table being saved into the database, a CSV file is generated for machine learning purposes. The manual data labelling is then being added to the CSV file to allow proper training of the binary classifiers.

## 7.5 FUTURE ADDITIONS FOR DATABASE

The thermal cooking database currently has 129 tables. Even though the values of an analysis table are in the testdata table and testdataWithId table, there are no connections between the tables. The current code is designed to write a new dataset into a new analysis table, the video table, the testdata table and the testdataWithId table.

Future project teams should investigate in jointing the tables instead of putting repeated values in different tables separately. With a jointed table, the time required to write the dataset into multiple tables should be reduced.

Furthermore, future project teams should also consider writing a code for running all the test data videos at once instead of using the dataClient application and manually selecting each video from the Test Data folder. During this project, this problem has arisen twice as we created a new database schema and re-ran all the thermal videos through the dataClient application. Therefore, developing a code for running all the test data videos that performs feature extraction and writes all the new datasets into the database for all test data videos would be beneficial.

# 8. DATA COLLECTION

## 8.1 TYPES OF VIDEOS

In this project, 7 types of thermal videos were recorded, which are boiling an egg, frying an egg, leave stove on, leave stove off, the stove cooling off, leave stove on with a pan and leave stove on until water in a pot was totally streamed off. While each type of thermal videos includes the same set of features, they have different values. This section will describe and provide visualization of data extracted from these thermal videos.

### 8.1.1 SAMPLE DATA OF BOILING AN EGG

Figure 15 shows the data of boiling an egg in a line chart. In the manual data labelling process, boiling an egg is to set the state, type, safety as on, boiling and safe, which are 1, 0 and 0, respectively. The process of boiling an egg includes an increasing temperature while water, egg being boiling and cooling down eventually. Since the egg is in the water while boiling, the temperature of the boiling egg, which is not extremely high. Time measurements were also being considered as the time of duration of the boiling process. For defining the safety of the stove, we have included the cooling process of the stove after boiling an egg in the thermal video.

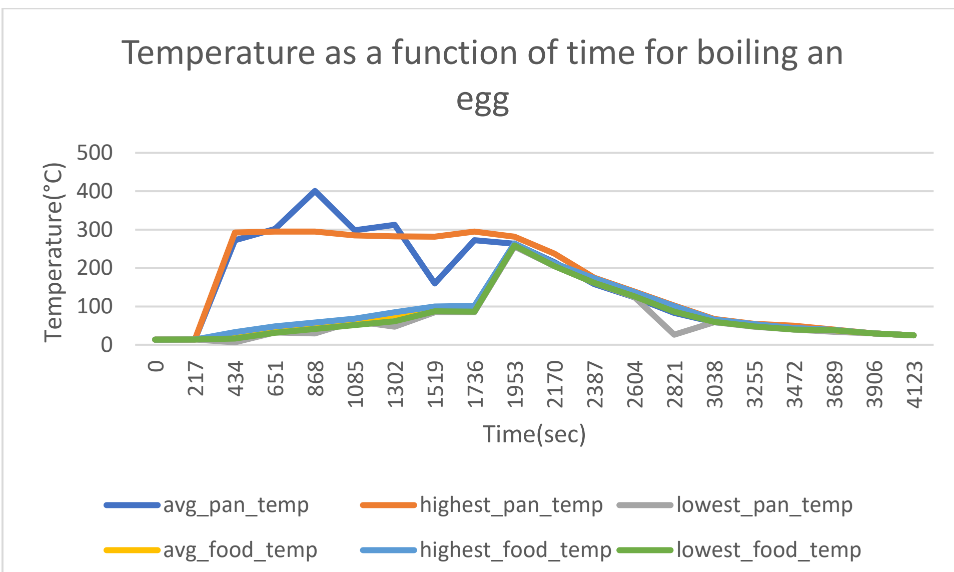


**Figure 15: Data Visualization when Boiling an Egg**

### 8.1.2 SAMPLE DATA OF FRYING AN EGG

Figure 16 shows the data of frying an egg in a line chart. In the manual data labelling process, frying an egg is to set the state, type, safety as on, frying and safe, which are 1, 1 and 0, respectively. During the process of frying an egg, the pan temperature and food temperature are both high. According to Figure 16, the highest pan temperature and food temperature are at 250 °C, which are very similar as the highest temperature we extracted out of the thermal video. In this project, not only the temperature was considered, but also the time factor. Between frying an egg and boiling an egg, one of the differences is the time that the egg is being cooked. For defining the safety of the stove, we have included the cooling process of the stove after frying an egg in the thermal video.

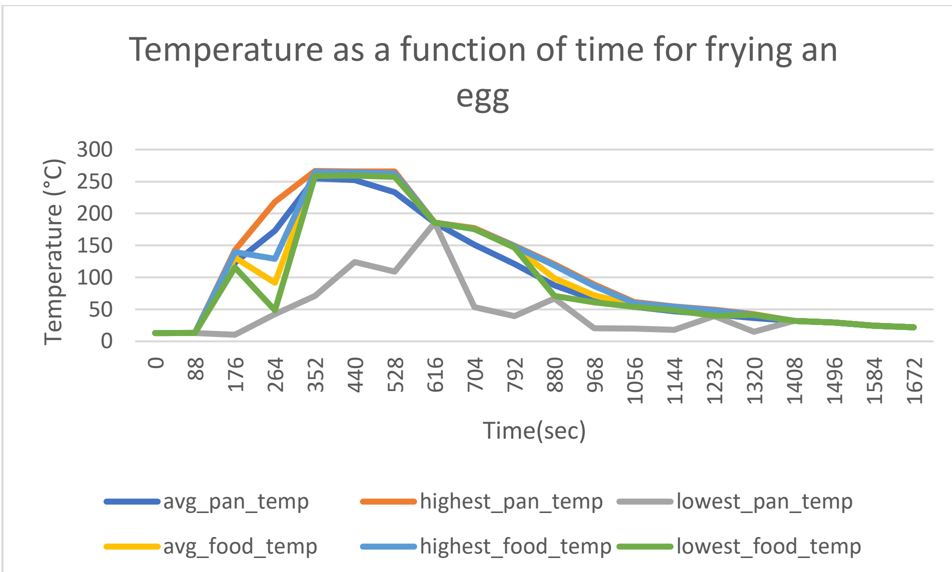


**Figure 16: Data Visualization when Frying an Egg**

### 8.1.3 SAMPLE DATA OF LEAVE THE STOVE ON

Figure 17 shows the data of leaving the stove in a line chart. In the manual data labelling process, leaving the stove on is to set the state, type, safety as on, none and unsafe, which are 1, null and 1, respectively. In the case of leaving the stove on, the pan and food temperature will be the same as it can only record the temperature out of the stove in the thermal video. Also, the temperature of the pan and food will be the maximum temperature in the recorded thermal video, which was extracted using the SeekOFix application and the functions of the previous team.

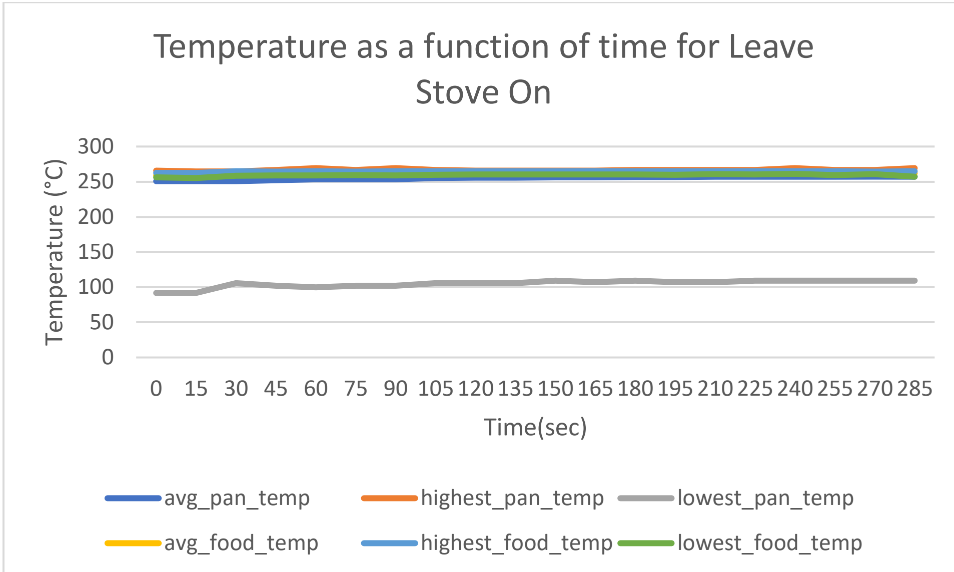


Figure 17: Data Visualization when Stove is Left On

### 8.1.4 SAMPLE DATA OF LEAVE THE STOVE OFF

Figure 18 shows the data of leave the stove off in a line chart. In the manual data labelling process, leaving the stove off is to set the state, type, safety as off, none and safe, which are 0, null and 0, respectively. With the stove being off, all temperatures around the pan and food are in the range of 5 °C to 20°C, which is around room temperature.

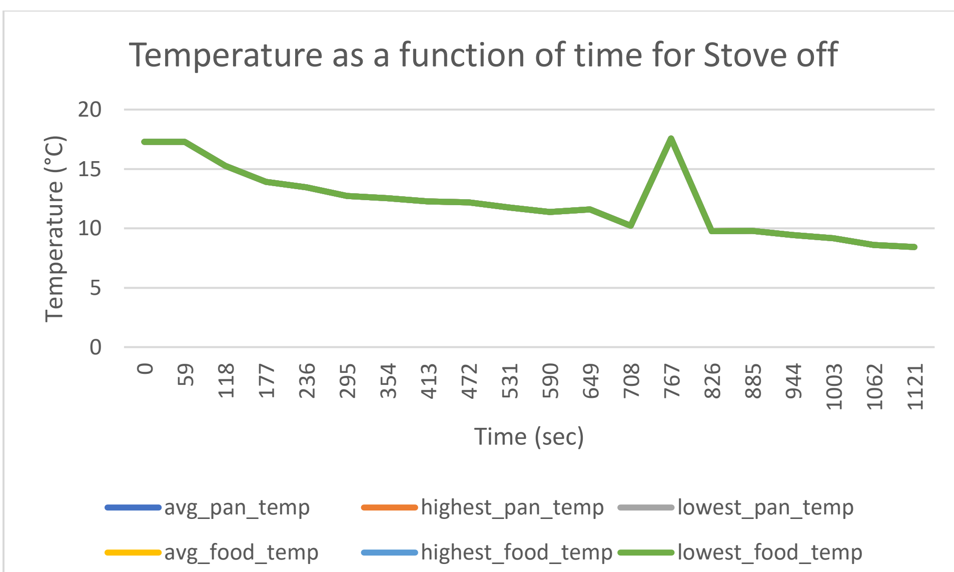


Figure 18: Data Visualization when Stove is Off

## 8.1.5 SAMPLE DATA OF THE STOVE COOLING DOWN

Figure 19 shows the data of the stove cooling off in a line chart. In the manual data labelling process, stove cooling down is to set the state, type, safety as off, none and safe, which are 0, null and 0, respectively. With the stove cooling down, the temperature of food and pan both came off a high temperature and created a decreasing slope as time passed and temperature dropped back to the room temperature.

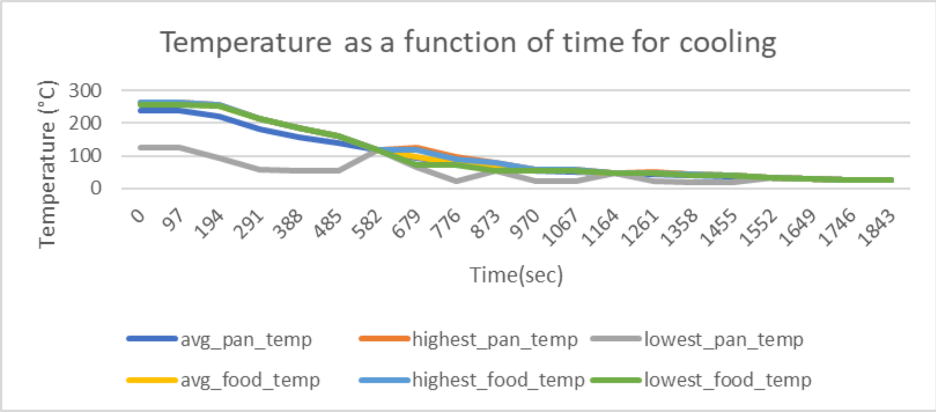


**Figure 19: Data Visualization when Stove is Cooling Down**

## 8.1.6 SAMPLE DATA OF LEAVE THE STOVE ON WITH A PAN

Figure 20 shows the data of leave the stove on with a pan in a line chart. In the manual data labelling process, leaving the stove on with a pan is to set the state, type, safety as on, none and unsafe, which are 1, null, 1, respectively. With the stove on with a pan, the temperature of food and pan started from room temperature and created an increasing slope as time passed and temperature increased to the maximum temperature we can obtained from the thermal video.

