Sitting Posture Detection and Prevention of Office Syndrome Using MediaPipe Technology

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Abstract
With the increasing prevalence of office syndrome caused by prolonged sitting and poor posture, this paper proposes a real-time posture detection system aimed at improving ergonomic practices in the workplace. The system leverages the MediaPipe Framework, an advanced deep learning-based tool for human pose estimation, to monitor and assess upper body posture. This study aims to assess the accuracy and responsiveness of a MediaPipe-based system in detecting incorrect sitting postures associated with office syndrome. The proposed system continuously tracks posture throughout work hours, thereby reducing the likelihood of developing musculoskeletal pain. The research process began with the development of a posture detection algorithm that utilized MediaPipe's pose estimation model to calculate angular deviations based on landmarks for the shoulder and head. This was followed by the implementation of the system, real-time testing, and performance evaluation under simulated office conditions. Through an experiment with 10 volunteers, selected to represent a manageable and diverse group for initial validation. The system's accuracy was evaluated by comparing the calculated angles with the actual angles in three key positions: neutral, left-side tilt, and right-side tilt. The results showed that the system performed with high accuracy in the neutral position, with a Mean Absolute Error (MAE) close to 0%, but had a higher MAE of approximately 20% in the tilted positions. The system demonstrated an average processing time of 0.20 seconds per frame, which corresponds to approximately 5 frames per second, indicating its potential for real-time posture monitoring. This study contributes to the development of efficient workplace health technologies that promote better posture and reduce the risk of office syndrome.

Keywords: Posture Detection, Human Pose Estimation, MediaPipe Framework, Office Syndrome

1. Introduction
The rapid advancement of digital technologies in the workplace has greatly transformed the nature of office-based work. Tools for data storage, accounting, procurement, and other essential business functions are now predominantly computer-based, offering significant convenience and efficiency to office employees. However, this technological shift has also introduced unintended health consequences, particularly as employees increasingly spend over seven hours a day interacting with computers and other digital devices. While technology has enhanced productivity, it has inadvertently contributed to a rising concern: musculoskeletal pain among office workers.

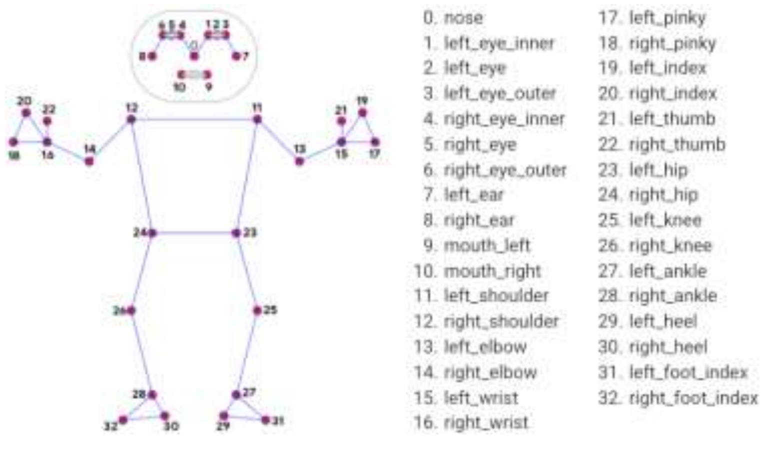

Figure 1 MediaPipe Pose Landmarks (Kim et al., 2023)

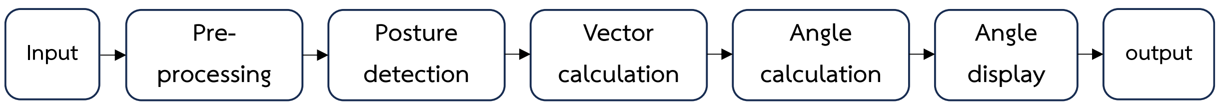

Figure 2 Posture Detection Process Flow

Recent studies have highlighted the widespread occurrence of musculoskeletal disorders among office employees, especially those engaged in sedentary work. Research by (Lazko et al., 2021) indicates that 44.2% of female office employees report experiencing wrist pain (radiocarpal), 40.4% suffer from neck pain, and 38.5% do not report pain, suggesting a significant issue with workplace ergonomics. This pain is often attributed to factors such as prolonged sitting, incorrect posture, and insufficient physical activity throughout the workday. Musculoskeletal pain, resulting from poor ergonomic practices, is a key contributor to what is increasingly recognized as "office syndrome" a collection of conditions that affect the musculoskeletal and nervous systems due to long periods of poor posture and sedentary behavior.

The rise in the office syndrome has led to significant concerns not only about the well-being of employees but also about the long-term impact on productivity. The root causes of these disorders include prolonged sitting, lack of movement, poor ergonomics, and inadequate posture. A lack of proper ergonomic practices, such as sitting with poor posture or without appropriate breaks, can lead to pain in the wrist, neck, shoulders, and back, which, in turn, can escalate into more severe conditions like chronic pain or repetitive strain injuries (RSI). As such, addressing these issues has become a key challenge in improving workplace health and preventing long-term physical harm to employees.

Several technological solutions have been proposed to address this growing problem. (Paliyawan et al., 2014). introduced a novel approach for preventing office syndrome by detecting prolonged sitting using a model that utilizes Kinect cameras and data mining classification. The Kinect camera can monitor body posture and movements, alerting employees to the need to adjust their positions or take breaks. Similarly, (Srahongthong, et al.,2023) developed an application that uses augmented reality (AR) to provide personalized treatment programs for office syndrome. The AR system uses a user questionnaire to propose therapy programs tailored to individual needs, such as specific exercises or stretches to alleviate pain and prevent further injury.

In another approach, (Amin et al., 2024) examined the effectiveness of an app-based neck exercise program grounded in the McKenzie protocol, which was shown to reduce pain intensity by 46%. This program offers six neck movements designed to help relieve tension and reduce discomfort. Likewise, (Lee et al., 2017) proposed a series of stretching exercises aimed at reducing neck and shoulder pain, demonstrating the positive impact of such routines when practiced consistently over four weeks.

Additionally, (Kim et al., 2023) leveraged deep learning models such as MediaPipe to optimize human pose detection for applications that monitor the movements of individuals, providing real-time alerts in cases of falls or injuries at home. MediaPipe, a tool developed for accurate pose tracking, uses pre-trained deep-learning models to monitor and analyze human movements, providing valuable insights for both injury detection and prevention.

Despite these promising advancements, most solutions still focus on postural correction in specific instances, rather than providing a comprehensive, real-time solution that proactively helps employees avoid developing musculoskeletal pain in the first place. There is a growing need for an integrated system that combines the principles of ergonomics with real-time feedback to detect and correct sitting posture before it leads to discomfort or injury.

This research aims to fill that gap by developing and testing a real-time sitting posture detection system based on MediaPipe, an advanced deep learning-based tool that specializes in human pose detection. The proposed system will provide continuous feedback to office workers, allowing them to adjust their posture during work hours and reduce the likelihood of developing office syndrome. By incorporating ergonomic principles into the detection and analysis of sitting posture, this system will help promote healthier work habits and minimize the risk of musculoskeletal pain. In doing so, this research contributes to the growing body of work in workplace health technology, offering a proactive approach to managing and preventing office syndrome.

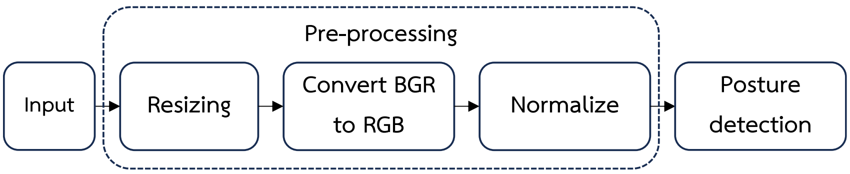

Figure 3 Pre-processing Flow

Furthermore, this paper will explore the theoretical underpinnings of ergonomic design in office work, the specific role of posture in preventing musculoskeletal disorders, and the potential benefits of integrating deep learning technologies like MediaPipe into real-time posture detection systems. The study will also evaluate the effectiveness of such a system in a workplace setting, examining both the technological feasibility and the potential for widespread adoption to improve employee health and productivity.

