University of Cabuyao
Laguna, Philippines 4025

COLLEGE OF ENGINEERING

REAL-TIME CROWD BEHAVIOR CONTROL AND MONITORING SYSTEM USING 3D-CONVOLUTIONAL NEURAL NETWORK

A Project Design Engineering Research Presented to
the Faculty of the College of Engineering
Pamantasan ng Cabuyao

In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science in Computer Engineering

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Approval Sheet

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Pamantasan ng Cabuyao
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Approval Sheet

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CERTIFICATION OF ORIGINALITY AND AUTHENTICITY

Research Title: Real-Time Crowd Behavior Control and Monitoring System Using 3D-Convolutional Neural Network

Department: College of Engineering

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ABSTRACT

Managing large crowds and ensuring public safety during mass gatherings is a growing global challenge. The concentration of people in specific areas during large events presents critical issues, especially as urbanization and transportation systems improve, and large-scale events become more frequent. Public spaces in cities are becoming increasingly crowded, and while many countries have started adopting advanced technologies for crowd management, more effective strategies are needed to maintain order and safety. This study aims to design and develop a real-time crowd behavior control and monitoring system to enhance public safety, providing valuable insights for event organizers, urban authorities, and emergency teams. The use of the 3D-CNN algorithm for real-time crowd behavior monitoring significantly improves the ability to identify and predict potential safety risks before they escalate. The model's accuracy leveled off between 88.33% and 91.67%, showing that it had learned essential patterns and performed well. The validation accuracy ranged from 83% to 88.33%, indicating consistent improvement on new, unseen data. To ensure an adaptive development process, the researchers employed the Agile Development Methodology, allowing continuous feedback and refinement. This process involved camera integration, model development with TensorFlow, IoT-based system implementation, user interface design, testing, and prototype deployment. The study also followed a comprehensive machine learning workflow from data preprocessing to model training, evaluation, and deployment, ensuring scalability and accuracy in dynamic, real-world environments. Together, these approaches helped create a robust solution that meets both technical and real-time application needs.

Keywords: *3D-Convolutional Neural Network, Computer Vision, Deep Learning, Crowd Behavior, Crowd Monitoring, Artificial Intelligence, Internet of Things*

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To our esteemed Panelists, we are sincerely grateful for your valuable time, constructive feedback, and intellectual contributions. Your questions, comments, and evaluations have challenged us to think more critically and have significantly contributed to the academic rigor and depth of our research. Your expertise and thoughtful engagement helped shape this study into a more comprehensive and meaningful work.

To all of you, thank you for being part of this meaningful journey. Your contributions will always be remembered with deep appreciation and respect.

DEDICATION

With heartfelt gratitude, we dedicate this research to the individuals who have played a pivotal role throughout this journey. To our family, thank you for your unwavering love, constant encouragement, and the many sacrifices you've made along the way. Your support has been the foundation of our strength and perseverance, and we are deeply grateful for everything you have done to help us reach this point.

To our co-researchers, your resilience and commitment in the face of numerous challenges were truly inspiring. This endeavor would not have been as enriching or fulfilling without your hard work, collaboration, and determination. We are proud of what we have achieved together.

Above all, we offer my deepest thanks to God. In moments of uncertainty and difficulty, His presence provided clarity, strength, and purpose. It is through His guidance that we found the courage to continue, and through His grace that this work has come to fruition.

This research is not merely an academic accomplishment—it is a reflection of the support, collaboration, and faith that carried us through. To everyone who stood beside us, thank you from the depths of our heart.

- Researchers

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INTRODUCTION

The issues of managing and regulating crowds are rather critical since many people are concentrated in certain areas and during specific events. It can be said that conventional crowd management strategies are insufficient to guarantee order and prevent possible violence or unlawful actions. In this regard, new approaches are being considered to improve the Crowd Management Center's crowd management capacity. The solution involves the implementation of the Internet of Things with other technologies such as computer vision and machine learning. Connected-camera-based IoT systems can utilize the extensive worldwide network of IoT devices to gather and process data in real-time from different sources, including cameras. Intelligent crowd behavior control and monitoring systems can therefore be designed by using the capabilities of IoT, and this would enable the reduction of the risks associated with crowd behavior.

This study assesses the possibility and efficiency of IoT-based systems incorporating cameras to detect crowd behavior and apply control in real-time. The study assessed how such a system can be used under different circumstances, such as during public events in schools and urban centers. The present system may be helpful in crowd safety and security by evaluating crowd characteristics, assessing possible threats, and timely inclusion of corrective measures. The study's primary goal in this paper is to design an integrated IoT real-time system that can efficiently monitor and control crowd behavior, identifying crowd patterns and potential threats. The real-time video feed was obtained through the camera, and computer vision was employed to extract data concerning crowd density, movements, and behavior. Data from different sources can improve the assessments of the crowd's behavior and can detect issues that might lead to risks earlier.