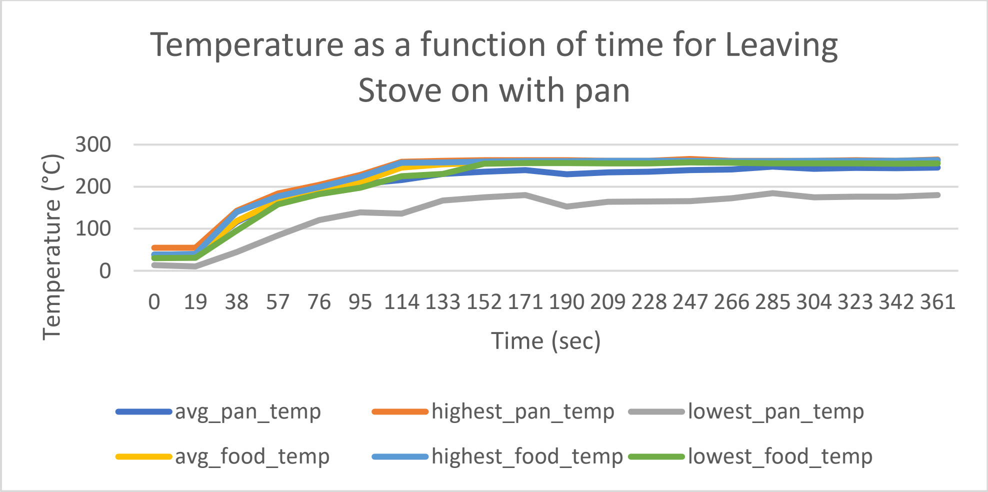


**Figure 20: Data Visualization when Stove is On with Pan**

### 8.1.7 SAMPLE DATA OF LEAVE THE STOVE ON UNTIL WATER TOTALLY STEAMED OFF

Figure 21 shows the data of leaving the stove on until water totally steamed off in a line chart. In the manual data labelling process, leaving the stove on until water totally streamed off is to set the state, type, safety as on, none and unsafe, which are 1, null, 1, respectively. In the case of the stove is on until water totally steamed off, from the beginning to the middle of the cooking process, the water is still in the pot. However, starting from the middle of the cooking process, the temperature of the pan and food, which in this case is the temperature of the pot and water, starting to increase from the range of 100°C to 200°C to the maximum temperature we can obtained from the thermal video.

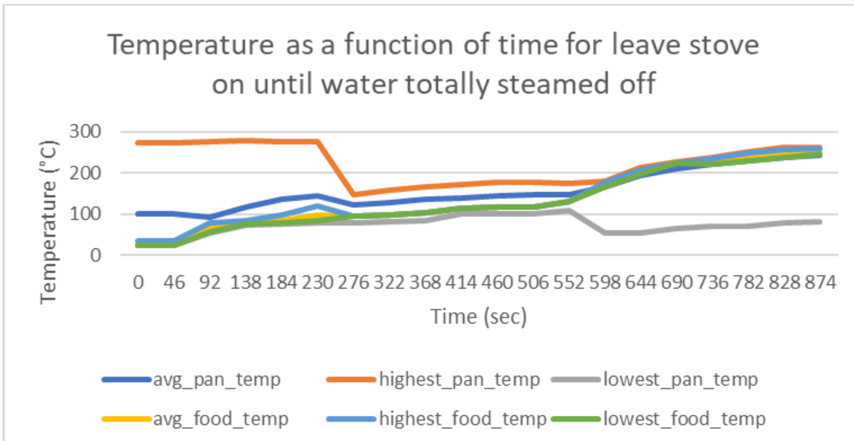


**Figure 21: Data Visualization when Stove is On and Water Completely Steams Off**

## 8.2 THERMAL VIDEO RATIO

Thermal video was recorded with two different types of stove top, which are the metal stovetop by Hanan and glass stovetop by Jaime. Setup of the camera with the two different types of stove top was mentioned in Section 5. Figure 22 shows the number of videos by types and the ratio of datasets.

| | Videos | Types | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total | Boil | Fry | On | Off (No heat) | Off (Cooling) | Safe | Unsafe (Stove On) | Unsafe(A little water boil off) | Unsafe (Pan with nothing) |
| Hanan | 24 | 3 | 2 | 19 | 5 | 0 | 10 | 7 | 4 | 3 |
| Jaime | 101 | 15 | 18 | 66 | 21 | 14 | 68 | 9 | 7 | 17 |
| Total | 125 | 18 | 20 | 85 | 26 | 14 | 78 | 16 | 11 | 20 |
| | | | | | | | | | | |
| | | Total Boil vs Fry | | Total ON vs Off | | Total Off | Total Safe vs Unsafe | | Total Unsafe | |
| | | 38 | | 125 | | 40 | 125 | | 47 | |

**Figure 22: Ratio of Thermal Video Recordings**

All the thermal videos were processed using the databaseClient application and successfully written into the thermal cooking database. As mentioned in Section 8.1.1 and 8.1.2, the boiling and frying videos were manually labelled as on and safe with each of their types. Thermal videos that did not involve boiling or frying an egg are set as type none. Therefore, the total datasets available for each case of binary classification differs. The binary classification of on/off and safe/unsafe can use all 125 datasets, while the binary classification of boiling/frying can only use 38 datasets to train and test the machine learning model.

## 8.3 FUTURE ADDITIONS FOR DATA COLLECTION

Despite using SMOTE to address the problem of imbalanced datasets for the on/off and safe/unsafe cases, it is better to use real data. More thermal data of unsafe and off are needed to get to a balanced dataset according to Figure 22. Another factor contributing to the imbalanced dataset is the number of thermal videos recorded using stove 1 or stove 2. As everyone has a different cooking habit and a different type of stove, generates a slightly different dataset. Therefore, the imbalanced datasets between stoves were also a concern.

Future project groups can expand the types of thermal video recording. With other types of thermal video, the machine learning algorithms can also be expanded to classify other cooking complexities.

## 9. MACHINE LEARNING USING BINARY CLASSIFICATION

Preprocessing data is a critical step when applying classification machine learning methods to ensure that the data is appropriate for the models. This process involves handling missing values, scaling, or normalizing numerical features such as temperature or time, and dividing the information into training and testing groups.

In the previous year's iteration of the project, a basic classifier was hardcoded with predetermined thresholds to identify the status of a stove, the cooking technique utilized, and the safety of the stove. However, this approach had numerous issues due to the varying cooking temperatures across households, resulting in false alerts. Additionally, the hardcoding approach was laborious, leading the team to shift to machine learning-based classification models.

The classification process was divided into three significant sections that could be resolved using binary classification – whether the stove is off or on, whether it is safe or unsafe, and whether the cooking method entails boiling or frying. For this project, the scope of cooking methods was restricted to boiling and frying eggs.

### 9.1 FRYING/BOILING OF AN EGG

To establish the most suitable binary classification algorithm for determining whether an egg was boiled or fried, the dataset underwent training and testing with several machine learning models which can be seen in Figure 23 below.

The dataset was loaded, and the data with null values were dropped as they were not related to the frying or boiling data. The dataset was then split using 20% of the data as the test set. The values were then normalized in order to stabilize the data. Multiple models were then initialized and trained by looping them through the dataset and recording their values in multiple lists. The values in these lists were then used to determine the accuracy, precision, recall and F1 score in bid to aid in the selection of the model which would perform best for this classification. The findings revealed that the top-performing models for the classification were the Logistic Regression and Support Vector Machines.

| | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Logistic Regression | 0.818182 | 0.714286 | 1.00 | 0.833333 |
| Support Vector Machines | 0.818182 | 0.714286 | 1.00 | 0.833333 |
| Decision Trees | 0.545455 | 0.428571 | 0.75 | 0.545455 |
| Random Forest | 0.727273 | 0.571429 | 1.00 | 0.727273 |
| Naive Bayes | 0.636364 | 0.428571 | 1.00 | 0.600000 |
| K-Nearest Neighbor | 0.363636 | 0.000000 | 0.00 | 0.000000 |

Figure 23: Performance of Various Algorithms in Distinguishing Between Boiling and Frying

After a thorough evaluation, the Logistic Regression Algorithm was chosen over the Support Vector Machines due to its simple nature and ease of interpretability [39]. Given the limited size of the dataset, a 5-fold train and test approach was adopted for cross-validation purposes, which led to an enhanced model accuracy of 100%. This was due to the fact that the model was trained on every sample in the dataset by shuffling through the data iteratively, where after 5 iterations, every data point would have been used for training and testing. The accuracy was then averaged across these 5 iterations and a confusion matrix was generated. This confusion matrix for this analysis can be seen in Figure 24 below.

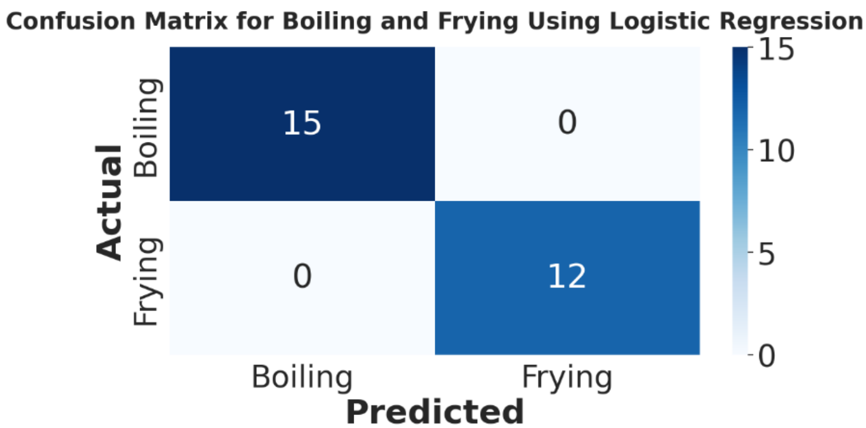


Figure 24: Confusion Matrix - Boiling vs. Frying

Subsequently, the trained model was serialized using the pickling technique to enable its deployment in combination with other models.

## 9.2 ON/OFF

Due to its capacity to recognize patterns and generate predictions based on vast volumes of data, machine learning can be used to determine if a stove top is ON or OFF. When there are only a few variables to take into account, using an if statement to detect the condition of a stove top can be efficient. However, it can become laborious and unreliable in more complex situations.

The condition of the stove top is just one of several variables that might affect the dynamic process of cooking. A stove top's On and Off states result from a complicated interplay between the stove top, the cooking vessel, and the food being cooked rather than being a static binary situation. Hence, machine learning is the appropriate and the best approach for the purpose of this project.

A stovetop can be in one of two states: On or Off. These states were presented using binary values, where 0 represents "off" and 1 represents "on". The data collected from the stove top regarding these states were fed into different machine learning classifiers, which then analyzed the data and made predictions.

Logistic regression, support vector machines, decision trees, random forests, naive bayes, and k-nearest neighbour were among the classifiers used to train the model. A full assessment of each classifier's performance in terms of accuracy and precision was provided in the form of an accuracy table, which allowed for an expedient and straightforward comparison of the models in order to determine which is the best classifier.

The accuracy table presented in Figure 25, showed that multiple classifiers had a 100% accuracy rate in classifying the On and Off states. The Support Vector Machines model, however, was chosen as the best model to train for the stove states. Support Vector Machine is known to be less prone to overfitting and can provide better generalization performance.

| | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| **Logistic Regression** | 1.000000 | 1.0 | 1.000000 | 1.000000 |
| **Support Vector Machines** | 1.000000 | 1.0 | 1.000000 | 1.000000 |
| **Decision Trees** | 0.962963 | 1.0 | 0.941176 | 0.969697 |
| **Random Forest** | 1.000000 | 1.0 | 1.000000 | 1.000000 |
| **Naive Bayes** | 0.962963 | 1.0 | 0.941176 | 0.969697 |
| **K-Nearest Neighbor** | 1.000000 | 1.0 | 1.000000 | 1.000000 |

Figure 25: Performance of Various Algorithms in Distinguishing Between On and Off

The confusion matrix in Figure 26 provided a more detailed analysis of a classifier's performance. By displaying the number of true and false positives and negatives, it offers a clearer understanding of a model's strengths and weaknesses. Although this model achieves 100% accuracy, this makes it a weakness, because it is likely overfitting, meaning that it has memorized the training data instead of learning the underlying patterns. Such a model is not reliable and will not perform well on new, unseen data, resulting in biased results.

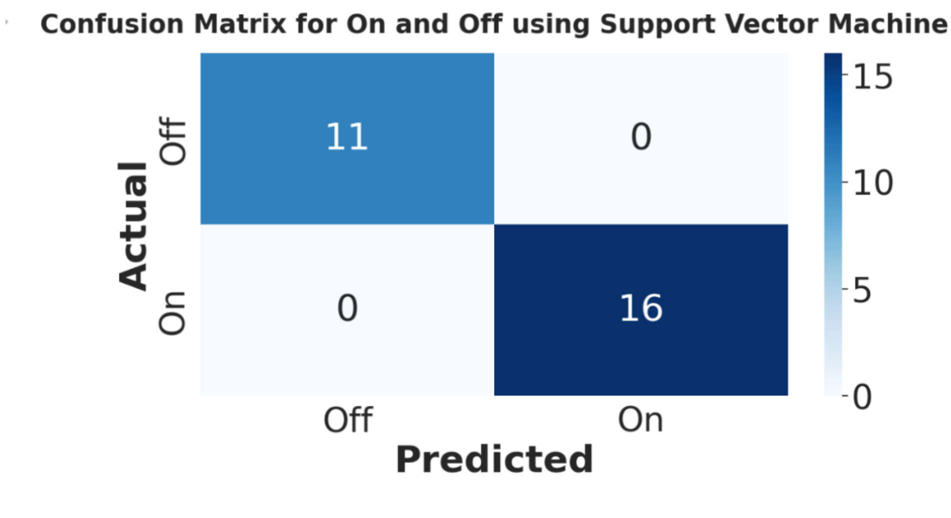


Figure 26: Confusion Matrix - On vs. Off

Overfitting can be caused by various factors, including unbalanced data, where one class has significantly fewer samples than the others. To address this issue, we used SMOTE which is explained in detail in Section 9.4. This helped balance the data and improve the model's performance on the minority class, reducing the risk of overfitting.