2. Methodology

2.1 System Design

The proposed system utilizes the MediaPipe Framework, an open-source solution developed by Google, to detect and analyze upper-body posture in real time. MediaPipe supports detection of 33 key landmarks across the human body, which are used for posture classification as illustrated in Figure 1. The system is designed to operate efficiently on standard computing devices, ensuring responsive performance during prolonged work sessions. The overall process follows four key stages: Pre-processing, Posture Detection, Vector Calculation, and Angle Calculation, as shown in Figure 2.

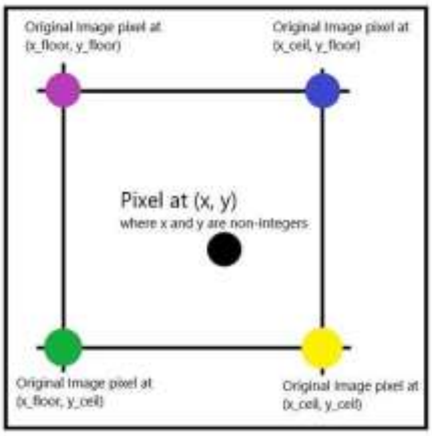

Figure 4 Linear Interpolation [7]

2.2 Pre-processing

The input image is first resized to 640x480 pixels to optimize processing speed without significant loss in quality. The resizing is achieved using the Bilinear interpolation method, which balances the preservation of image quality with the need for improved processing efficiency. Bilinear interpolation works by considering four neighboring pixels surrounding the target point. These four pixels, typically arranged in a rectangle, are selected based on their proximity to the target point. The algorithm then performs linear interpolation first along one axis (typically the x-axis) and then along the second axis (typically the y-axis). This approach ensures that the resizing process is computationally efficient while maintaining an acceptable level of image detail, thereby allowing for smooth and timely ergonomic tracking according to Figure 3 and 4. Then, the color format is converted from BGR (default in OpenCV) to RGB, which is compatible with MediaPipe. Lastly, pixel values are normalized to the [0, 1] range by dividing each by 255. This standardization ensures consistent input for pose estimation.

2.3 Posture Detection

At this stage, the MediaPipe framework is utilized to identify specific anatomical landmarks crucial for upper-body posture analysis, including the nose (landmark 0), left shoulder (landmark 11), and right shoulder (landmark 12). These landmarks are tracked in three-dimensional space (x, y, z), enabling the system to monitor head and shoulder alignment in real-time and provide reliable spatial data for subsequent angle and vector calculations.

Figure 5 Pose Estimation and Angle Calculation

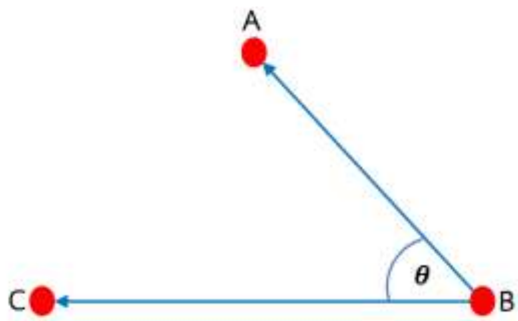

Figure 6 Corresponding Vector

MediaPipe's pose detection process operates through two key stages: person detection and landmark estimation. Initially, a lightweight bounding box detector identifies the presence and position of a person within the image frame. Once the individual is localized, a pose landmark model estimates the 3D coordinates of 33 key points across the body, including the head, shoulders, elbows, wrists, hips, knees, and ankles. These coordinates are continuously updated for each frame and normalized for image dimensions to ensure consistency.

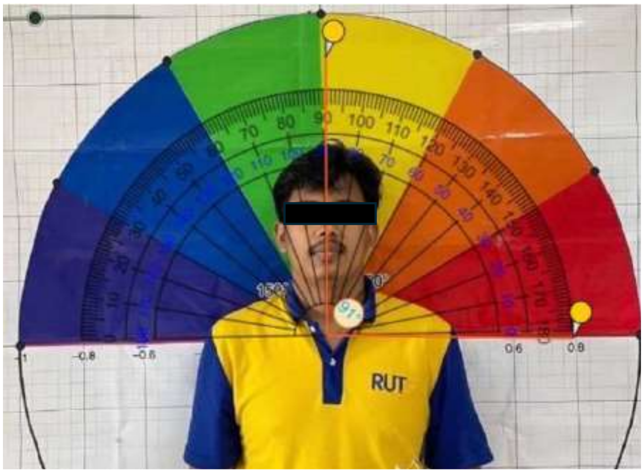

Figure 7 Actual Angle Measurement

Figure 8 Angle Tracking Result

2.4 Vector and Angle Calculation

To determine head posture, vectors are computed between key landmarks as illustrated in Figure 5 and 6. Specifically, point A represents the nose (landmark 0), while points B and C represent the left shoulder (landmark 11) and right shoulder (landmark 12), respectively. Two vectors are constructed: vector AB from the left shoulder to the nose, and vector BC from the left shoulder to the right shoulder. The angle between these vectors is calculated using the dot product formula, which provides a geometric measure of the orientation between the two vectors following to equation (1) to (5) respectively.

$$Dot\ product = AB_x \cdot BC_x + AB_y \cdot BC_y + AB_z \cdot BC_z \tag{1}$$

$$|AB| = \sqrt{AB_x^2 + AB_y^2 + AB_z^2} \tag{2}$$

$$|BC| = \sqrt{BC_x^2 + BC_y^2 + BC_z^2} \tag{3}$$

$$\cos\theta = \frac{dot\ product}{|AB| \cdot |BC|} \tag{4}$$

$$\theta = \cos^{-1}(\cos\theta) \tag{5}$$

To ensure that the calculated angles are consistent and independent of the image size or resolution, normalization is applied. Each coordinate (x, y) from the pose landmarks is divided by the corresponding width and height of the input image, respectively. This results in dimensionless values in the range [0, 1], which allows the angle computation to be invariant to scale. This is particularly important for real-time posture detection across different camera setups and environments.

2.5 Posture Classification Thresholds

Head posture classification is based on the angular deviation between the vector from the left shoulder to the nose (vector AB) and the vector from the left shoulder to the right shoulder (vector BC), as computed in the previous section. The resulting angle serves as a geometric indicator of head tilt direction.

To interpret these angles, thresholds were empirically defined through experimental calibration. A neutral posture is identified when the measured angle remains within ±10° of a reference baseline, typically centered around

90° in the vector configuration. If the angle decreases significantly (less than 70°), the posture is classified as a left-side tilt, indicating the nose is closer to the left shoulder. Conversely, an angle greater than 110° indicates a right-side tilt, where the nose is positioned closer to the right shoulder. These threshold values were validated using manual protractor measurements during the experiment and aligned with ergonomic literature, which identifies 15°–20° of lateral tilt as a common boundary for detecting non-neutral posture (Chapman et al., 2021; Mingels et al., 2016). This classification system allows the posture detection algorithm to reliably differentiate between normal and incorrect sitting positions associated with office syndrome risk.

3. Results and Discussion

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\theta_i^{measured} - \theta_i^{actual}| \quad (6)$$

Where $\theta_i^{measured}$ = the angle detected by the system
θ_i^{actual} = the manually measured angle
n = the number of observations

For the evaluation of the proposed system, an experimental setup was established in a controlled environment with a lighting level of approximately 300 LUX to simulate typical office conditions. The experiment involved 10 volunteers, comprising 6 females and 4 males, to assess the system's effectiveness in real-world scenarios. The volunteers were asked to perform standard office tasks while their posture was continuously monitored by the system. The data collected from these tests were used to evaluate the accuracy, responsiveness, and usability of the posture detection system, as well as its impact on promoting ergonomic practices.