Therefore, this research aimed to explore the potential of IoT-connected technologies combined with 3D Convolutional Neural Networks in addressing challenges related to crowd management. By designing a system capable of analyzing crowd behavior, detecting potential risks, and initiating appropriate control measures, this study seeks to contribute to the development of practical and effective solutions for safer and more efficient public space management.

Background of the study

Managing large crowds and ensuring public safety during mass gatherings is a growing challenge globally. As urbanization progresses, transportation systems improve, and large-scale events become more frequent, public spaces in cities worldwide are becoming increasingly crowded. This high population density in public spaces creates significant safety risks, particularly during large gatherings where the sheer volume of people can lead to accidents. Stampedes and other crowd-related disasters have been particularly troubling in recent decades. According to Wenguo Weng, Jiayue Wang, Liangchang Shen, and Yushan Song, "At least 440 human stampede incidents occurred between 1980 and 2022, causing over 13,700 deaths and 27,000 injuries" [1]. These statistics indicate the worldwide scale of the problem and emphasize the pressing need for more effective crowd management solutions to ensure public safety.

Many countries have started incorporating advanced technologies for crowd management, leaving behind the traditional manual observation and intervention, which are, in most cases, inefficient, prone to human error, and unreliable.

Real-time monitoring systems that use a variety of sensors and data analysis technologies have become more popular since they offer the most reliable and effective ways for crowd management. For example, a catastrophe scenario in Madagascar, where, following a human crush at Mahamasina Municipal Stadium before the 59th Independence Day concert celebrations, ended with the killing of 16 people and over 100 injured, highlights vulnerability when large crowds gather in less populous countries [2].

Even more so, the occasion shows how much nations will have to develop better crowd control systems to deal with such a situation while boosting public safety. The incidents such as the riot at the Negros fiesta and the scuffle at the public plaza of Leon in Iloilo reported by GMA News, public gatherings can easily turn hostile. The Negros fiesta, held in a covered court, turned into bedlam when allegedly drunken youthsters started fighting and attacking one another without considering the people in the surroundings. Such occurrences tend to reveal the vulnerability of public spaces to violence, especially alcohol and conflicts over social media-related issues. Similarly, reports say that the ruckus in Leon, Iloilo, was due to some tensions that had been mounting over the social media-related activities among female youths. These incidents prove that, even in public areas, conflicts and disturbances may crop up unexpectedly, thus creating a further need for advanced crowd management strategies to maintain order and safety in mass gatherings [5]. The urgency for effective crowd management is more critical. Urban regions are challenged to handle crowds in real-time with regular large-scale public events, concerts, markets, and festivals.

The growing reliance on real-time technologies, such as networked systems, cameras, and machine learning-driven video analysis, allows cities to better monitor crowd density, movement, and potential bottlenecks. These systems can generate timely data that enables security personnel to make informed decisions about deploying staff into critical areas before a situation aggravates. These technologies can be combined to create safer environments for mass gatherings, thereby reducing the likelihood of crowd-related accidents and enhancing overall public safety.

Objective of the Study

This study aimed to design and develop a real-time crowd behavior control and monitoring system using 3D Convolutional Neural Networks (CNN) and Open Computer Vision Library (OpenCV) to improve public safety and provide valuable insights for event organizers, urban authorities, and emergency teams. The study included the following specific objectives:

1. To design a flexible and dependable system incorporating a camera and machine learning to effectively monitor and manage crowds in tracking behavioral patterns;

    a) The system can display 85-90% accuracy in different crowd dynamics (100, 500, and 1000 crowd sizes), and different environments such as in a School Cafeteria and a school-based Event (Flag Ceremony).

b) A system able to monitor and manage the crowd with uptime from Monday to Saturday:

I. 7 am to 9 am in the Flag Ceremony; and

II. 11 am – 1 pm in the School Cafeteria;

c) The system output will be compared to the real-world observation of the behavioral pattern, including the following:

I. Violence and Brawl;

II. Seizure and Fainting; and

III. Behavioral Panic.

d) The system should have a latency of less than 2 seconds between collected data from the camera and the corresponding alert or notification displayed or updated on the user interface.

2. To utilize video processing and machine learning algorithms that can quickly spot crowd behaviors, and potential threats such as brawl and running in multiple directions, and potential health threats such as seizure and fainting as they happen;

3. To implement the system in different settings, like in School grounds, such as in School cafeterias, and during School events, like Flag ceremonies, so that it can give real-time support to event organizers, school officials, law

enforcement, and health services for better crowd management and public safety; and,

4. To evaluate the performance of the real-time crowd behavior control and monitoring system in various environments, focusing on its accuracy in detecting crowd behaviors and potential threats. Using ISO/IEC-25010 in terms of:

a) Accuracy;

b) Reliability;

c) Functionality; and

d) Performance Efficiency.