After applying SMOTE to balance the data, the classifiers were retrained, and a new confusion matrix was generated. The confusion matrix shown in Figure 27 reveals that when both the actual and predicted values are incorrect, the count is 10. When both values are correct, the count is "off". When the actual value is incorrect, but the predicted value is correct, the count is 1, and similarly, when the actual value is correct, but the predicted value is incorrect, the count is also 1. Based on these findings, the overall accuracy of the model is determined to be 91% for a data split ratio of 80-20. Hence the balanced data helped in overfitting, giving a more realistic prediction now that the data in balance.

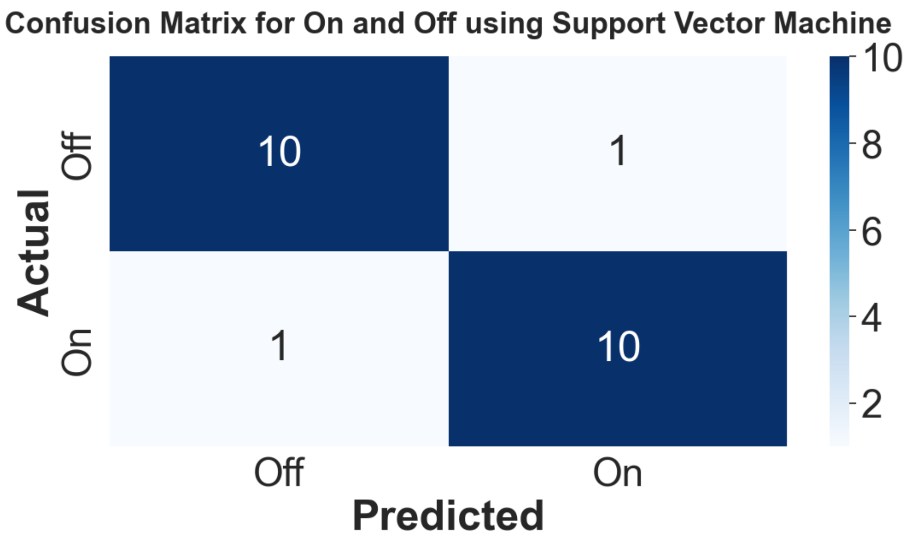


Figure 27: Confusion Matrix with SMOTE - On vs. Off

## 9.3 SAFE/UNSAFE

The performance of different machine learning classifiers for classifying secure and unsafe scenarios was compared using a provided dataset. Accuracy, precision, recall, and F1 score measures, as well as the confusion matrix, were used to evaluate each model, as shown in Figure 28

The accuracy table provided a summary of each model's results. The ideal model would exhibit high accuracy, precision, recall, and F1 score values. By comparing these metrics, the best models were identified as Naive Bayes and Decision Tree using a 50/50 ratio for testing and training. Although the values were tied for different ratios, Naive Bayes was found to perform best.

| | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Logistic Regression | 0.967742 | 0.916667 | 1.00 | 0.956522 |
| Support Vector Machines | 0.983871 | 0.958333 | 1.00 | 0.978723 |
| Decision Trees | 0.983871 | 1.000000 | 0.96 | 0.979592 |
| Random Forest | 0.967742 | 0.916667 | 1.00 | 0.956522 |
| Naive Bayes | 0.983871 | 1.000000 | 0.96 | 0.979592 |
| K-Nearest Neighbor | 0.967742 | 0.916667 | 1.00 | 0.956522 |

Figure 28: Performance of Various Algorithms Between Safe and Unsafe

By displaying the distribution of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions, the confusion matrix provided a more comprehensive perspective of the classifier's efficiency. This allowed for a more in-depth examination of each model's attributes as seen in the figure in the context of safe and unsafe classifications.

A high number of false positives, may result in unsafe situations being ignored, presenting a significant risk. It was feasible to determine which classifiers were better at minimising these unwanted results by comparing the numbers in the confusion matrix.

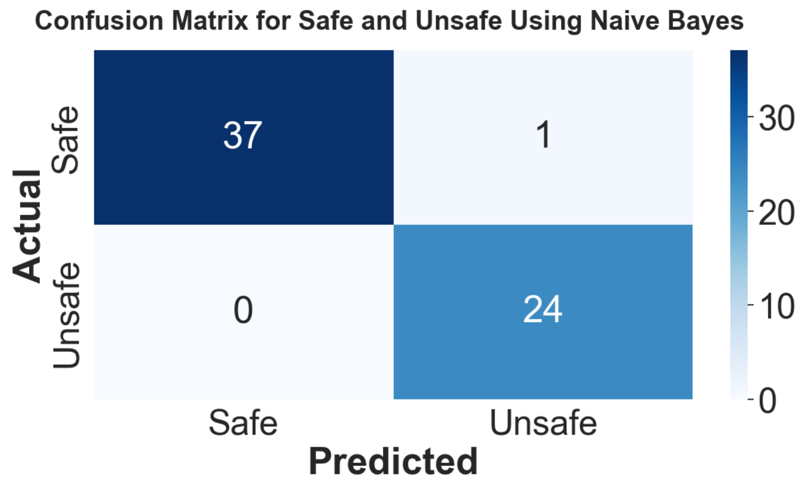


Figure 29: Confusion Matrix - Safe vs. Unsafe

After assessing each classifier's performance using both the accuracy table and the confusion matrix, inferences about their relative advantages and discrepancies were made. This information enabled a decision of choosing the best model for categorising safe and unsafe conditions in the provided dataset. Finally, the chosen model offered an adequate mix of accuracy, precision, recall, and F1 score while minimising false positives and false negatives in the classification process.

In which:

True Positives (TP): The number of instances correctly classified as unsafe.

False Positives (FP): The number of instances incorrectly classified as unsafe.

True Negatives (TN): The number of instances correctly classified as safe.

False Negatives (FN): The number of instances incorrectly classified as safe.

The distribution of data among classes in many real-world categorization issues is frequently imbalanced, with one class having considerably fewer examples than other classes. Because machine learning models have a bias towards the dominant class, this imbalance can contribute to unfavorable performance. When it comes to unsafe data collection an imbalance was evident with the unsafe data accounting for 47 out of 125. Due to that imbalance, SMOTE was implemented to balance the data.

The Synthetic Minority Over-Sampling Technique (SMOTE) was used to address this problem. As observed from the table below, balancing the data and applying smote significantly increased the accuracy for all models.

| | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Logistic Regression | 1.0 | 1.0 | 1.0 | 1.0 |
| Support Vector Machines | 1.0 | 1.0 | 1.0 | 1.0 |
| Decision Trees | 1.0 | 1.0 | 1.0 | 1.0 |
| Random Forest | 1.0 | 1.0 | 1.0 | 1.0 |
| Naive Bayes | 1.0 | 1.0 | 1.0 | 1.0 |
| K-Nearest Neighbor | 1.0 | 1.0 | 1.0 | 1.0 |

**Figure 30: Confusion Matrix with SMOTE - Safe vs. Unsafe**

Based on the gathered data, various machine learning algorithms were used to identify safe and unsafe situations. Logistic Regression, Support Vector Machines (SVM), Decision Trees, Random Forests, Naive Bayes, and K-Nearest Neighbors are among the methods used. (KNN). Using the balanced dataset produced by SMOTE, each algorithm was trained and evaluated.

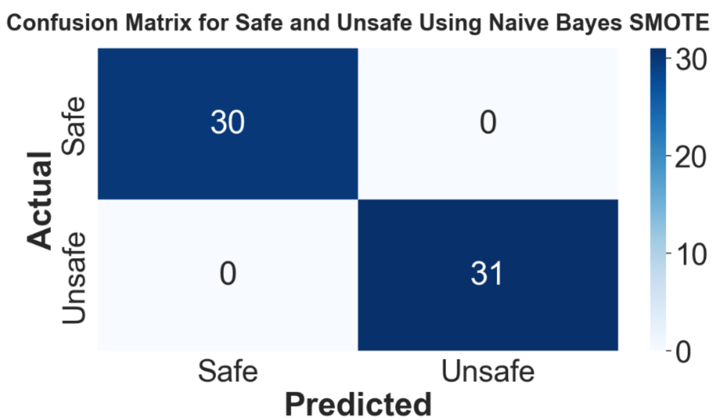


**Figure 31: Confusion Matrix with SMOTE - Safe vs. Unsafe**

## 9.4 SMOTE

SMOTE (Synthetic Minority Over-sampling Technique) is a machine learning tool that is used as a data augmentation technique to deal with the issue of unbalanced datasets. Datasets that are unbalanced have one class, the minority class, significantly underrepresented compared to the other class, the majority class. As a result, models that are biased may do a poor job of accurately categorising the minority class. This problem is addressed by SMOTE, which creates new minority class examples by interpolating between existing minority class examples. The dataset can then be balanced using these artificial examples, which will also help machine learning models perform better [40].

SMOTE also helps in preventing overfitting, which occurs when a model is trained on a dataset that is too small or unrepresentative of the true distribution of the data. By generating new synthetic examples, SMOTE can increase the size of the dataset and improve the model's ability to generalize to new, unseen data [41].

We used SMOTE for the on and off classification and for the safe and unsafe classification. The dataset, we were working with was imbalanced, with many of the examples belonging to the "off" class and only a small proportion belonging to the "on" class. SMOTE helped fixe that problem by balancing the data.

In the process of collecting data, there may be fewer instances of unsafe cooking activities compared to safe ones. This can be attributed to the notion that it may be difficult to intentionally create and record unsafe cooking scenarios due to potential risks. The variability in cooking practices further contributes to the dataset's imbalance, as consistent safe cooking methods are more prevalent across various techniques, while unsafe activities may be more sporadic and specific to certain situations or equipment. As a result, the dataset contains a higher proportion of safe cooking activities compared to unsafe ones.

## 9.5 COMBINATIONAL ALGORITHM

The combinational algorithm was split into two principal classes, namely, the database class and the classification class, and the main method. The database class comprised the path to the Firebase database, enabling the algorithm to record the outcomes in it. It permitted the user to write the stove id, state, safety, and cooking method to two paths, one that maintained a record of all the previous methods and the other for the current stove state, which would dynamically update as the stove's state altered.

The classification class facilitated the loading and manipulation of the dataset and allowed for the loading of models and retrieval of the stove and user id. As the data was not collected in real-time, a method was included to simulate a real-time application by enabling the prediction of one data point every five seconds. The prediction algorithm was set up to ascertain whether the stove was off or on, and the safety model was utilized for prediction purposes only if the stove was on. Furthermore, the frying and boiling models were exclusively executed if the stove was determined to be on.

The main python file was designed to load all pickled models, the dataset, and invoke all functions in the appropriate sequence to ensure seamless functionality.