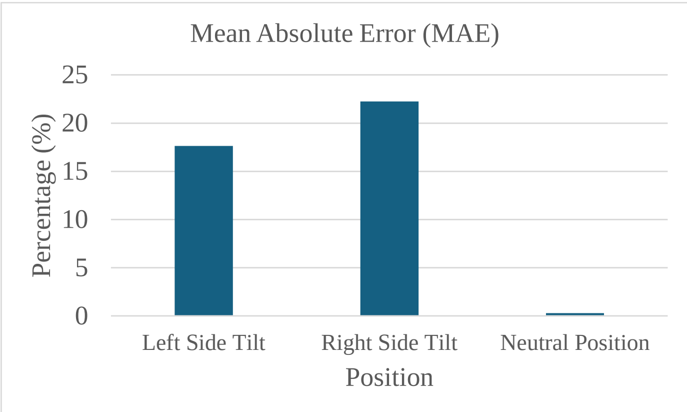

Figure 9 Mean Absolute Error (MAE) for Different Head Positions

To evaluate the accuracy of the proposed system, an experiment was conducted by comparing the actual angles (Figure 7) with the calculated angles (Figure 8) derived by the system. The experiment was divided into three parts: the first part involved measuring the angle in the neutral position, where the volunteer maintained a neutral head posture facing directly forward. The second part assessed the system's performance in detecting the angle during a left side tilt, where the volunteer tilted their head to the left. The final part measured the angle with the right-side tilt, where the volunteer tilted their head to the right. Each part of the experiment was conducted 20 times by 10 volunteers (6 females and 4 males) to ensure robust data collection. The calculated angles for each tilt position were compared with the actual angles to determine the system's accuracy and its ability to detect head movements in different directions. To validate the accuracy of the system, the actual angles were measured using a standard manual protractor application, which was placed and aligned along the participant's head and shoulder axis during each posture. These measurements served as reference angles for comparing against the automated detection angles calculated by the MediaPipe's pose estimation model according to Figure 8. The results were analyzed to assess the precision of the system in accurately detecting and calculating head posture.

To quantify the accuracy of the system, the Mean Absolute Error (MAE) was used as the primary metric for evaluating posture angle detection. For each trial, the angle calculated by the system using MediaPipe landmarks was compared to the corresponding actual angle, which was measured manually using a standard protractor aligned with the participant's head and shoulder axis. The absolute error for each instance was computed as the absolute difference between the measured angle and the actual reference angle. These individual errors were then averaged across all repetitions for each posture type—neutral, left tilt, and right tilt—to determine the final MAE, according to the equation (6).

The results of the Mean Absolute Error (MAE) analysis are presented in Figure 9, which shows the error percentages for three different head positions: Neutral Position, Left Side Tilt, and Right-Side Tilt. In the Neutral Position, the system demonstrated a very low MAE, close to 0%, indicating that the calculated angles closely match the actual angles when the head is in a neutral, straight-forward posture. This suggests that the system is highly accurate in detecting the posture in this position. However, as the head tilts to the left or right, the MAE increases, with both the Left Side Tilt and Right-Side Tilt showing an error of approximately 20%. These higher error values suggest that the system's accuracy decreases as the head tilts away from the neutral position. The increased MAE in tilted positions may be attributed to challenges in detecting and differentiating smaller changes in posture, or potential variations in individual head movements during tilting. Overall, while the system performs optimally in the neutral position, further refinement may be needed to improve accuracy in detecting head tilts.

Additionally, the processing time for the proposed system, executed on an **11**th Gen Intel® Core™ i**7-**1165G7 processor at 2.80 GHz, was evaluated. The system processed each frame with an average time of 0.20 seconds per frame, corresponding to approximately **5** frames per second (fps). This processing time demonstrates the system's capability to perform real-time posture detection efficiently, providing timely feedback for posture correction during typical office tasks.

4. Conclusions

This study presented the development of a real-time posture detection system utilizing the MediaPipe Framework to address the growing issue of office syndrome associated with prolonged sitting and poor ergonomic habits. The system was evaluated for its ability to detect head posture across various positions, demonstrating high accuracy in identifying neutral postures, with moderate deviations observed during head tilts.

Despite these limitations, the system’s consistent performance in neutral alignment and its low-latency operation underscores its potential for practical use in workplace environments. The findings also highlight the importance of further refinement, particularly in improving sensitivity to subtle postural deviations.

In addition, the analysis revealed that factors such as individual body structure, user height, camera angle, and involuntary movements can affect detection accuracy. These insights support the need for adaptive calibration strategies and personalized posture baselines to enhance system robustness across diverse users.

Overall, the proposed system offers an efficient and scalable approach for promoting ergonomic awareness and reducing musculoskeletal risks in office settings. Future work will aim to improve detection reliability, extend posture analysis to full-body tracking, and incorporate intelligent feedback mechanisms for real-time posture correction and user engagement.

5. Acknowledgements

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Real-Time pH Monitoring and Automated Control System for Sustainable Aquaculture

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Abstract

Fluctuations in pH levels can have a detrimental impact on the health, productivity, and ecosystem balance of aquatic organisms. Maintaining a stable pH within the optimal range is essential to ensure water quality and fish well-being. This study presents the design and validation of a real-time automated pH monitoring and control system to support sustainable aquaculture practices by regulating water pH using 0.2% (W/V) vinegar solution and 5% (W/V) dolomite solution. The system features real-time pH monitoring via a pH sensor and utilizes the ESP32 microcontroller to automate pH adjustments, with data logged to Google Sheets for remote tracking. The research process was conducted in two phases: The first phase involved determining the appropriate quantities of each solution for safe and effective pH regulation through incremental dosage trials, ensuring that the pH change did not exceed 2 units per day. The second phase evaluated the system's performance in actual control scenarios by adjusting the pH in a 1500 ml water container from acidic and basic conditions toward neutral, and by measuring the required time and solution saturation dynamics. The results show that the system can efficiently adjust the pH from acidic to neutral or from basic to neutral, with the required application of 4 ml of dolomite solution and 2 ml of vinegar solution per cycle. The time required for pH adjustment was approximately 1 day for changing pH from 4 to 7 and 1.5 days for adjusting pH from 8.5 to 7. These findings validate the effectiveness of the proposed system in controlling pH levels in aquaculture and demonstrate its potential for large-scale applications in water quality management.

Keywords: pH Control System, Aquaculture, Real-Time Monitoring, IoT-based Monitoring, Vinegar Solution, Dolomite Solution

1. Introduction

Fish farming has quickly become one of Thailand's most important agricultural industries, driven by the rising demand for domestic and international fish. As the global population grows and the need for sustainable seafood increases, the fish farming sector continues to expand, with various farming systems being employed to meet these needs. These systems include monoculture, extensive, and semi-intensive farming methods, each offering unique benefits and challenges based on the objectives of the operation (Soltan, 2016). Among these, monoculture has gained popularity due to its efficiency in managing feeding schedules and monitoring fish growth and health. The highly controlled environment of monoculture allows for higher production in a shorter time, making it an appealing choice for both small and large-scale operations.