Theoretical Framework

From the late 20th century until now, large gatherings at events and concerts have become increasingly popular. As the industry evolved, so did the same for other sectors such as technology and entertainment. From public gatherings to the concert, people attending the events physically remain as strong as ever. It may be amazing how people could gather in a place with different views and walks of life, but still have the same interests for the reason they gathered. This still presents a risk to the people participating when there are no crowd control measures. Public security and safety may be disturbed due to overcrowding, resulting in accidents and injuries.

Unfortunately, as is the case with many managements traditionally dealing with crowd control measures, which lack workforce and strategy. This lack of safety measures not only threatens the attendees but also strains the responders in case of an emergency. Therefore, designing and developing real-time behavior monitoring systems for crowd control and monitoring would bring more options and address the challenges in ensuring the safety and security of the event and the attendees.

Theories and models used

As the study used IoT technology as the central monitoring system, building a comprehensive model that enables the cameras to recognize and classify the behavior displayed on the live feed is essential. This framework drew on multiple domains, such as IoT Technology, real-time image/video processing, machine learning, and behavioral psychology.

IoT Technology

- IoT-enabled wireless transmission and data exchange locally or over the Internet are essential. The system needs to transmit data in real-time from the sensor to the core for processing.
- IoT devices such as cameras allowed a smooth transmission of real-time data for the crowd monitoring and control system with minimal human intervention.

Image Processing and Machine Learning

- A machine learning and 3D Convolutional Neural Networks (3D-CNN) algorithm was employed to analyze and process the video footage from the sensors, detecting unruly behavior and emergencies such as fighting, indiscriminate violence, fainting, and even crowd panic attacks.

- Machine learning algorithms could accurately recognize and classify the crowd behavior in real-time.

Modification and New Framework

Integrating IoT Technology and Machine Learning, a new framework and model of crowd behavior monitoring and control would be developed. The system connected an IoT camera to the edge devices, utilizing machine learning to interpret and analyze the data in real-time. Its framework linked the variables of crowd density, movement patterns, and individual behavior to alert authorities when dangerous situations arise.

Variables and Relationships:

- Independent Variables
    - Crowd Movement Patterns
    - Environmental and Event Factors
    - Footage Data
- Dependent Variables
    - Detection of Hazardous Behaviors
    - System response time to crowd behavior changes in real-time

- Relationship
    - There are many patterns and changes in crowd behavior, even in seconds. This affects how the system can respond and detect hazardous behavior in the crowd. The faster and more suspicious the crowd movement, the higher the chance of detecting such hazardous behavior and marking it for intervention by contacting authorities.