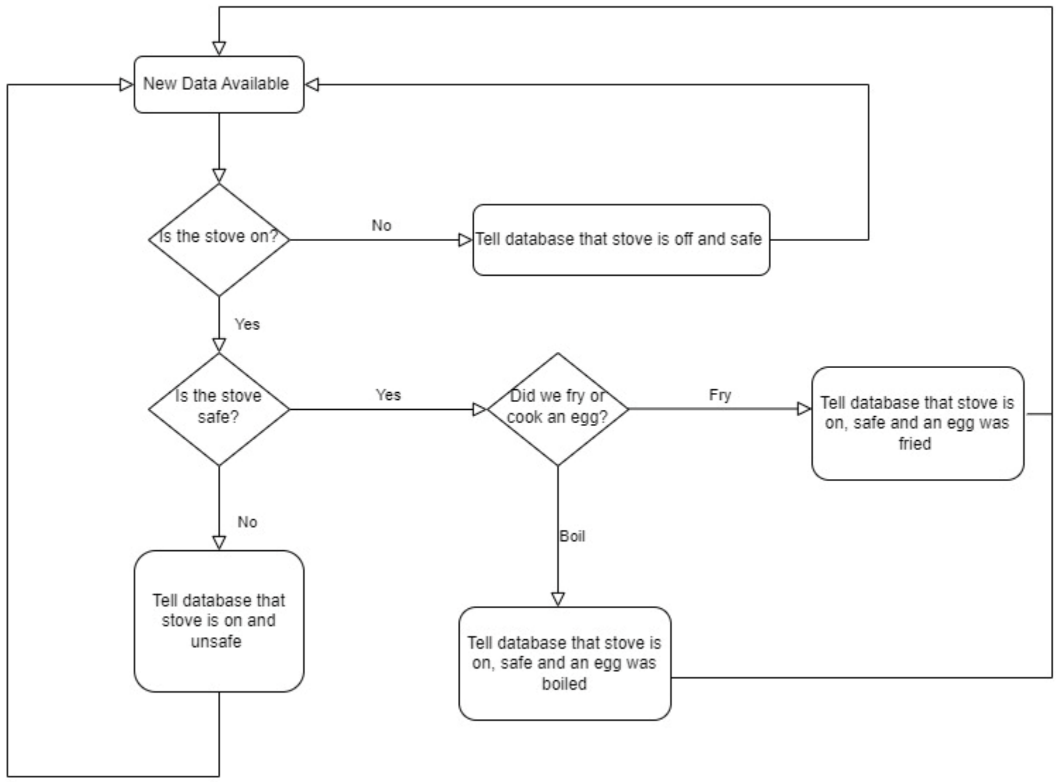


**Figure 32: Flowchart Depicting Decision Making Structure**

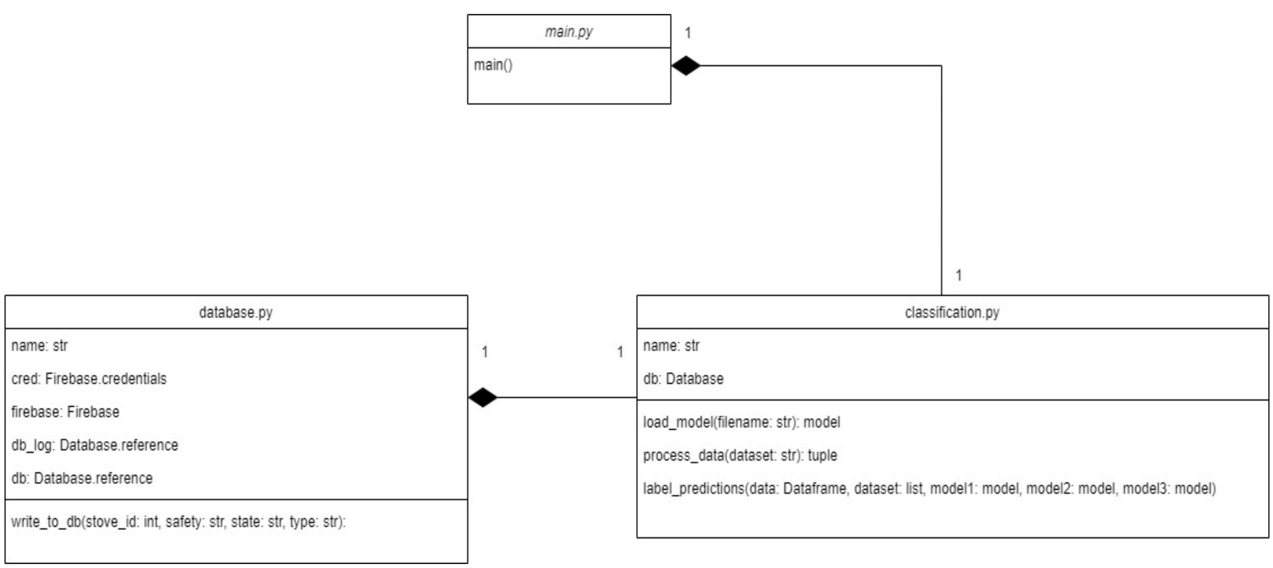


**Figure 33: UML Diagram for Machine Learning Classification**

## 9.6 FUTURE ADDITIONS FOR CLASSIFICATION

Currently, the machine learning models work on preprocessed data which is not very feasible in real world applications. To better achieve our goal, the state and safety model would need to be converted to real time processing algorithms, thus allowing for immediate alerts. The model for determining the cooking method could also be converted from binary to multiclass to include various cooking methods of different complexities.

The use of unsupervised learning methods can be investigated to discover unusual patterns in data that may correlate with unsafe circumstances. These methods, when used in conjunction with supervised learning classifiers, can offer additional insight into the issue. Cooking is a continuous process encompassing various activities and interactions that can differ between occurrences. Due to this variability, relying solely on conventional supervised learning methods may not result in error-free solutions for identifying unsafe situations.

Unsupervised learning methods, such as clustering or autoencoders, provide the advantage of not requiring labeled data for training. They can identify patterns or relationships in data that might be difficult to detect through human perception or supervised learning techniques [42].

As the dataset grows, these techniques could become more applicable and valuable. Unsupervised learning methods are particularly useful in identifying anomalies or unusual trends in data. However, our dataset size was insufficient to justify the use of these methods at the time of our research. Incorporating unsupervised learning techniques as the dataset expands can offer valuable insights and contribute to a more comprehensive understanding of both safe and unsafe cooking scenarios.

## 10. FIREBASE STRUCTURE

Figure 34 below shows how the messages can be sent and received between nodes. There are two node-to-node interfaces, including Web application and Database, Classification and Database.

| Web application and Database | | | |
|---|---|---|---|
| Sender | Receiver | Message | Data Format |
| Web application | Database | addContact | con1@ddd.com |
| Web application | Database | getCurrentUserId | 2 |
| Database | Web | showStoveID | 1 |
| Database | Web | showState | "On" |
| Database | Web | showType | "Boiling" |
| Database | Web | showSafety | "Safe" |

| Classification and Database | | | |
|---|---|---|---|
| Sender | Receiver | Message | Data Format |
| Database | Classification | readUserID | 1 |
| Classification | Database | addStoveID | 2 |
| Classification | Database | addState | "On" |
| Classification | Database | addType | "Boiling" |
| Classification | Database | addSafety | "Safe" |

Figure 34: Communication Protocol Table (Between Nodes)

Figure 35 below displays the summarized version of communication protocol Table using JSON format.

| Sender | Receiver | MessageContent |
|---|---|---|
| Classification | Database | {"receiveDataFromClassification": {"EntryId": TEXT, "userId": INT, "stoveId": INT, "Safety": TEXT, "State" : TEXT, "Type": TEXT}} |
| Database | Classification | {"receiveDataFromDatabase": {"currentUserId": INT}} |
| Database | Web Application | {"receiveDataFromWeb":{"currentUserId" : INT, "stoveId": INT, "Safety": TEXT, "State" : TEXT, "Type": TEXT}} |
| Web Application | Database | {"sendContactFromWeb":{"currentUserId": INT, "Email": TEXT}} |

Figure 35: Communication Protocol Table in JSON Format

The structure of the database is shown in Figure 36 below. The database has three indices, which are Users, Log and Admin.

Under Users, the user Id is used as the index. Under the user Id, there are 5 different pieces of information, including Name, Email, Password, Contacts and StoveManagement. Under Contacts, the contact Id is used as the index. Under the contact Id, the email of the contact will be shown. Under StoveManagement, there are 4 different pieces of information, including Safety, State, Type, and the id of the stove, which will be shown respectively.

Under Log, a unique key is used as the index. Under every unique key, there are 4 different pieces of information that are the same as the information under StoveManagement. The difference is that the ones under StoveManagement will keep changing while Log will keep track of every set of Safety, State, Type, and the id of the stove using a unique key as its index.

Under Admin, it included the currentUserId of the web application to keep track of who is currently using the application.

| Users | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | 2 | | | | | | |
| Name | Email | Password | Contacts | | | | StoveManagement | | Name | Email | Password | Contacts | | StoveManagement | |
| Jaime | jaime@gmail.com | pw123 | 1 | | 2 | | Safety | Unsafe | Eline | eline@gmail.com | elinePw | 1 | | Safety | Safe |
| | | | Email | con1@email.com | Email | con2@email.com | State | On | | | | Email | con3@email.com | State | On |
| | | | | | | | Type | None | | | | | | Type | Frying |
| | | | | | | | stoveId | 2 | | | | | | stoveId | 1 |

| Log | | | |
|---|---|---|---|
| uniquekey | | uniquekey | |
| Safety | Unsafe | Safety | Safe |
| State | On | State | On |
| Type | None | Type | Frying |
| stoveId | 2 | stoveId | 1 |

| Admin |
|---|
| currentUserId |
| 1 |

Figure 36: Database Structure

In future additions, the password passed into the database by the users can be hashed using SHA-3 for enhanced data integrity. Password hashing can transform the password into a non-readable format. This can make sensitive information like user credentials more secure and protect users from unauthorized access.

# 11. THE OLD-GUARD APPLICATION ("THE-OG")

The term "The-OG" was coined to convey our mission to assist the elderly while acknowledging that they are not our exclusive focus. This terminology was adopted playfully while remaining relevant to the fact that cognitive impairment issues are not solely confined to the elderly population.

The primary purpose of this application was to enable the contacts and caretakers of our monitoring and classification system's users to stay informed and confident that the stove is being utilized safely and that the user is consuming meals regularly. The interface of the application was designed in a way that constantly updates the display as and when new data is appended to the database. This makes it easier for future integrations of a live classification model, as users would be able to see changes as and when they happen.

In order to implement this basic functionality, the Firebase Realtime Database was used. Firebase was chosen because of its easy integration, scalability, security, and cost-effectiveness. Firebase SDK provides functionalities that make the process easy. Since Firebase can handle very large amounts of data, it was very feasible in the context of our project since we are constantly storing the stove's status, safety, and cooking methods in the database.  Since Firebase has data persistence, it makes it possible to extract nutritional benefits in future iterations of the project. Firebase also protects the data from unauthorized access.

The application sets up a listener for various fields in the Firebase database, and that is what enables the values displayed to constantly change when the database is updated. This also allows for sending alerts when a specific value is seen in the database.

The utilization of React, Node.js, Express, and Bootstrap frameworks in the creation of the web application offers several benefits. React, a popular JavaScript library, simplifies the creation of user interfaces and improves application performance through its virtual DOM implementation[43]. Node.js, a server-side JavaScript runtime, offers improved scalability and allows for the development of high-performance applications[44]. Express, a lightweight framework for Node.js, simplifies the creation of server-side applications and offers several built-in features such as middleware for handling HTTP requests [45]. Bootstrap, a popular CSS framework, provides pre-designed UI components that streamline the creation of responsive and visually appealing web applications[46]. By incorporating these frameworks, the web application not only offers a seamless user experience but also ensures optimal performance and security.

Additionally, to ensure the integrity and security of the login and registration processes, the application implements the use of Regex (Regular Expressions) to validate email addresses. This crucial step guarantees that users can only log in or register with a valid email address. Specifically, a validation function is employed to assess the format of email inputs and determine whether they meet the standards of a valid email address. In the absence of this function, the submit button would still operate even though the input does not satisfy the criteria for a valid email. This highlights the necessity of using Regex expressions to confirm the validity of user inputs, given that relying solely on the email input type attribute would not suffice. Overall, the incorporation of Regex validation in the web application is a critical component of ensuring the accuracy and security of user data.

## 11.1. APPLICATION DEVELOPMENT

In the design of “The-OG”, the Agile methodology was implemented in order to ensure flexibility and continuous improvement as the application development was started late into the project, reasons for the late start can be seen in the problems faced under Section 11.2. Therefore, this design approach allowed for the quick creation of an application to meet user needs.

The Agile process of designing our web application involved weekly meetings, sprint planning, and demonstrations for the team. GitHub and Microsoft Teams were used as tools to manage and track the progress of the application.

This agile process was important in successfully creating the application. By breaking down this process into smaller deliverables, it enabled functionalities to be developed quickly and allowed for any changes that needed to be made as problems arose. Meetings were held to keep other team members up to date with the progress of the application, and to keep them informed on the changes that would require changes in the implementation of an application’s functionalities.

### 11.1.1 LOGIN PAGE

The login page of the application permits an existing user to enter their email and password to gain access to the home page. These fields are mandatory for successful login functionality. Additionally, a sign-up button is provided for new users to register an account. Below is a wireframe model of the application.


Figure 37: Wireframe for Login page

### 11.1.2 SIGN UP PAGE

The Sign-Up page provides an avenue for users to register using their name, email, and password. A password confirmation field is also included to ensure consistency between the passwords entered by the user. Additionally, users are prompted to enable notifications before proceeding with the sign-up process.

All user details are securely stored in a private database to safeguard user privacy. Upon successful registration, the user is directed to the home page of the application.


Figure 38: Wireframe for Sign Up page

### 11.1.3 HOME PAGE

The home page of the application retrieves the most up-to-date stove status information from the database and displays it to the user. The ID of the stove is also shown on the home page to facilitate identification of the active stove. Additionally, the home page provides a feature that enables users to add contacts that will receive alerts if the system state changes from safe to unsafe.

Figure 39: Wireframe for Home page

### 11.1.4 ALERTS

The alert functionality is a critical component of our project, as it is designed to provide caretakers and families of individuals with cognitive impairment with the assurance that they need to leave their loved ones in their own care, rather than being admitted into long-term care facilities. The functionality of adding contacts was considered necessary to achieve this objective.

The inclusion of this feature has the potential to bring about a transformative shift in the lives of those impacted by cognitive impairment, as it allows them to lead more independent lives without sacrificing safety. By predicting an unsafe situation through the use of machine learning code, the system can quickly and efficiently respond to the situation by writing it into the database, then notify the user via an alert and an audible sound.

This immediate response provides caregivers with the necessary information to check on their patient, family member, or friend. It also offers the patient a sense of security knowing that if something goes wrong, someone will be alerted to their situation.

In addition to these features, our project has also integrated email functionality, which enables the sending of future alerts via email. This feature is particularly useful for caretakers and families who are not physically present but still want to remain informed about the well-being of their loved ones.

Overall, the alert functionality and the integration of contact and email functionality have been essential in ensuring the safety and well-being of individuals with cognitive impairment. The implementation of these features has brought us closer to our goal of empowering individuals with cognitive impairment to live independently and confidently.

## 11.2 PROBLEMS FACED

At the outset of the project, our team had intended to repurpose and modify the ThermSAS application, which had been developed by the preceding team. The ThermSAS application allows users to access stove data, add contacts, and view messages after the feature extraction process, as well as log in to their accounts. Regrettably, upon downloading the Android application, it was discovered that the login and register pages were non-functional, with no error messages provided to indicate the cause of the issue. Consequently, our team resolved to abandon the pre-existing Android application and instead design a new web application, which we have named The-OG.

This unexpected development resulted in an additional predicament, namely that of workload prioritization. The need for this course of action became apparent at a later stage in the project, leaving us with a constrained timeframe and limited resources. In view of this, our team opted to first focus on establishing a working display, deferring the development of alerts and contact addition for subsequent stages. However, it soon became evident that the amount of work required to finalize the alert-sending and authentication features had been underestimated.