However, while monoculture offers significant advantages in terms of productivity, it also comes with a range of challenges that must be addressed to ensure sustainability over the long term. One of the most pressing issues associated with monoculture farming is water quality degradation. The high density of fish in these systems puts considerable strain on the water, leading to the accumulation of waste products like ammonia and organic matter. This can create a harmful environment for the fish, with poor water quality often causing stress, diseases, and slower growth rates. Additionally, the buildup of nutrients in the water can disrupt the balance of the ecosystem, diminish biodiversity and interfere with natural biological processes. Furthermore, monoculture farming tends to rely heavily on large quantities of feed and chemicals, which not only leads to inefficient use of natural resources but also contributes to environmental pollution. Therefore, while monoculture is a highly productive and profitable method of fish farming, it is crucial to address these challenges to ensure that the system remains ecologically balanced and sustainable in the long run.

One of the most important factors influencing the success of fish farming is water quality, specifically the pH level. The pH of water affects the health and growth of fish, and maintaining a stable pH within an optimal range is crucial for maximizing productivity. Various factors, including ammonia levels, water temperature, and dissolved oxygen, interact to determine the overall water quality. Among these, pH levels play a critical role in fish health, and it has been widely recognized that water pH should remain between 6.5 and 8.5 for optimal fish growth (Craig et al., 2008). However, pH levels in natural waters tend to fluctuate, with pH typically around 5.6 due to dissolved carbon dioxide, which forms carbonic acid. During daylight hours, photosynthesis by aquatic plants removes carbon dioxide from the water, causing a rise in pH. Conversely, in the evening when photosynthesis decreases, carbon dioxide accumulates, leading to a decrease in pH. This diurnal variation can be problematic in fish farming, where maintaining a stable pH is critical for fish well-being.

To address this challenge, various strategies have been proposed for controlling and balancing the pH of water in aquaculture systems. One such method involves the use of vinegar solutions to lower the pH. Studies have shown that apple cider vinegar (ACV) and coconut sap vinegar (CSV) can significantly improve shrimp growth performance by maintaining a stable pH of approximately 7.9 in the water (Jamis et al., 2018). In situations where the water becomes too acidic, limestone has been used successfully to raise the pH to a more favorable level (Queiroz et al., 2004), with improvements observed within two weeks of application. These solutions, combined with technological advancements such as the Internet of Things (IoT), offer an integrated approach for real-time monitoring and management of water quality.

The integration of IoT-based systems in aquaculture has revolutionized the ability to monitor water quality in real time. IoT sensors can continuously track parameters such as pH, temperature, and dissolved oxygen, and send this data to a central control system. This allows for precise adjustments to be made automatically to maintain optimal water quality. Sodium carbonate and calcium carbonate are commonly used to buffer the water and prevent drastic fluctuations in pH levels (Abinaya et al., 2019). In addition to these methods, acidic liquids can be applied to neutralize high pH levels, particularly when the pH exceeds 7.5 (Budiman et al., 2019).

Despite the availability of these methods, there is still a need for more efficient and automated systems that can effectively balance the pH levels in fish farming environments. This work aims to develop a comprehensive pH monitoring and control system for fish farming, utilizing vinegar and dolomite solutions to adjust pH levels. The proposed system will automatically dispense vinegar solutions when the pH exceeds 8 and use dolomite solutions to raise the pH when the water becomes too acidic. By integrating real-time monitoring and automated control, this system will help maintain water quality within the optimal range for fish farming, thereby improving fish health, growth, and overall productivity.

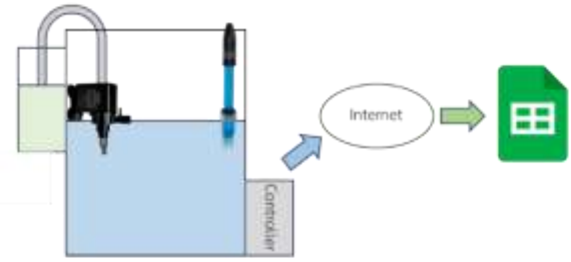

Figure 1 Proposed system installation

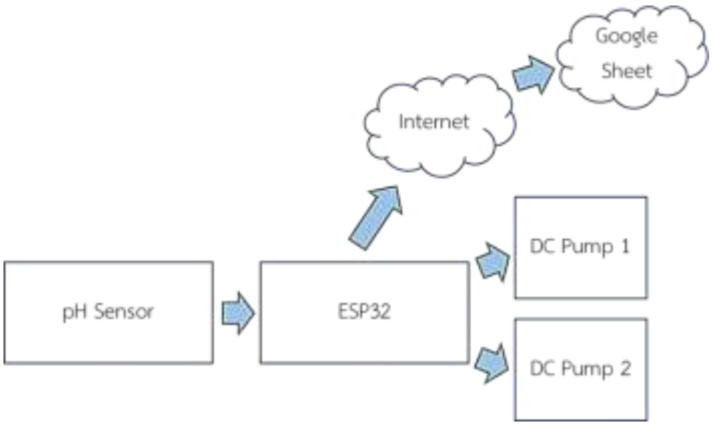

Figure 2 Proposed system block diagram

2. Methodology

In the proposed system, water pH is regulated using a 0.2% (W/V) vinegar solution as an acidifying agent and a 5% (W/V) dolomite solution as an alkalizing agent, with real-time monitoring and data logging performed via Google Sheebts through the ESP32 microcontroller. The 0.2% (W/V) vinegar solution was prepared by dissolving 2 grams of vinegar in 1 liter of water. Given that commercial vinegar typically contains 5% acetic acid, this results in an approximate acetic acid concentration of 0.01% (100 mg/L) in the working solution. During system operation, 2 ml of this vinegar solution was added to a 1,500 ml water tank, resulting in an acetic acid concentration of approximately 0.133 mg/L in the tank. This value is significantly lower than reported LC_{50} values for acetic acid (typically ranging from 45 to 1,000 mg/L), indicating the solution's safe application in aquatic environments. The 5% (W/V) dolomite solution was prepared by dissolving 5 grams of dolomite powder in 100 ml of water, yielding a mineral concentration of 50 g/L. For each alkalizing cycle, 4 ml of this solution was dispensed into the 1,500 ml water tank, resulting in an added mineral content of approximately 133 mg/L. This dosage is also well below known toxicity thresholds and was selected to gradually buffer the pH toward neutral without adversely affecting aquatic organisms.

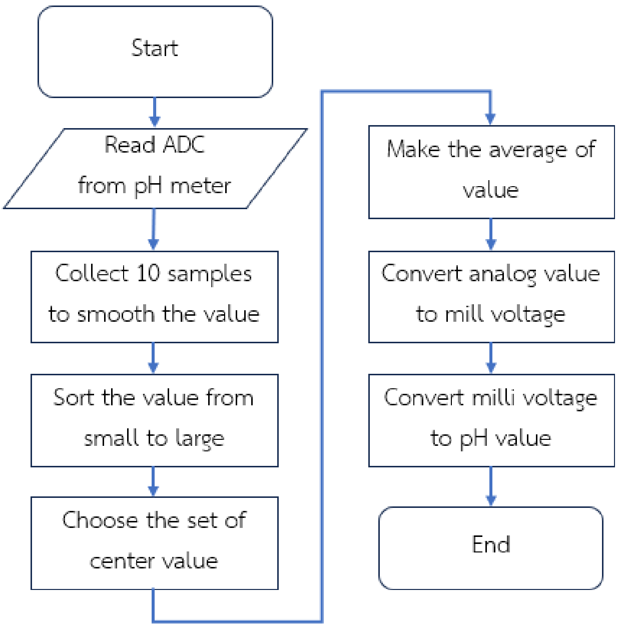

Figure 3. Data Acquisition

Figure 1 illustrates the setup of the proposed system. The system includes a pH sensor, and an oxygen pump installed inside the tank. The pH sensor continuously measures the water's pH level, while the oxygen pump ensures adequate water circulation. The dispensers for the acid and base solutions, along with their controllers, are positioned on the side of the tank.

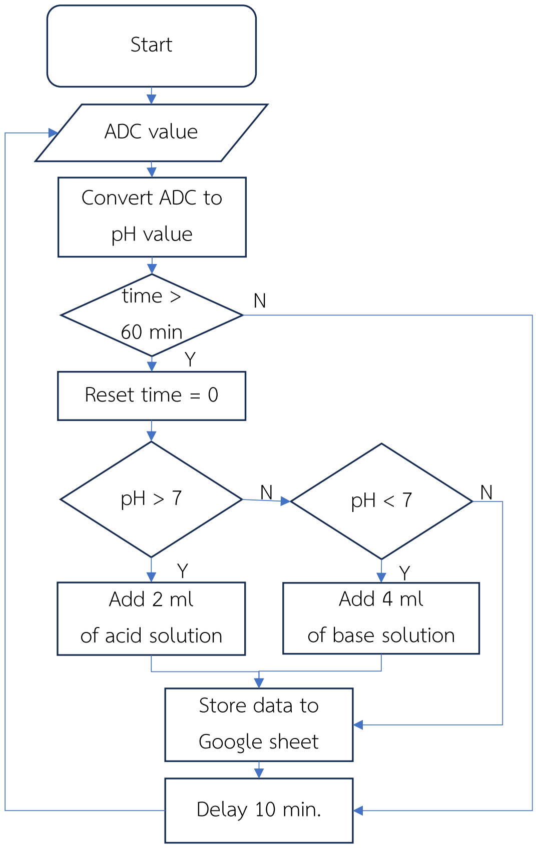

Figure 4 Control System Design

Figure 2 presents the block diagram of the proposed system, outlining the interactions between the pH sensor, controller, pumps, and the Google Sheets interface. The pH sensor serves as the input device to capture the water's pH readings, which are then transmitted to the ESP32 controller. Based on these readings, the controller determines when to activate the DC pumps (DC pump 1 and DC pump 2) to correct any pH imbalances. The system is designed to adjust the pH by dispensing either vinegar or dolomite solution, depending on whether the water is too acidic or basic. Additionally, the pH values are logged in real-time to Google Sheets via the controller's internet connection, providing remote monitoring and tracking of the pH levels.

2.1 Data Acquisition

The pH measurement and control system begin according to Figure 3 by acquiring the analog signal from the pH sensor, which is then converted into a digital value by the ESP32 microcontroller's ADC using the equation (1). To enhance accuracy and reduce noise, 10 samples are collected, sorted from smallest to largest, and the center values are averaged. The digital value is subsequently converted back to the analog voltage using equation (2). Finally, the analog voltage is mapped to a pH value using the linear calibration formula in equation (3) where m is the slope and b is the intercept derived from sensor calibration. This method ensures accurate real-time pH monitoring, allowing for precise control over water quality in aquaculture environments.

2.2 Control Design

The control system of the proposed design is illustrated in Figure 4. The proposed pH control system utilizes real-time monitoring and automated pH adjustments to maintain optimal water quality in aquaculture. The system is equipped with a pH sensor that continuously measures the water's pH, which is then processed by an ESP32 microcontroller. Based on the measured pH, the system activates either a 0.2% (W/V) vinegar solution or a 5% (W/V) dolomite solution to adjust the pH levels, ensuring they stay within the desired range. The pH values and adjustment data are logged in Google Sheets, enabling remote tracking and real-time monitoring. The system employs a controlled dispensing mechanism that ensures pH changes do not exceed 2 units per day, and each solution is applied in precise amounts based on the pH level. A critical feature of the system is that after each adjustment, a minimum of 60 minutes is allowed to pass before the process continues, ensuring that the pH has stabilized before further changes are made. This automated approach, coupled with data logging and time checking, ensures efficient and accurate pH regulation, contributing to better water quality management in aquaculture.

$$\text{Digital value} = \left(\frac{\text{Analog input voltage}}{5.0}\right) \times 4095 \quad (1)$$

$$\text{pH} = \text{m} \times V_{\text{analog}} + \text{b} \quad (2)$$

Table 1 pH Difference of Dolomite Solution at Various Quantities

Quantity of solution	pH value (before adding solution)	pH value (after adding solution)	pH difference
8 ml	6.83	7.11	0.28
6 ml	6.82	7.07	0.25
4 ml	6.71	6.82	0.11
3 ml	6.32	6.39	0.07
2 ml	6.69	6.73	0.04

Table 2 pH Difference of Vinegar Solution at Various Quantities

Quantity of solution	pH value (before adding solution)	pH value (after adding solution)	pH difference
8 ml	6.87	6.43	0.44
6 ml	6.82	6.53	0.29
4 ml	6.84	6.63	0.21
2 ml	6.84	6.72	0.12

3. Result

The pH control system was developed and tested through a two-part experiment. The first part involved solution analysis, where vinegar and dolomite solutions were selected as the pH control agents. The goal of this phase was to determine the appropriate quantities of each solution required for effective pH regulation.

The mock container, holding 1500 ml of water, was used for the experiment. The quantity of solution added was adjusted based on the principle of pH adjustment in aquaculture, where the pH change should not exceed 2 units per day. As shown in Table 1, it was determined that the maximum allowable quantity of 5% (W/V) dolomite solution to be added to the container at any given time is 4 ml. Similarly, as indicated in Table 2, the maximum allowable quantity of 0.2% (W/V) vinegar solution is 2 ml per application.

In the second part of the experiment, we investigated the saturation time of pH changes when each solution was applied. The results revealed that the 5% (W/V) dolomite solution reached its saturation point in approximately 10 minutes, as illustrated in Figure 1. Similarly, the 0.2% (W/V) vinegar solution also reached its saturation point within the same timeframe of 10 minutes, as shown in Figure 5.

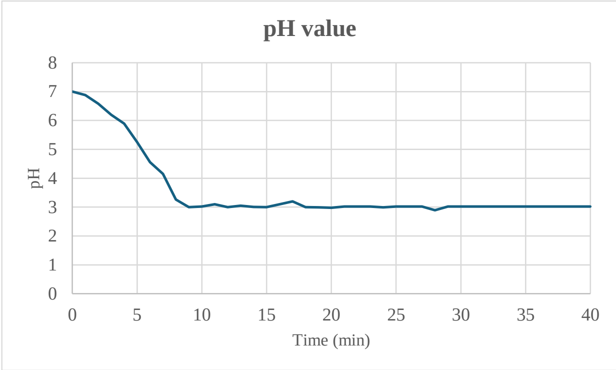

Figure 5 saturation time of pH value of vinegar solution

These findings provide valuable data for optimizing the pH control system and ensuring that both dolomite and vinegar solutions are used effectively without exceeding the maximum allowable pH changes for aquaculture environments.

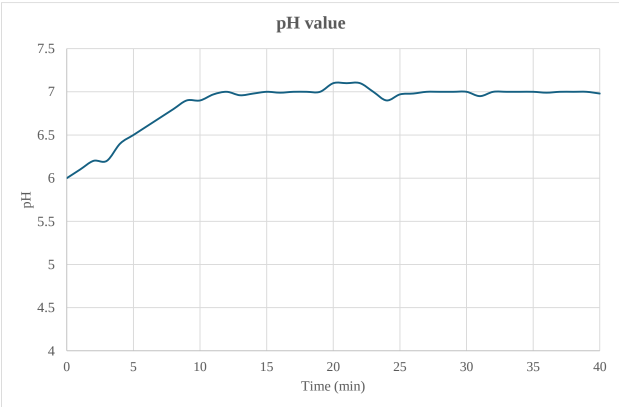

Figure 6 saturation time of pH value of dolomite solution

The second phase of the experiment aimed to evaluate the effectiveness of the pH-controlling system. A test container, holding 1500 ml of water, was equipped with an oxygen pump to facilitate water circulation. To adjust the pH from acidic to neutral, a 5% (W/V) dolomite solution was used, while a 0.2% (W/V) vinegar solution was employed to adjust the pH from basic to neutral. Each experiment was repeated three times for consistency.