Compounding our difficulties, the constantly evolving versions of Node and Express meant that dependencies had to be continually reviewed and updated, as earlier versions became obsolete. Moreover, the varying versioning of packages, such as cors, prototype, and webpack, posed significant challenges, as it became increasingly challenging to identify compatible dependencies.

## 11.3 FUTURE ADDITIONS

### 11.3.1 LIVE VIEWING

If the libraries of the thermal camera were modified to enable live data transmission, a new feature could be added to the application. This capability would allow caregivers or family members to monitor stove activity in real-time. To ensure the privacy of individuals with cognitive impairment, this feature would only be activated when the stove is in use. During the registration of the stove, the user could specify whether live viewing is restricted to unsafe situations or only when the stove is in use. This additional feature would provide an extra layer of safety and peace of mind to caregivers and family members, while also maintaining the privacy of the individual with cognitive impairment.

### 11.3.2 LIVE ALERTS

The current version of the app is not able to provide real-time alerts to users regarding stove risks, as it relies on pre-recorded cooking videos to analyze and detect potential hazards. Instead, the user must manually select a video for the app to analyze. To improve the app's functionality, a possible future development would be to integrate the thermal camera to record live, enabling the app to continuously monitor the stove for risks. This could be accomplished through cloud-based data collection on remote servers. This will enable the collection as well as the transmission of stove data to a remote server, where it could be stored and analyzed.

### 11.3.3 STATISTICS PAGE

To enhance the functionality of the application, a feature can be added to convert a person's cooking patterns into trends and display them on a dedicated web application page. By analyzing the trends, physicians, caretakers, and family members can identify any decline in the cooking complexity or eating habits of the individual with cognitive impairment. This can serve as a warning sign to check on the person's health status and potentially improve their overall well-being. The integration of this feature into the application can be a valuable tool in tracking the health status of individuals with cognitive impairment and providing timely interventions to prevent any adverse health outcomes.

### 11.3.4 EMAIL AND SMS NOTIFICATIONS

To enhance the alert feature of the application additional notification options such as email and SMS could be included. With these options, caregivers and family members can receive alerts regardless of their location, ensuring that they are promptly informed of any issues that arise. This feature would provide peace of mind for individuals who are frequently on the move, as they would still be able to receive important alerts even when they are away from their primary devices. Overall, the inclusion of email and SMS notifications would significantly improve the functionality and practicality of the alert system, making it a more effective tool for caretakers and family members of individuals with cognitive impairment.

## 12. SEQUENCE DIAGRAM

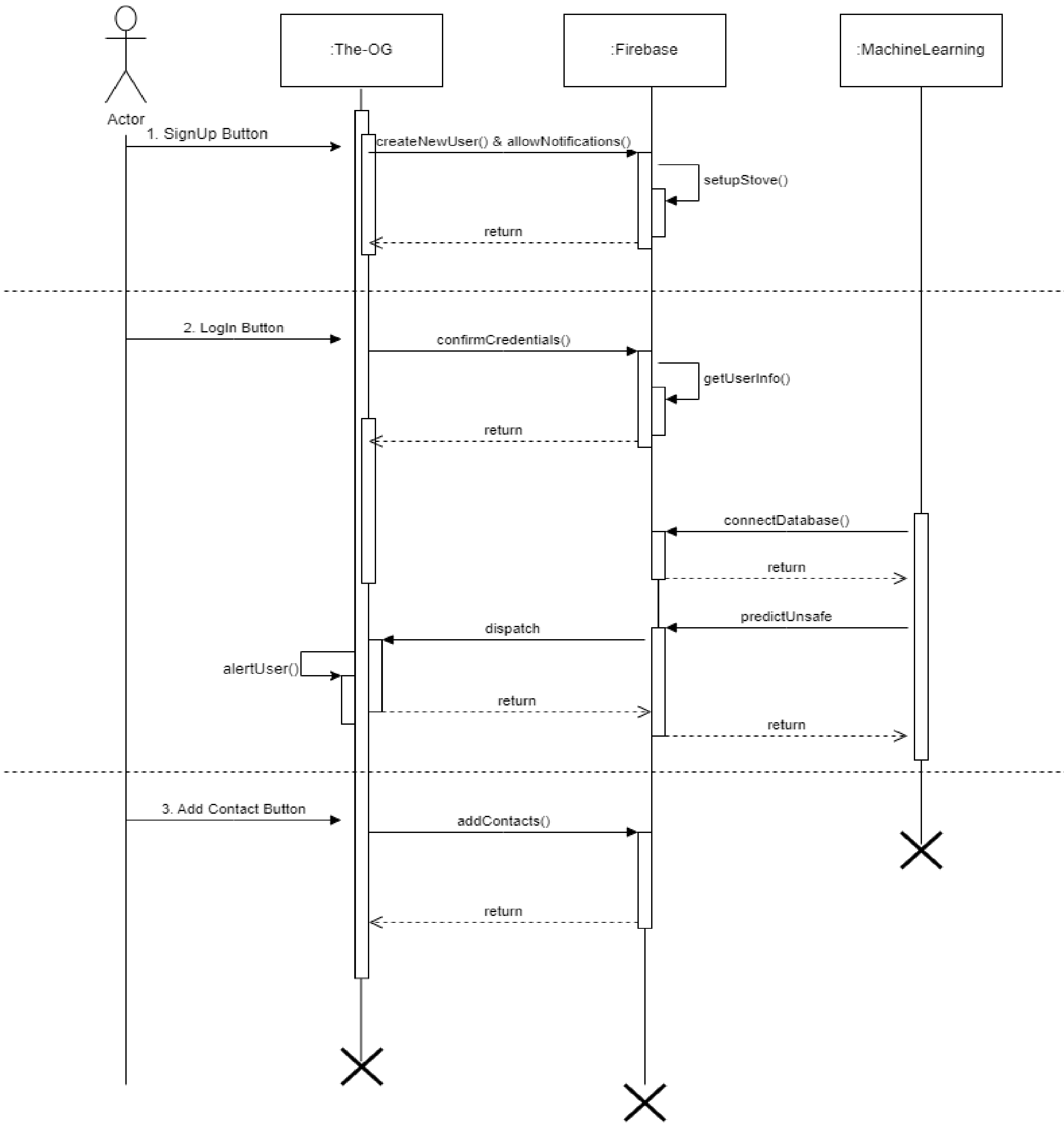


**Figure 40: Sequence Diagram Showing App Functionality**

Figure 40 above is a comprehensive representation of the various interactions between the application, database, and classification model that controls the functionality of our system. The figure presents a visual overview of the sequence of events that occur when a new user attempts to sign up for the service, as well as when an existing user logs in to access their account.

Notably, the figure explains the mechanisms by which the machine learning model writes data to the database, thereby facilitating the presentation of alerts within the application. This functionality is critical to the success of our system, as it enables caretakers and families to remain informed and updated about their loved one's well-being, even when they are not physically present.

Moreover, the figure provides insight into the process of adding contacts to the system, which is a crucial component of our design. Through this feature, caretakers and families can ensure that the appropriate individuals are notified in the event of an emergency, thereby enabling a prompt and effective response to any potential safety concerns.

Taken together, Figure 40 serves as a valuable reference point for understanding the complex web of interactions that enable our system to operate seamlessly while ensuring the safety and well-being of individuals with cognitive impairments.

## 13. TESTING

Testing is an important part of engineering projects. It is necessary to identify bugs and any other issues that could affect the performance, functionality, and security of a product. Proper testing needed to be done to ensure that the functional and non-functional requirements were met and that the product works under various conditions. In this section, the various testing methods for the development of the database, machine learning models, the web application and their combination would be discussed, including the types of tests performed and their results.

### 13.1 DATABASE

Since the database was a significant part of this process, testing the database was very crucial in making sure everything worked as planned. Testing the database involved evaluation of its performance, functions, and security to make sure that it was meeting the requirements created.

Unit tests were performed on the database to identify defects in the code. This involved testing the various functions, procedures, and triggers to make sure they work as expected. Table 4 below shows a detailed breakdown of the tests held results done on the database and its input.

For testing purposes, the code for writing data into the database was copied and pasted into the unit testing file and was edited. The edited code no longer writes into the database but returns values that the functions wanted to pass into the database. The edited code ran once before running all the test functions.

**Table 4: Database Testing for New Models**

| **Length of the array before writing into the objects (Array was obtained using the edited code)** | | |
|---|---|---|
| **Object** | **Expected** | **Actual** |
| TestData | 143 | 143 |
| TestDataWithId (not counting data id as it was automatically incremented) | 144 | 144 |
| **Number of elements in the object after passing in the array** | | |
| **Object** | **Expected** | **Actual** |
| TestData | 143 | 143 |
| TestDataWithId (not counting data id as it was automatically incremented) | 144 | 144 |

### 13.2 MACHINE LEARNING MODELS

Testing the machine learning models was a critical part in the development of the model. The performances of the models were evaluated on both new and unseen data in order to determine their accuracy, reliability, and effectiveness. Testing machine learning models is an iterative process, and as the models were updated and retrained, they were retested to ensure they were performing as expected. Some of the techniques used for testing the models are highlighted in the sections that follow.

#### 13.2.1 A/B TESTING

This testing involved the comparison of the performance of different models using the same dataset. This was the method that helped determine the best-performing model for the various classifications.

#### 13.2.2 HOLDOUT TESTING

This testing involved splitting the dataset into a training and test set, where the training set was used to train the model, and the test set was used to evaluate the performance of the model.

#### 13.2.3 CROSS-VALIDATION

The specific technique used was the 5-fold train and test method. This technique involved the partitioning of the dataset into five folds and using each fold as a test set while training the model on the remaining folds. This helped the model generalize well to new data.

#### 13.2.4 OUT-OF-SAMPLE TESTING

This testing technique involved the evaluation of the performance of the trained models on a separate dataset outside of the training data. This helped to ensure that the model could generalize to new unseen data.

### 13.3 APPLICATION

A strong emphasis on user feedback was taken into consideration throughout the design process. Fellow students and some professors were consulted to provide feedback on the design of the application. This feedback was critical in shaping the simplistic design of the application as we did not want to overwhelm users with an overly complex layout.

Demonstrations were held anytime there was a new addition to the application in order to make sure it was working as expected. This was also done to allow for quick alterations. A detailed list of the acceptance tests for the application is highlighted in Table 5 below.

**Table 5: Acceptance Testing for The-OG**

| Test Number | Description | Steps | Pass Condition |
|---|---|---|---|
| **1** | User Sign Up | 1. Enter a name, an email, and select a password and confirm it.<br>2. Allow Notifications<br>3. Select “Sign Up” | Information about the new user is only written to the database if an email was inputted, passwords match, and notifications were allowed. |
| **2** | User Login | 1. Enter a valid email and password.<br>2. Select “Login” | Access to the home page is only given to a user if their credentials are valid. |

| | | | |
|---|---|---|---|
| **3** | Adding Contacts | 1. Enter a valid email into the "Add Contacts" section.<br>2. Select "Add" | New Contact information is added to the database. |
| **4** | Sending Alerts | 1. The safety of the stove is changed in the database from "Safe" to "Unsafe" | An alert is sent immediately after a change occurs. |

## 13.4 COMBINATIONAL TESTS

After testing each of the nodes in our project individually, integration tests were performed to ensure that everything worked together as expected. The whole system was tested together with the addition of new functionalities. Table 6 below gives more information about the tests and how they confirmed we had met our requirements.

**Table 6: Combinational Testing for Activity of Daily Living Assessment - Stove Use**

| Test Number | Description | Steps | Pass Condition |
|---|---|---|---|
| **1** | Machine Learning Models | 1. Train models on a given dataset.<br>2. Test models on a completely new and unseen dataset. | A manually labelled dataset confirms if the data is being read and the predictions are being done as expected. |
| **2** | Database Integration Testing | 1. Model predictions are written into the database periodically. | The values in the database change with the changing predictions causing the display on the application to change as well. |
| **3** | Response Testing | 1. Set the safety of the stove to "Unsafe" | The application sends an alert immediately after an unsafe state is detected. |

## 14. CONCLUSION

The importance of monitoring nutrition for dietary evaluation and health observation has become widespread due to the essential nutrients that the human body needs to function properly. Healthy eating habits can help prevent chronic diseases and improve mental health, but physical limitations and disorders can hinder a person's ability to maintain these habits. In the case of a fire, awareness, consciousness, behavioural patterns, and physical limitations can influence a person's emergency response, particularly for older adults who are at a higher risk of unintentional fire-related deaths. Our project addressed these concerns by providing a single solution that monitors the stove use and promotes safety in the aging population through image processing and classification while ensuring stove safety by sending alerts in case unsafe situations are detected.

## 15. REFLECTIONS

Over the course of the past eight months, the team has made significant progress towards achieving the outlined goals in both the proposal and progress report. Through the team's diligent efforts, successful outcomes were achieved, including the successful training of models to identify stove states, safety statuses, and cooking methods. Additionally, the alert system was effectively implemented. While the major goals were met, there remains an opportunity for further development in the area of real-time video feedback to determine stove state and cooking safety. Such future research and development would further advance the project's objectives.

## REFERENCES


[1] J. R. L. Lieffers and R. M. Hanning, 'Dietary assessment and self-monitoring with nutrition applications for mobile devices', *Can J Diet Pract Res*, vol. 73, no. 3, pp. e253-260, 2012, doi: 10.3148/73.3.2012.e253. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/22958633/. [Accessed: 17-Oct-2022].