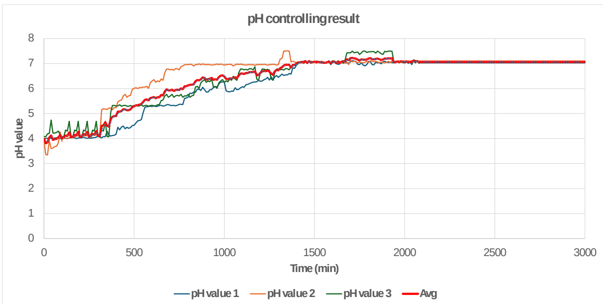

Figure 7 effectiveness of the pH-controlling system

As shown in Figure 6, the average time required to adjust the pH from 4 to 7 was approximately 1500 minutes, or about 1 day. Similarly, Figure 7 illustrates that the average time required to adjust the pH from 8.5 to 7 was approximately 2000 minutes, or 1 day and a half.

These results demonstrate the efficiency of the pH-controlling system in restoring water to a neutral pH within a reasonable time frame for both acidic and basic conditions.

4. Conclusion

The proposed pH control system demonstrated effective and efficient regulation of pH levels in aquaculture environments. By utilizing a combination of 0.2% (W/V) vinegar solution and 5% (W/V) dolomite solution, the system successfully adjusted the pH from both acidic and basic conditions to neutral, within the optimal range. The experiment confirmed that the maximum allowable quantities of each solution (4 ml of dolomite and 2 ml of vinegar) did not exceed the recommended pH change of 2 units per day, ensuring water quality stability.

The system's performance was further validated by testing its saturation time for pH changes. Results showed that both the vinegar and dolomite solutions reached their saturation points in approximately 10 minutes, highlighting the system's quick response. Additionally, the time required to adjust pH from 4 to 7 and from 8.5 to 7 was approximately 1 day and 1.5 days, respectively, indicating the system's efficiency in maintaining stable pH levels over a reasonable period.

These findings suggest that the integration of real-time pH monitoring with automated pH adjustment can significantly improve control over water conditions in aquaculture. Future developments will focus on enhancing the system's scalability and efficiency for broader applications in various water quality management scenarios.

Although the experiments were conducted in a fixed volume of 1500 ml, the system design is inherently modular and suitable for scale-up. Adapting the system to larger tanks or ponds would require proportional calibration of dosing volumes, optimization of sensor positioning, and enhancements in water circulation and mixing. However, in larger-scale deployments, additional factors such as buffering capacity, non-uniform pH gradients, and slower reaction kinetics must be considered. Future work will focus on evaluating the system's performance in larger aquaculture environments and under variable field conditions. Investigations will include scalability assessment, adaptive control strategies, and integration with multi-parameter water quality monitoring to support broader applications in sustainable aquaculture and environmental management.

5. Acknowledgment

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IoT-Based Remote Monitoring and Alert System for Bedridden Patient Care in Thailand

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Abstract

An increasing aging population in Thailand has placed a growing burden on healthcare resources. By 2030, the number of bedridden elderly is expected to reach 153,000, nearly three times the current figure. To address this, we have developed an IoT-based remote monitoring and alert system designed to assist caregivers in patient management. This system integrates smart sensors and cloud connectivity to provide real-time monitoring and alerts. A mobile application prototype, built using Google Sheets and AppSheet, offers real-time data visualization and allows caregivers and doctors to remotely track patient conditions. The app provides two access levels: caregivers or doctors can monitor multiple patients, while patients can view their own records. Instant alerts notify caregivers of critical changes ensuring timely intervention. Two IoT medical devices are implemented within this framework. The first device is an automatic hospital bed equipped with an inertial measurement unit and radar sensors to track patient activities, and head of bed elevation. The second device is a blood pressure and heart rate monitoring device that measures vital signs in intervals. Enabling IoT functionality increases the power consumption of both tested devices compared to their non-IoT versions. This power increase is observed in idle states and is also evident during active operational modes of the second device due to the demands of active components.

Keywords: IoT-based healthcare integration, caregiver alert system, real-time health monitoring

1. Introduction

Thailand is experiencing a significant demographic shift characterized by a rapidly aging population. This trend is projected to result in a substantial increase in the number of bedridden elderly, reaching an estimated 153,000 by 2030, nearly triple the current figures (Tantirat, Suphanchaimat, Rattanathumsakul, & Noree, 2020) [1]. This escalating need places a growing strain on the nation's healthcare resources. Remote patient monitoring (RPM) is increasingly recognized as a valuable tool for managing chronic conditions, facilitating the early detection of health deterioration, and improving patient outcomes (Malasinghe, Ramzan, & Dahal, 2019) [2]. However, while a growing number of medical devices are equipped with integrated IoT capabilities, a significant portion of existing equipment lacks direct network connectivity. Replacing all non-IoT devices with their smart counterparts can be financially prohibitive for many healthcare providers and individuals (Chakravarty, 2022) [3]. Adding another layer of complexity is the reality that while IoT-enabled medical devices are increasing, a substantial amount of existing equipment lacks direct network connectivity Kane, Bakker, & Balkenende, (2018) [4]. The prohibitive cost of replacing all these legacy devices underscores the critical need for innovative solutions that can bridge the gap between this existing infrastructure and modern cloud-based platforms.

This paper presents a case study focused on the development of an innovative IoT-based remote monitoring and alert system designed to empower caregivers in managing their patients more effectively. This system combines smart sensors and cloud connectivity to deliver real-time patient monitoring and timely alerts. A mobile app prototype, created with Google Sheets and AppSheet (Ferreira, 2014) [5], offers real-time data visualization and allows caregivers and doctors to remotely monitor patient conditions with different access levels for comprehensive and individual views. The system currently integrates two key IoT medical devices: an automatic hospital bed equipped with movement and elevation sensors, and a continuous blood pressure and heart rate monitoring device, laying a foundation for future integration of additional medical IoT technologies.

2. Methodology

2.1 Remote Monitoring Framework

The depicted system architecture represents a layered approach to IoT-based remote patient monitoring, aligning with established principles in distributed systems as shown in Figure 1. The perception layer, comprising sensor-equipped IoT medical devices, facilitates real-time data acquisition. This data is subsequently relayed via an Application Programming Interface (API) to the network layer, where Google Cloud is employed as a cloud-based server performing critical functions including data ingestion, processing, and persistent storage within a database. Google Cloud is utilized alongside AppScripts, a cloud-based scripting language by Google designed for automating tasks (Hassan, Mohd Rusli, & Mohd Salleh, 2023; Kurniawan, Wardani, & Zaki Hamidi, 2023). [6], [7]. The application layer provides a user-centric mobile interface, enabling remote visualization of patient data and the dissemination of timely alerts to caregivers. AppSheet is used to develop this mobile application as a no-code platform that provides an interface for caregivers, doctors, and patients to monitor and interact with system data hosted on Google Cloud. It also allows the use of AppScripts for custom functionalities and integrations.

The provision of differentiated access levels within the mobile application is a critical design consideration that addresses the diverse needs and roles of stakeholders in the healthcare ecosystem. Caregivers and doctors can monitor multiple patients, improving oversight and resource management through real-time data. The cloud server offers scalable data storage, real-time visualization, historical trend analysis, and integration with systems like Electronics Health Records (EHRs) or nurse alerting systems. Conversely, granting patients access only to their own records promotes transparency and empowers them to actively participate in their health management. This patient-centric approach can enhance understanding of their condition, encourage adherence to treatment protocols, and foster a greater sense of control over their well-being [8]. Furthermore, these distinct access levels are crucial for maintaining data privacy and security, ensuring that sensitive patient information is appropriately restricted and accessible only to authorized individuals.

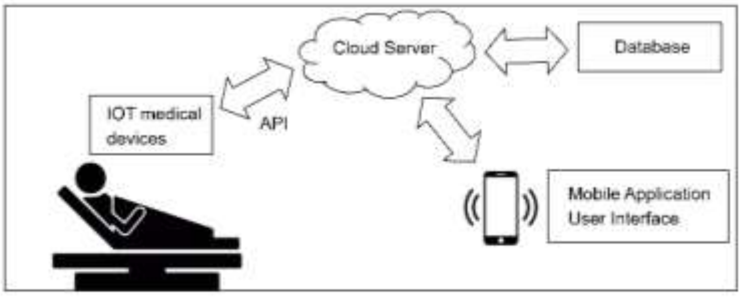

Figure 1 A framework for remote monitoring

2.2 IOT enablement and retrofitting

A significant aspect of this research involves the digitalization and IoT enablement of conventional medical devices through targeted hardware and software integration and retrofitting. The strategy of retrofitting existing infrastructure with IoT capabilities is a recognized and cost-effective approach for upgrading systems in various sectors (Pietrangeli, Mazzuto, Ciarapica, & Bevilacqua, 2023). [8]. In this study, we focus on enhancing two devices to improve the efficiency of caregivers and doctors. The first device is a motor-driven bed modified to provide adjustable head of bed elevation (HOBE) and track patient activity, discerning if they are sitting, lying, or off the bed. Adjustable HOBE is recommended for patients receiving enteral feeding to reduce aspiration pneumonia risk and for individuals with certain respiratory conditions to improve oxygenation and ventilation in Positional Obstructive Sleep Apnea (POSA) (Iannella, G., et al., 2022). [9]. This integrated activity tracking facilitates more efficient remote monitoring of the patient's status. The modification process is performed by retrofitting existing standard motor-driven bedframes with an external IoT-based sensor module. The head of bed elevation (HOBE) monitoring is achieved by retrofitting the existing mechanical structure of the motor-driven bedframe with an Inertial Measurement Unit (IMU) to capture angular orientation and acceleration data to monitor head of bed elevation and activity of the patient, respectively as shown in Figure 2. The sensor module is designed to be attached to the existing mechanical structure of a motor-driven bed frame as shown on the right of This section of the frame can elevate the patient up and down. In this study, MPU6050, a 6-axis sensor that integrates a 3-axis accelerometer and a 3-axis gyroscope on a single chip, is chosen. This combination allows it to measure both linear acceleration and angular velocity, providing comprehensive data about a device's movement Figure 3. and orientation in three dimensions. A key feature is its onboard Digital Motion Processor (DMP), which can handle complex sensor fusion algorithms, offloading processing tasks from the main microcontroller and providing more accurate orientation data, especially the calculation of the HOBE. This module uses a DC 24V from external power supply and the IMU communicates with an ESP8266 via an Inter-Integrated Circuit (I²C) interface with a sampling time of 10 seconds.

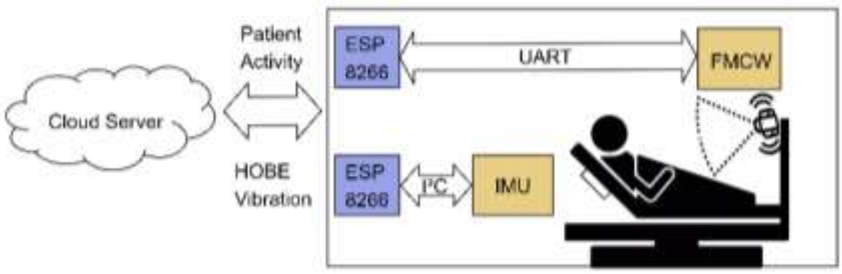

Figure 2 A framework of IoT-enabled hospital bed

Another module that tracks patient activity incorporates non-contact sensing technology to monitor patient discreetly without requiring wearables or direct contact. A non-contact monitoring system is less constrained by monitoring conditions and accommodates long-term signal detection needs while minimizing discomfort from the detection process (Lv, He, Lin, & Miao, (2021) [10]. Here, A Frequency-Modulated Continuous-Wave (FMCW) radar sensor is chosen. The sensor transmits a continuous chirp signal of slope m during the signal's round trip to the target and back (τ), the received signal's frequency is offset from the frequency being transmitted at the moment of reception. This frequency difference is called the Doppler shift or beat frequency (f_b), and it is directly proportional to both the chirp slope and the time delay as $f_b = m \cdot \tau$. Since the time delay is also directly proportional to the target's range (R) and the speed of light (c), specifically $\tau = \frac{2R}{c}$, substituting this into the beat frequency equation reveals a direct relationship between the beat frequency and the target's range as $R = \frac{c \cdot f_b}{2m}$. Therefore, by measuring f_b, the sensor can detect the presence, position (such as sitting or lying, which affects range and angular position), and micro-movements of a patient on the bed. In this application the LD2420, which communicates via a Universal Asynchronous Receiver-Transmitter (UART) interface is chosen. The LD2420 is a 24GHz millimeter wave (mmWave) radar sensor module specifically designed for intelligent human body detection. Operating at 3.3V, this compact module offers a configurable detection range up to 8 meters, and 60° field of view. The sensor is integrated into ESP8266 with UART with a sampling time of 10 seconds. As shown on the left of Figure 3, the module is mounted on the bottom panel of the bed frame and operated with 24 V from external power supply.

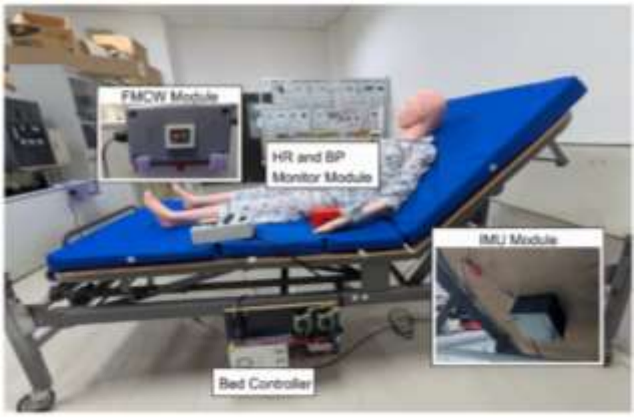

Figure3 A hospital motor-driven bed frame with IOT-enabled features

The second device focuses on enabling capabilities for a standard heart rate and blood pressure (HR and BP) monitor for IOT connectivity. This was achieved through the development of a custom embedded system prototype board (See Figure 4). The non-IoT HR and BP monitor underwent modification to interface with this newly designed board, allowing for the decoding of its communication protocol and data format. The board was specifically designed to communicate with the monitor's internal Inter Integrate Circuit (I²C) bus. By reverse engineering the monitor's hardware, the specific data fields representing HR, systolic BP, and diastolic BP readings were successfully identified. Operating in an I²C master configuration, the custom board initiates data requests and receives the raw physiological data from the monitor's internal controller, which is then transmitted to an ESP8266. Data handling and processing are executed after the successful acquisition of the HR and BP measurements. The original user interface of the monitor, including its physical buttons, remains operational. The combination of the custom-designed board and the ESP8266 thus forms a system that imbues the monitor with IoT functionality.