[2] N. Mohammadzadeh and R. Safdari, 'Patient Monitoring in Mobile Health: Opportunities and Challenges', *Med Arch*, vol. 68, no. 1, pp. 57–60, Feb. 2014, doi: 10.5455/medarh.2014.68.57-60. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4272470/. [Accessed: 17-Oct-2022].

[3] T. Ljungberg, E. Bondza, and C. Lethin, "Evidence of the importance of dietary habits regarding depressive symptoms and depression," *International journal of environmental research and public health*, 02-Mar-2020. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7084175/. [Accessed: 17-Oct-2022].

[4] "Eating and drinking," *Alzheimer's Society*, 13-Apr-2018. [Online]. Available: https://www.alzheimers.org.uk/get-support/daily-living/eating-drinking#content-start. [Accessed: 17-Oct-2022].

[5] A. P. Harpur, K. E. Boyce, and N. C. McConnell, 'An Investigation into the Circumstances Surrounding Elderly Dwelling Fire Fatalities and the Barriers to Implementing Fire Safety Strategies among this Group', *Fire Safety Science*, vol. 11, pp. 1144–1159, 2014, doi: 10.3801/IAFSS.FSS.11-1144. Available: https://publications.iafss.org/publications/fss/11/1144/. [Accessed: 17-Oct-2022].

[6] "Circumstances surrounding unintentional fire-related deaths, 2011 to 2020," *The Daily*, 16-Jun-2022. [Online]. Available: https://www150.statcan.gc.ca/n1/daily-quotidien/220616/dq220616b-eng.htm. [Accessed: 17-Oct-2022].

[7] "Canadian survey on disability, 2017," *The Daily*, 28-Nov-2018. [Online]. Available: https://www150.statcan.gc.ca/n1/daily-quotidien/181128/dq181128a-eng.htm. [Accessed: 17-Oct-2022].

[8] R. Jurdi-Hage, "Home cooking structure fires in four Canadian jurisdictions," *Home Cooking Structure Fires in Four Canadian Jurisdictions: Analyses of the National Fire Information Database, 2005 to 2014*, Apr-2018. [Online]. Available: https://cjr.ufv.ca/wp-content/uploads/2018/04/University-of-Regina-Home-Cooking-Fires-in-4-Canadian-Jurisdictions.pdf. [Accessed: 17-Oct-2022].

[9] P. Khosravi and A. H. Ghapanchi, "Investigating the effectiveness of technologies applied to assist seniors: A systematic literature review," International Journal of Medical Informatics, vol. 85, no. 1, pp. 17–26, Jan. 2016, doi: 10.1016/j.ijmedinf.2015.05.014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1386505615300034. [Accessed: 17-Oct-2022].

[10] I. Adami et al., “Monitoring Health Parameters of Elders to Support Independent Living and Improve Their Quality of Life,” Sensors, vol. 21, no. 2, p. 517, Jan. [Online]. Available: https://www.mdpi.com/1424-8220/21/2/517. [Accessed: March 15, 2023].

[11] A. R. Heid, F. Cartwright, M. Wilson-Genderson, and R. Pruchno, “Challenges Experienced by Older People During the Initial Months of the COVID-19 Pandemic,” The Gerontologist, vol. 61, no. 1, Sep. 2020, doi: 10.1093/geront/gnaa138. [Online]. Available: https://academic.oup.com/gerontologist/article/61/1/48/5909436. [Accessed: 17-Oct-2022].

[12] “General Demographics,” Ottawa Insights. [Online]. Available: https://www.ottawainsights.ca/themes/general-demographics/#:~:text=Population%20distribution%20by%20age&text=Those%20over%2065%20made%20up,grow%20to%2020%25%20by%202031. [Accessed: 17-Oct-2022].

[13] e-con Systems, "What are RGBD Cameras? Why RGBD Cameras are Preferred in Some Embedded Vision Applications," e-con Systems Blog, May 19, 2022. [Online]. Available: https://www.e-consystems.com/blog/camera/technology/what-are-rgbd-cameras-why-rgbd-cameras-are-preferred-in-some-embedded-vision-applications/. [Accessed: April 12, 2023].

[14] FLIR Systems, "How Do Thermal Cameras Work?" FLIR. [Online]. Available: https://www.flir.ca/discover/rd-science/how-do-thermal-cameras-work/. [Accessed: April 12, 2023].

[15] I. Azurmendi, E. Zulueta, J. M. Lopez-Guede, J. Azkarate, and M. González, “Cooktop Sensing Based on a YOLO Object Detection Algorithm,” *Sensors*, vol. 23, no. 5, p. 2780, Jan. 2023, doi: https://doi.org/10.3390/s23052780. [Online]. Available: https://www.mdpi.com/1424-8220/23/5/2780. [Accessed: March 15, 2023].

[16] AAA Testers, ‘FLIR ThermoVision A40 30Hz 320 × 240 Infrared Thermal Imager’. [Online]. Available: https://www.aaatesters.com/flir-a40-infrared-thermal-imager-a-40-flir-40.html. [Accessed: March 15, 2023].

[17] Yuan, Ming & Green, James & Goubran, Rafik., “Stove Top Thermal Monitoring for Assisted Living at Home”, 2008, doi:10.13140/2.1.3328.3521. [Online]. Available: https://proceedings.cmbes.ca/index.php/proceedings/article/view/363. [Accessed: March 15, 2023].

[18] AAA Testers, ‘FLIR ThermoVision A40 30Hz 320 × 240 Infrared Thermal Imager’. [Online]. Available: https://www.aaatesters.com/flir-a40-infrared-thermal-imager-a-40-flir-40.html. [Accessed: March 15, 2023].

[19] Reitman Centre Team, "Cooking and dementia: challenges, concerns and strategies from the caregivers’ perspective," Dementia Caregivers Resources, Oct 11, 2019. [Online]. Available: https://www.dementiacarers.ca/cooking-and-dementia-challenges-concerns-strategies-from-the-caregivers-perspective/#respond. [Accessed: Apr 12, 2023].

[20] CDC, “Cognitive impairment: A Call for Action, Now!,” 2011. [Online]. Available: https://www.cdc.gov/aging/pdf/cognitive_impairment/cogimp_poilicy_final.pdf. [Accessed: Apr 12, 2023].

[21] Alzheimer's Association, “What Is Dementia?,” *Alzheimer’s Disease and Dementia*, 2022. [Online]. Available: https://www.alz.org/alzheimers-dementia/what-is-dementia. [Accessed: Apr 12, 2023].

[22] World Health Organisation, “Ageing and health,” *www.who.int*, Oct. 01, 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health#:~:text=By%202050%2C%20the%20world [Accessed: Apr 12, 2023].

[23] GBD 2019 Dementia Forecasting Collaborators, “Estimation of the global prevalence of dementia in 2019 and forecasted prevalence in 2050: an analysis for the Global Burden of Disease Study 2019,” *The Lancet Public Health*, vol. 7, no. 2, Jan. 2022, doi: https://doi.org/10.1016/s2468-2667(21)00249-8. Available: https://www.sciencedirect.com/science/article/pii/S2468266721002498?via%3Dihub. [Accessed: Apr 12, 2023].

[24] A. Kimura, T. Sugimoto, S. Niida, K. Toba, and T. Sakurai, “Association Between Appetite and Sarcopenia in Patients With Mild Cognitive Impairment and Early-Stage Alzheimer’s Disease: A Case-Control Study,” *Frontiers in Nutrition*, vol. 5, Dec. 2018, doi: https://doi.org/10.3389/fnut.2018.00128. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2468266721002498?via%3Dihub. [Accessed: Apr 12, 2023].Available: https://www.frontiersin.org/articles/10.3389/fnut.2018.00128/full. [Accessed: Apr 12, 2023].

[25] *Hmpgloballearningnetwork.com*, 2023. [Online]. Available: https://www.hmpgloballearningnetwork.com/site/pcn/article/frontotemporal-dementia-boosts-sweet-food-preference. [Accessed: Apr 12, 2023].

[26] efetherston, “Loss of Smell – A Hallmark of Parkinson’s Disease and Lewy Body Dementia,” *Lewy Body Dementia Association*, Jan. 28, 2022. [Online]. Available: https://www.lbda.org/blog/loss-of-smell-a-hallmark-of-parkinsons-disease-and-lewy-body-dementia/#:~:text=Loss%20of%20the%20sense%20of [Accessed: Apr 12, 2023].

[27] Alzheimer's Association, “Food and Eating,” *Alzheimer’s Disease and Dementia*, 2019. [Online]. Available: https://www.alz.org/help-support/caregiving/daily-care/food-eating . [Accessed: April 13, 2023].

[28] A. Coronato and G. Paragliola, "A Safe Kitchen for Cognitive Impaired People," in Proceedings of the International Conference on Ubiquitous Computing and Ambient Intelligence, Dec. 2013, doi: 10.1007/978-3-319-03176-7_3. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-319-03176-7_3. [Accessed: April 13, 2023].

[29] M. Ikeda, “Changes in appetite, food preference, and eating habits in frontotemporal dementia and Alzheimer’s disease,” *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 73, no. 4, pp. 371–376, Oct. 2002, doi: https://doi.org/10.1136/jnnp.73.4.371. [Online]. Available: https://jnnp.bmj.com/content/73/4/371. [Accessed: April 13, 2023].

[30] A. C. Thompson, “iGuardStove Intelligent review: Turning off the stove when you forget,” CNET. [Online]. Available: https://www.cnet.com/reviews/iguardstove-intelligent-review/. [Accessed: April 13, 2023].

[31] “Products – iGuardFire,” iguardfire.com. [Online]. Available: https://iguardfire.com/shop/. [Accessed: April 13, 2023].

[32] "DALSA Corporation -- The Camera's Too Hot!?," *Automate*. [Online]. Available: https://www.automate.org/tech-papers/the-cameras-too-hot#:~:text=If%20the%20temperature%20inside%20of. [Accessed: April 13, 2023].
[33] H. Canada, "Cooking safety," aem, Apr. 05, 2012. [Online]. Available: https://www.canada.ca/en/health-canada/services/general-food-safety-tips/cooking-safety.html. [Accessed: April 13, 2023].
[34] 'Seek Thermal CW-AAA Compact-All-Purpose Thermal Imaging Camera for Android USB-C'. [Online]. Available: https://www.amazon.ca/Thermal-Compact-All-Purpose-Imaging-Camera-Android/dp/B07RQ3J27Y/ref=asc_df_B07RQ3J27Y/?tag=googleshopc0c-20&linkCode=df0&hvadid=384267320537&hvpos=&hvnetw=g&hvrand=2614545969662269109&hvpone=&hvptwo=&hvqmt=&hvdev=c&hvdvcmdl=&hvlocint=&hvlocphy=9000673&hvtargid=pla-784819076836&psc=1. [Accessed: March 15, 2023].
[35] 'USB C Extension Cable 6.6ft Bohconn Type-C Male to Female Fast Charge Data Extender Cord USB 3.2 Gen2 Thunderbolt 3 Port Compatible 4K Video for MacBook Pro, Galaxy S22/21, PS5, USB-C Hub: Amazon.ca: Electronics'. [Online]. Available: https://www.amazon.ca/Extension-Bohconn-Extender-Thunderbolt-Compatible/dp/B0B2W9QHTW/ref=sr_1_8?keywords=usb+c+extension+cable&qid=1681349835&sr=8-8. [Accessed Apr. 12, 2023].
[36] 'Lamicall Gooseneck Phone Holder for Bed - Overall Length 38.6in, Flexible Leather Wrapped Arm, 360 Adjustable Clamp Clip, Overhead Cell Phone Mount Stand for Desk, Compatible with all Cellphone (4-7") : Amazon.ca: Electronics'. https://www.amazon.ca/dp/B08MZGPMPX/ref=cm_sw_r_api_i_dl_E7XW25VHZACZHPQP199G_0. [Accessed Apr. 12, 2023].
[37] K. Franci, frenkinet/SeekOFix. 2021. [Online]. Available: https://github.com/frenkinet/SeekOFix. [Accessed: 29-Nov-2022].
[38] E. Boulay, J. Mack, C. Ratsamany and A. Rafiq, "Activity of Daily Living Assessment – Stove/Oven Use," Carleton University, 2022.

[39] A. B. Musa, "Comparative study on classification performance between support vector machine and logistic regression," *Int. J. Mach. Learn. & Cyber,* vol. 4, no. 1, pp. 13-24, February 2013. [Online]. Available: https://doi.org/10.1007/s13042-012-0068-x. [Accessed Apr. 5, 2023].

[40] J. Brownlee, "SMOTE for Imbalanced Classification with Python," Machine Learning Mastery, Jan. 16, 2020. [Online]. Available: https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/. [Accessed Apr. 5, 2023]
[41] Ganganwar, V., "An overview of classification algorithms for imbalanced datasets," International Journal of Emerging Technology and Advanced Engineering, vol. 2, no. 4, pp. 2250-2259, 2012.
[42] G. Boesch, "Supervised vs Unsupervised Learning for Computer Vision (2022 Guide)," viso.ai, Jul. 13, 2022. [Online]. Available: https://viso.ai/deep-learning/supervised-vs-unsupervised-learning/. [Accessed: April 12, 2023]

[43] Radixweb, Using React.JS for Frontend Development : Features and Benefits. [Online]. Available: https://radixweb.com/blog/react-js-for-frontend-development-features-benefits, August 25, 2022. [Accessed: April 12, 2023]

[44] Node.js, About. [Online]. Available: https://nodejs.org/en/about [Accessed: Apr. 12, 2023]

[45] Express, Node.js web application framework. [Online]. Available: https://expressjs.com/ [Accessed: Apr.12, 2023]

[46] Bookstrap, Bootstrap · The most popular HTML, CSS, and JS library in the world. [Online]. Available: https://ncarb.github.io/bootstrap/. [Accessed: Apr. 12, 2023]

# SYSC4907

# CAPSTONE ENGINEERING PROJECT PROPOSAL

# ACTIVITY OF DAILY LIVING ASSESSMENT - STOVE/OVEN USE

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## INTRODUCTION

Monitoring nutrition has gained widespread interest since it aids in documenting intake for dietary evaluation and health observation [1]. Furthermore, preventing chronic diseases and managing appropriate health activities through patient monitoring are the best ways to lower health facility costs and enhance people's sense of autonomy [2]. Human bodies receive the essential nutrients they need to function properly from the food they consume. The nutrients obtained from our food are converted into energy which is then used for bodily functions ranging from physical to mental. The better we feel, the healthier we eat which in turn gives us more energy and even clearer thoughts. Individuals who practice healthy eating habits are less likely to experience depression or mood disorders, according to research findings [3]. Some disorders can cause people to forget to eat, thus worsening their state. As an example, a person with dementia may forget to eat or lose their appetite due to their dementia progressing [4]. In some cases, physical restrictions can also constrain a person from eating or cooking.

Awareness, consciousness, behavioral patterns, and physical limitations are factors that have been discovered to influence people's emergency response in case of a fire [5]. The majority of unintended fire-related deaths in Canada occur in residential buildings [6]. Older people are more likely to pass away in a residential fire, as found in prior research [6]. Individuals aged seventy (70) and older accounted for nearly one-third of fatalities caused by unintentional residential fires in Canada, despite representing one-eighth of the population in 2020 [6]. According to the 2017 Canadian Survey on Disability, seniors are more likely to have disabilities (such as mobility impairments). These impairments might hinder a person's capability to react to or evacuate from a fire [7]. Leaving the stove unattended while turned on is a major safety issue. Unsupervised cooking equipment was the main cause of home food preparation fires in Ontario, whilst human error (examples: lack of consciousness, getting easily distracted, misunderstanding of hazards) and mishandling of substances burned were responsible for three-quarters and one-half of each British Columbian and Albertan kitchen fires, respectively [8].

Our project aims to create a single solution. One that helps to understand and provide knowledge to improve nutrition in the aging population by monitoring what they consume through image processing and classification of images and also provides a device that sends alerts in case of stove safety concerns, preventing the worsening of health concerns which would increase the risks associated with stove safety.

## OBJECTIVE

The objective of this project is to create an analytics system through image processing and classification to use a thermal camera to identify the stove use of aging adults. The analytics system takes images from the video feed and classifies stove use into normal use, safe and unsafe use, which is when the burner is left on, and complexity of use. The system can be integrated into a smart application that gives supportive reminders to the aging adult.

## REQUIREMENTS

**Table 7: Table highlighting the functional and non-functional requirements of the project**

| | |
|---|---|
| Functional Requirements | 1. The system shall be able to distinguish between boiling an egg and frying an egg, and between an empty stove that is off and an empty stove that is on.<br>2. The database shall hold information relating to the stove use.<br>3. The application shall be able to send an alert if the stove is on with nothing on top of it. |
| Non-Functional Requirements | 1. When the stove is on with nothing on top of it, the user is alerted within 4 minutes.<br>2. When the user has been frying an egg for 5 minutes, an alert is sent.<br>3. When a temperature above 190°C is detected, an alert is sent to the user within 2 minutes. |

## BACKGROUND

With medical and technological advancements, the quality of life has significantly improved as compared to the last decade, leading people to live longer and lead healthier lives [9]. These advancements have made it possible for seniors to lead more independent lives, by providing easily accessible mobile apps that can track fitness, health, nutrition, and heart rate. They have also made it possible for health professionals to keep track of seniors' health via medical alert systems that are easily installed in their smart homes [9].

However, the pandemic of COVID 19 has made us aware of new challenges that people, specifically seniors, face daily [10]. Growing older comes with its unique set of challenges. The senior population makes up 23% of Canada's population and 7% of the population in Ottawa [11]. With this growing statistic, it has become increasingly important to ensure that aging adults can maintain healthy nutrition, and that they can be safe from any hazards while in the kitchen.

An average aging adult's challenges can vary from the limitation in mobility and reduction in cognitive ability to simply cooking a healthy meal [12]. The main and most prominent challenge with cooking is that it poses a variety of hazards that an aging adult can be susceptible to [5]. Having slower mobility - not getting to the stove fast enough - can put them at risk of fire hazards. Being forgetful can also cause the same outcome [5]. Having an organised and healthy cooking habit can significantly improve one's quality of life in a major way [2]. This project will focus on identifying some cooking patterns and hazards.

The project will use thermal cameras as the main component to reach the goal. Thermal cameras are preferred over regular cameras in this project because, thermal cameras can detect a potential rise in the temperature of a surface, area, or room. That makes them an excellent choice to detect fire hazards and/or unsafe stove uses. The thermal camera chosen for this project has proven to be low-cost and can be easily purchased. One of the project's goals is to develop the device to be user-friendly.

The purpose of the project is to detect the unsafe use of a stove. The thermal camera will be used to identify this unsafe use, as well as the cooking pattern (frying or boiling). It will also analyze video feeds via image processing. The thermal camera can easily be set up in smart home systems and will send friendly reminders if the stove is left on and unattended. The focus of the project would be to set up the device externally to acquire video feed of the stovetop. The previous team was successful in setting up the camera and recording the video feed. The images could be analysed manually for each picture, this is where our focus comes in. Our goal is to classify images via our software code that will be developed, and have this code analyse the pictures instead of doing it manually.

The second focus of the project would be to identify cooking patterns. Monitoring the cooking patterns identifies the types of meals consumed. This helps to track one's health and know whether the individual is getting the full nutrition needed. Healthy nutrition is important, especially for aging adults to maintain a healthy life. Identifying the cooking patterns alternatively helps identify unhealthy meals that might be harmful to the individual. This focus will help health care professionals in identifying any underlying issues or health problems and eventually in addressing them accordingly, and just as importantly, in a timely manner.

## QUALIFICATIONS

Menna Abdelhadi is a fourth-year Biomedical Electrical Engineering student at Carleton University. During her school years, she has learned the foundation of imperative programming from SYSC 2006 which taught her to code in C programming. She also learned to code in C++ from ECOR 2606, Numerical Methods. She has basic knowledge of MATLAB modeling and Simulink from SYSC 3610, Systems modeling and control. She is currently taking SYSC 4405 to strengthen her knowledge in digital signal processing techniques to better analyze images and signals. To further fulfill her passion for programming, Menna self-taught the basics of Python and Java via online courses, such as Coursera. These opportunities have provided her with the necessary skillset needed to undertake the challenges of this project. She now has the amazing opportunity to implement her knowledge and her programming experience in collecting thermal data and to contribute to implementing test coverage. This project will provide her with a solid understanding of Machine Learning and Image processing.

Hanan Alshatti is a fourth-year Electrical Engineering student at Carleton University. As a fourth-year electrical engineering student, she has gained knowledge of coding in python from ECOR1051, MATLAB modeling of advanced devices from ELEC4700, foundations of imperative programming from SYSC 2006 and object-oriented software development from SYSC 2004. For the third-year project, her knowledge of python coding was implemented during her third-year project to read data acquired from an MLX90640 thermal camera in which the maximum pixel value from six arrays is taken to compute an individual's temperature. She is currently taking SYSC 4405 to strengthen her knowledge in digital signal processing to better analyze images and signals. From her knowledge, she will undertake the task of classifying a certain cooking method from another.

Eline Elorm Nuviadenu is a fourth-year Computer Systems Engineering student with experience in Full Stack Development through participating in various programs such as Google's Software Program Sprint and working as a software lead for Carleton's Electric Self Driving Car club. Her interests lie in User Interface and Experience, Web, and Embedded development. During her course of study at Carleton University, Eline has gathered a repertoire of programming skills (C, Python and Java among others) through participating in Carleton's Students as Partners Program, where she assisted in creating and curating content for a C programming course for non-programming graduate students, and by taking courses such as Data Structures and Algorithms, Object Oriented Programming, Software Architecture, and a Computer Systems project course. Her knowledge gained from self-study, as well as from these courses mentioned above, equip her with the necessary skills to research and work on the classification of the images from the thermal camera, as well as the addition of various functionalities to the mobile application.

Hiu Sum Jaime Yue is a fourth-year Computer Systems Engineering student. In her three school years in the Computer System Engineering program, she has gained a solid foundation in Python, Java, and C. During the SYSC 3010 project, she has the chance to create an app using Android studio with Java. The app was designed to show data and control the robot using Firebase, which is a database. But more importantly, it will send an alert notification to the user if the robot senses fire. Other than Firebase, she also has experience with using MySQL, which is a relational database. With her prior experience with databases, her focus on this project is to get the collected thermal data from the video feed, analyze the thermal data, and store them in the database.

## PROJECT PLAN

This section is meant to highlight our plans as a team, which are geared toward the completion of this project. We plan to use Trello as well as a Gantt chart created in Excel to keep track of each task and to ensure its completion. Our team also has a GitHub repository as well as a shared Citrix folder to keep track of the files for the project. Weekly meetings on Microsoft Teams are held to communicate our progress with each other and plans for the weeks ahead.

Currently, our team is gathering the code from previous teams to set up the camera to record the video feed. Furthermore, to be able to record a video feed, a code was developed by Aidan Lochbihler that allows us to analyze and process the images more efficiently. Upon studying the code base developed by the previous team, it was realized that a solution was created using data structures and algorithms. Our team plans to study the old code and rewrite a solution by implementing machine learning for the classification of different cooking tasks and adding a concept of time to allow the monitoring of the sequences of images in addition to the images themselves. We have also deliberated on various requirements we would want to meet and have shortlisted them in Table 7 above. We have considered diverse options like the types of cooking methods we would like to tackle, and the types of items being cooked that we would want to distinguish between. The team settled on the boiling and frying of an egg.

Due to the out-of-pocket purchase of a camera stand by the previous team, our team is in the process of acquiring one to start the data collection process. Our team has discussed various camera mounts to determine the best fit which would allow us to utilize the data collected from previous years and have made steps towards purchasing one. We concluded that being able to replicate the setup from the previous year would allow us to use the thermal videos and images collected in addition to our data. This would create a more varied dataset which would help save us time and improve the classification of the data. Moreover, this would allow us to acquire a non-biased dataset to employ during testing.

Intensive research into machine learning algorithms has been started to determine which algorithms and libraries are best to proceed with. We have determined that as this aspect would form most of the project, we would channel most of our resources and brain power into this image classification aspect. While the machine learning process is underway, we plan to work on the mobile application simultaneously to save time. The first step would be to figure out the previous development of the application and to decide which features we would like to keep and/or improve. We will then integrate and evaluate all the components individually and together, to ensure proper functionality.

## PROPOSED TIMETABLE (GANTT CHART)

| PROJECT NAME | START DATE | END DATE | OVERALL PROGRESS | PROJECT MANAGER |
|---|---|---|---|---|
| ADLA Stove/Oven Use | 07-Sep | 12-Apr | | Dr. Bruce Wallace and Dr. Fateme Rajabiyazdi |

| AT RISK | TASK NAME | START | FINISH | DURATION (DAYS) | STATUS | COMMENTS |
|---|---|---|---|---|---|---|
| ☐ | Project Proposal | 9-7-22 | 10-21-22 | 44 | In Progress | |
| ☐ | Finalize Requirements | 9-7-22 | 10-7-22 | 30 | In Progress | |
| ☐ | Proposal Draft | 10-4-22 | 10-10-22 | 6 | In Progress | |
| ☐ | Finalize Proposal | 10-10-22 | 10-21-22 | 11 | In Progress | |
| ☐ | Image Processing | 9-20-22 | 3-10-23 | 171 | In Progress | |
| ☐ | Research Phase | 9-20-22 | 11-1-22 | 42 | In Progress | |
| ☐ | Data collection | 10-25-22 | 3-10-23 | 136 | Not Started | |
| ☐ | Data Processing | 11-1-22 | 3-10-23 | 129 | In Progress | |
| ☐ | Database | 10-20-22 | 12-1-22 | 42 | Not Started | |
| ☐ | Finalize database schema | 10-20-22 | 12-1-22 | 42 | Not Started | |
| ☐ | Phone Application | 9-20-22 | 4-10-23 | 202 | Not Started | |
| ☐ | Finalize app plan | 9-20-22 | 10-30-22 | 40 | Not Started | |
| ☐ | Decide additional features | 9-20-22 | 11-5-22 | 46 | Not Started | |
| ☐ | Implement features | 11-5-22 | 3-30-23 | 145 | Not Started | |
| ☐ | Progress Report | 10-21-22 | 12-9-22 | 49 | Not Started | |
| ☐ | Finalize Draft | 11-20-22 | 12-1-22 | 11 | Not Started | |
| ☐ | Finalize and submit report | 12-1-22 | 12-9-22 | 8 | Not Started | |
| ☐ | Oral Presentation | 12-7-22 | 1-27-23 | 51 | Not Started | |
| ☐ | Oral Presentation Choice | 12-7-22 | 12-9-22 | 2 | Not Started | |
| ☐ | Finalize Presentation | 12-10-22 | 1-23-23 | 44 | Not Started | |
| ☐ | Deliver Presentation | 1-23-23 | 1-27-23 | 4 | Not Started | |
| ☐ | Merging Components | 3-20-23 | 4-10-23 | 21 | Not Started | |
| ☐ | Database and mobile app test | 4-6-23 | 4-8-23 | 2 | Not Started | |
| ☐ | Camera and database test | 4-8-23 | 4-10-23 | 2 | Not Started | |
| ☐ | Poster Fair | 3-10-23 | 3-17-23 | 7 | Not Started | |
| ☐ | Poster Fair Presentation | 3-10-23 | 3-17-23 | 7 | Not Started | |
| ☐ | Final Report | 1-7-23 | 4-12-23 | 95 | Not Started | |
| ☐ | Complete final report draft | 1-7-23 | 3-14-23 | 66 | Not Started | |
| ☐ | Complete final report | 3-16-23 | 4-12-23 | 27 | Not Started | |
| ☐ | Video Presentation | 3-16-23 | 4-12-23 | 27 | Not Started | |