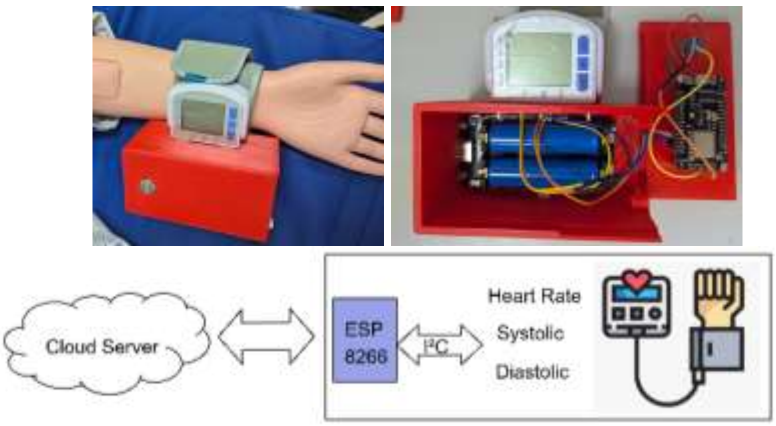

Figure 4 IoT-enabled blood pressure and heart rate monitor

3. Results and Discussion

3.1 Application Interface

The application interface shown in Figure 5 initiates with a secure login (top-left), requiring username and password, with a status indicator and a logout option. Upon successful login, the application presents a concise list of individuals currently being monitored. Each entry provides essential identification through Name and a unique ID. The accompanying Edit icon allows the authorized users to manage the profiles of these individuals, including updating assigned monitoring devices, or other relevant administrative details. This screen acts as a central hub for selecting a specific patient to access their real-time and historical health data transmitted from the connected IoT devices.

Selecting a patient from the list navigates the user to their dedicated profile screen, where Name and ID can be edited. The modifiable field represents monitored conditions such as "heart diseases," "kidney complications," or "stroke", can be checked or unchecked for each field for individual patients. Patient profiles can be appended with extra medical details and monitoring instructions via the "Add" button. Photos can be edited using icons. The lower section of Figure 5 presents specific connected IoT devices connected to specific patients. These tiles provide a direct interface for monitoring device status. The first icon (1) provides a more detailed view of the blood pressure and heart rate data. The second icon (2) indicates the status of the HOBE of the adjustable bed. The last icon (3) indicates whether the patient is detected in bed within the vicinity of a microwave motion sensor. Each of the data is labeled with date and timestamps. In addition, the data is stored in Google Sheets for a comprehensive record of each patient.

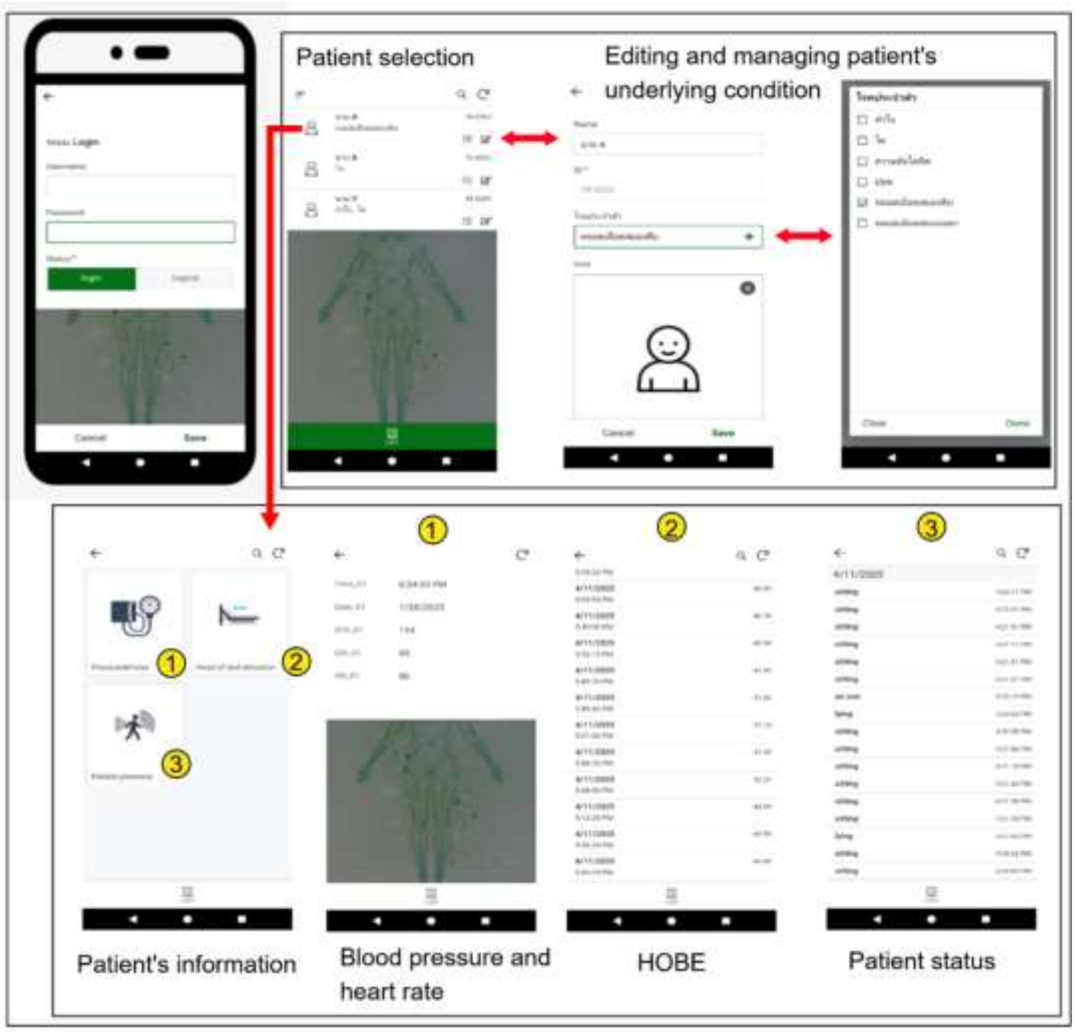

Figure 5 Application User Interface

3.2 Power Consumption Comparison

To assess the power consumption of both devices, the IOT is enabled and disabled to compare the current consumption Here Fluke 117 multimeter is used to measure the power consumption in each scenario. The IOT Bed device exhibits an idle power consumption of 1.09 W, which decreases to 0.86 W when its IOT functionality is disabled, indicating a power contribution from these smart features; notably, the FMCW component is the most significant power consumer, accounting for 63.6% of the total energy usage. Table 1 summarizes the electrical current consumption of the second device, comparing both its non-IoT version and our modified IoT-enabled variant across different operational modes: *Idle*, *Pump*, *Measure*, and *Upload*. The data reveals a more nuanced picture. While the idle current is slightly higher for the IoT version, the active states (*Pump* and *Measure*) also show increased power consumption, suggesting that the integration of sensing, processing, and network connectivity concurrently demands more power.

Table 1 Current consumption of blood pressure and heart rate monitor

	Idle (A)	**Pump (A)**	**Measure (A)**	**Upload (A)**
Non-IOT	0	0.27	0.11	N/A
IOT	0.06	0.35	0.18	0.07

4. Conclusions

This paper details the development of an innovative IoT-based remote monitoring and alert system aimed at enhancing caregiver effectiveness through smart sensors, Google Cloud connectivity, and a user-friendly mobile application prototype providing real-time data visualization and differentiated access. The system integrates a retrofitted smart bed that includes monitoring movement, head of bed elevation, and status of the patient. The system also enables the IoT capabilities of a digitized blood pressure and heart rate monitor. Both devices can transmit the data wirelessly to the cloud database and ultimately the application. The power consumption analysis reveals an energy overhead associated with IoT enablement in both devices during data transmission and active operation compared to their traditional counterparts, offering foundational insights into the power implications of IoT integration for remote patient monitoring. Power consumption analysis revealed that enabling IoT features increases the power usage of both tested devices. The bed's idle power consumption rose from 0.86 W to 1.09 W, with the FMCW component accounting for a significant 63.6% of its energy usage. For the second device, integrating IoT resulted in higher current consumption not only in idle but also during active Pump and Measure states, indicating that concurrent sensing, processing, and network connectivity demand more power. These two devices are integrated into the system, enabling compatibility with additional IoT medical devices in the future.

5. Acknowledgements

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