| STATUS |
|---|
| Complete |
| Overdue |
| In Progress |
| Not Started |

**Figure 41: Screenshot of the tentative proposal timeline**

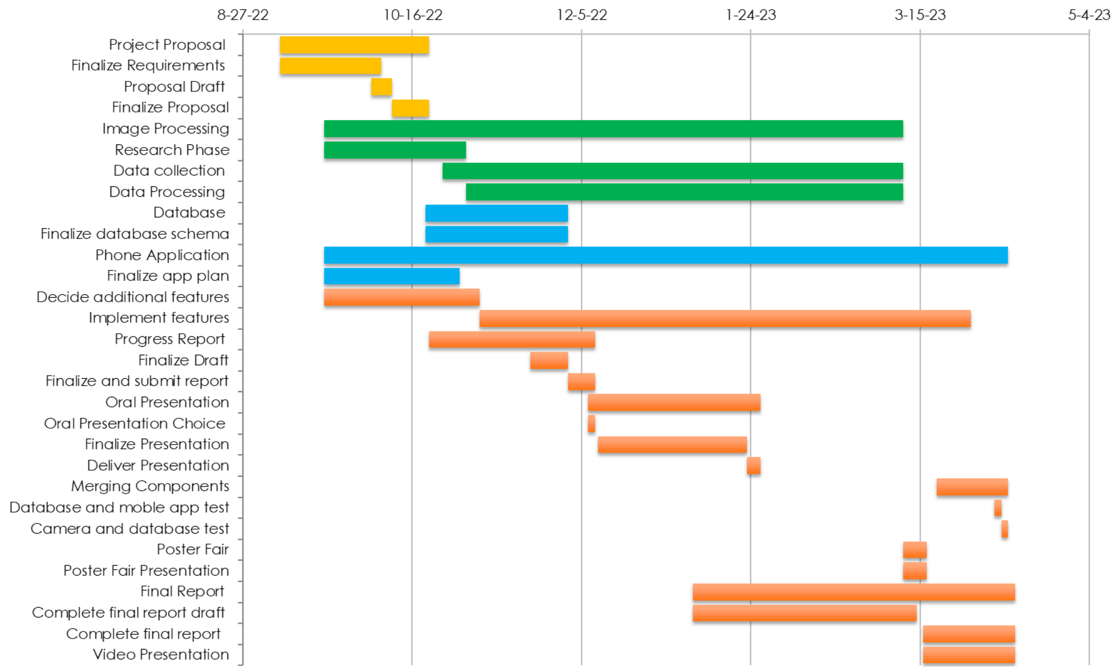


**Figure 42: Gantt Chart showing the tentative project timeline**

**Table 8: Table showing tentative distribution of tasks**

| **Tasks** | | **Responsible** | **Approver** |
|---|---|---|---|
| Project Proposal | Intro | Hanan | Eline |
| | Objective | Jaime | Menna |
| | Requirements | All | All |
| | Background | Menna | Hanan |
| | Qualifications | All | All |
| | Project Plan | Eline | Hanan |
| | Proposed Timetable | Eline | Jaime |
| | Deployment Diagram | Hanan/Jaime | Eline |
| | Potential Risks | Jaime | Eline |
| | Special Components | Jaime | Hanan |
| Image Processing | Gathering data | Jaime | Hanan<br>Eline<br>Menna |
| | Curating data | Jaime | |
| Data Classification | Safe / Unsafe | Hanan<br>Eline | Jaime |
| | Boiling / Frying | | |

| | | | |
|---|---|---|---|
| | Cooking / Idle | Menna | |
| Phone Application | | Eline | Jaime |
| Progress Report | | All | All |
| Final Report | | | |
| Oral Presentation | | | |
| Poster Fair | | | |

## OVERVIEW

### DEPLOYMENT DIAGRAM

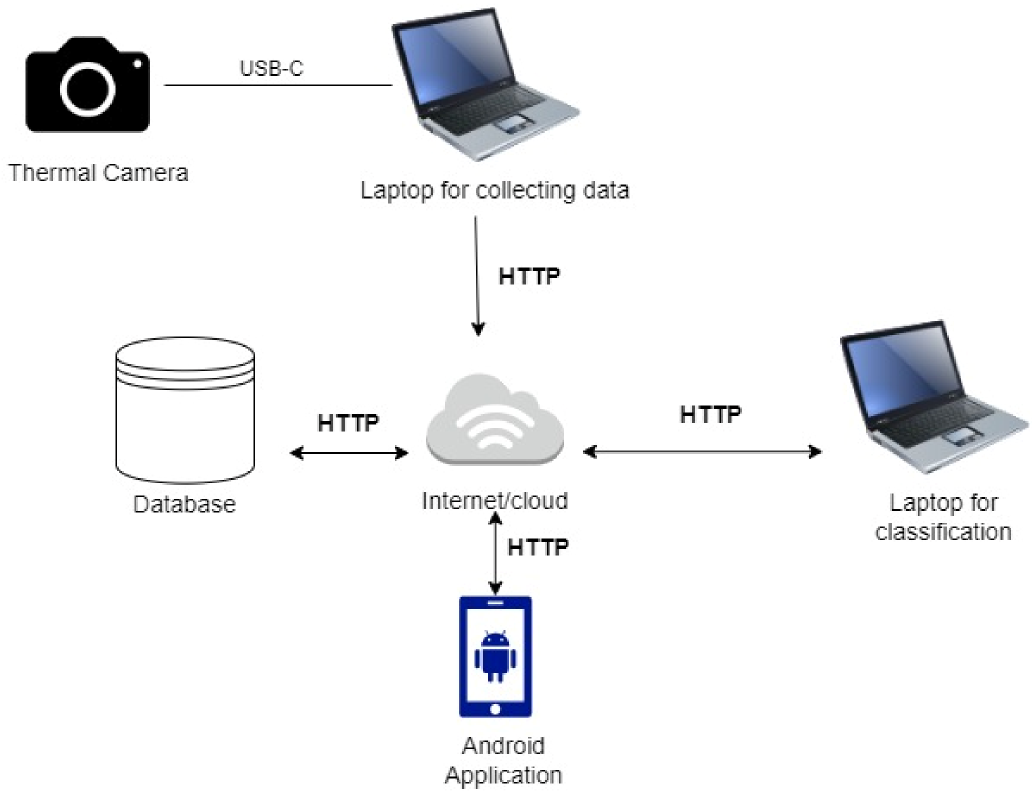


**Figure 43: Deployment diagram showing communication of the system**

Figure 43 above, shows the general deployment design for this project. The laptop for collecting the data, the laptop for classifying the data, the database and the Android application communicate using the Internet. On the physical layer of the system, the laptop for collecting data is connected to a thermal camera using a USB-C cord. This camera will be used to collect the thermal data which will be sent to the cloud. The laptop which would run the code for the classification would then get the thermal data from the cloud, execute the code, and return the output to the cloud to be placed into the database. An Android application, using wireless UDP on the transport layer of the system, would then send and receive messages to and from the database.

### PROJECT RISKS

#### 1. DATABASE

Once the program starts running, the thermal camera will continue acquiring images and save them into the database. If the thermal camera stays on for too long, the database will eventually run out of space due to being overloaded and may crash, causing the data to be corrupted or lost permanently.

### 2. SETUP OF THE THERMAL CAMERA

The thermal camera must be installed safely. The thermal camera will be placed close to the stove to monitor and collect thermal data while the stove is on. The position of the thermal camera needs to be at an appropriate angle to collect the thermal data. The thermal camera needs to be still, stable, and not at risk of dropping on the stove.

### 3. TIME TO REORGANIZE THE WORK THAT WAS DONE PREVIOUSLY

People outside of our project group did thermal camera research prior to the start of this project. When the team took over the project resources, the team struggled to understand the progress of the previous project. Also, a new code for the thermal camera was created after the last project group finished their part of the project. Decisions needed to be made on using the new code or using the previous project group's code. Both codes were installed and used by the team to acquire images from the camera, and it was decided that the newest code would be used going forward with the project.

## SPECIAL COMPONENTS AND FACILITIES

The main component needed in this project is a Seek Thermal Compact thermal camera. The team is using Seek Thermal CW-AAA Compact-All-Purpose Thermal Imaging Camera for Android USB-C. The seek thermal camera that the team uses costs around $400 on Amazon. To collect data of the stove, a USB-C extension cord will be used to connect the thermal camera to the computer of the user. A USB-C extension cord costs around $10 to $20 on Amazon. Furthermore, the placement of the thermal camera can make an impact on collecting the data from the video feed. Therefore, a tripod mount or a webcam stand is required to clamp onto an object near the stove for proper data collection. In the case of special facilities required, the only facility that is needed for this project is a stove to collect data while cooking.

## REFERENCES


[1] J. R. L. Lieffers and R. M. Hanning, 'Dietary assessment and self-monitoring with nutrition applications for mobile devices', *Can J Diet Pract Res*, vol. 73, no. 3, pp. e253-260, 2012, doi: 10.3148/73.3.2012.e253. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/22958633/. [Accessed: 17-Oct-2022].

[2] N. Mohammadzadeh and R. Safdari, 'Patient Monitoring in Mobile Health: Opportunities and Challenges', *Med Arch*, vol. 68, no. 1, pp. 57–60, Feb. 2014, doi: 10.5455/medarh.2014.68.57-60. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4272470/. [Accessed: 17-Oct-2022].

[3] T. Ljungberg, E. Bondza, and C. Lethin, "Evidence of the importance of dietary habits regarding depressive symptoms and depression," *International journal of environmental research and public health*, 02-Mar-2020. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7084175/. [Accessed: 17-Oct-2022].

[4] "Eating and drinking," *Alzheimer's Society*, 13-Apr-2018. [Online]. Available: https://www.alzheimers.org.uk/get-support/daily-living/eating-drinking#content-start. [Accessed: 17-Oct-2022].

[5] A. P. Harpur, K. E. Boyce, and N. C. McConnell, 'An Investigation into the Circumstances Surrounding Elderly Dwelling Fire Fatalities and the Barriers to Implementing Fire Safety Strategies among this Group', *Fire Safety Science*, vol. 11, pp. 1144–1159, 2014, doi: 10.3801/IAFSS.FSS.11-1144. Available: https://publications.iafss.org/publications/fss/11/1144/. [Accessed: 17-Oct-2022].

[6] "Circumstances surrounding unintentional fire-related deaths, 2011 to 2020," *The Daily*, 16-Jun-2022. [Online]. Available: https://www150.statcan.gc.ca/n1/daily-quotidien/220616/dq220616b-eng.htm. [Accessed: 17-Oct-2022].

[7] "Canadian survey on disability, 2017," *The Daily*, 28-Nov-2018. [Online]. Available: https://www150.statcan.gc.ca/n1/daily-quotidien/181128/dq181128a-eng.htm. [Accessed: 17-Oct-2022].

[8] R. Jurdi-Hage, “Home cooking structure fires in four Canadian jurisdictions,” *Home Cooking Structure Fires in Four Canadian Jurisdictions: Analyses of the National Fire Information Database, 2005 to 2014*, Apr-2018. [Online]. Available: https://cjr.ufv.ca/wp-content/uploads/2018/04/University-of-Regina-Home-Cooking-Fires-in-4-Canadian-Jurisdictions.pdf. [Accessed: 17-Oct-2022].

[9] P. Khosravi and A. H. Ghapanchi, “Investigating the effectiveness of technologies applied to assist seniors: A systematic literature review,” *International Journal of Medical Informatics*, vol. 85, no. 1, pp. 17–26, Jan. 2016, doi: 10.1016/j.ijmedinf.2015.05.014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1386505615300034. [Accessed: 17-Oct-2022].

[10] A. R. Heid, F. Cartwright, M. Wilson-Genderson, and R. Pruchno, “Challenges Experienced by Older People During the Initial Months of the COVID-19 Pandemic,” *The Gerontologist*, vol. 61, no. 1, Sep. 2020, doi: 10.1093/geront/gnaa138. [Online]. Available: https://academic.oup.com/gerontologist/article/61/1/48/5909436. [Accessed: 17-Oct-2022].

[11] “General Demographics,” *Ottawa Insights*. [Online]. Available: https://www.ottawainsights.ca/themes/general-demographics/#:~:text=Population%20distribution%20by%20age&text=Those%20over%2065%20made%20up,grow%20to%2020%25%20by%202031. [Accessed: 17-Oct-2022].

[12] A. M. Warren, E. A. Frongillo, S. Alford, and E. McDonald, “Taxonomy of Seniors’ Needs for Food and Food Assistance in the United States,” *Qualitative Health Research*, p. 104973232090614, Feb. 2020, doi: 10.1177/1049732320906143. [Online]. Available: https://journals.sagepub.com/doi/full/10.1177/1049732320906143. [Accessed: 17-Oct-2022].