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Conceptual Framework

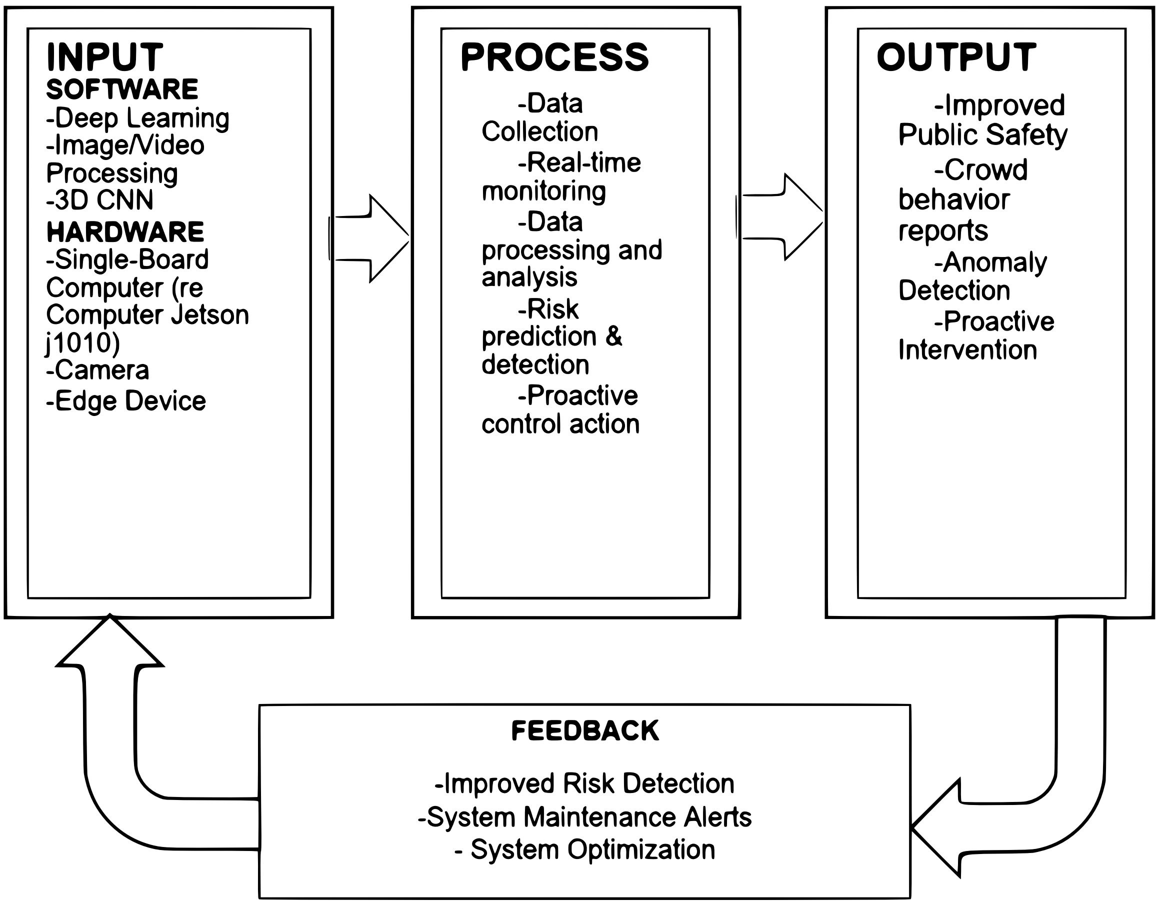


Figure 1

Conceptual Framework of Real-time Crowd Behavior Control and Monitoring System using 3D-CNN

The conceptual framework of a Real-time crowd behavior control and monitoring system using cameras. The input sections have two sub-sections: the software and hardware components essential for data collection and processing. On the hardware side, the system utilizes an NVIDIA Jetson Nano J1010 single-board computer (SBC), which serves as the primary edge device for handling tasks such as video capture, real-time processing, and data transmission to remote servers. A camera is interfaced with the Jetson Nano to collect live video feeds, which are analyzed using a 3D-CNN for deep learning-based crowd behavior recognition. Operating as an edge AI device, the Jetson Nano significantly reduces latency and bandwidth usage by processing data locally.

On the software side, the system incorporates machine learning techniques and computer vision algorithms implemented using OpenCV, enabling visual data analysis such as crowd density and movement. Image and video processing methods are also employed to extract meaningful patterns and behavioral indicators from the captured footage.

In the process, data collection was carried out on the crowd movement and individual behavior. Real-time monitoring that allowed the authorities to monitor crowds in real-time. Data processing and analysis that transmitted the collected data to the central system for real-time analysis using machine learning models. Those models analyzed the potential threats in events or crowds. Risk prediction & detection that the machine learning assessed the incidents, such as stampede, erratic behavior, health emergencies, or health issues of a person. Based on the data insights, proactive control action was taken, such as rerouting crowd flows, increasing the security presence, or increasing security in the surroundings to prevent a possible event threat.

Lastly, the feedback mechanism integrated lessons from prior crowd behavior analysis, enabling continuous system improvements and more accurate future predictions.

Significance of the Study

An IoT-based control and monitoring crowd behavior system using cameras is a new approach to managing real-time crowds. It benefits all stakeholders and helps improve crowd control efficiency, hence safety measures in populous regions.

This research will be beneficial to the following:

Event Organizer: This system will enable the organizers to receive data and analytics regarding crowd density, how they move, and areas likely to be congested. Issues are detected and dealt with immediately, enabling the event organizers to prevent overcrowding, bottlenecks, stampedes, panic, riots, and ensure an efficient, smooth, and safe event.

Local Government:

A.) **City Planners and Urban Authorities:** Implementing this system would benefit city planners and authorities in urban spaces. The system can be added to the infrastructure of smart cities to monitor pedestrian flow and give early warning for overcrowding in crowded high-density areas, where the foot traffic is comparatively much more critical in shopping centers, transportation terminals, tourist destinations, and city parks.

B.) **Law Enforcement Agencies and Security Personnel:** This Crowd and its behavior can be monitored in real time; law enforcement agencies and security personnel must acquire such a tool in high-risk and sensitive situations. It allows the authorities to respond rapidly in case of abnormal crowd movements, like sudden surges, aggressive actions, or panic. By detecting such behavior, they can analyze the data gathered from the cameras.

C.) **Healthcare and Emergency Response Personnel:** It can detect people in distress, including seizures, fainting, and falls, and automatically alert the nearby medical personnel or first responders. It is quite specifically valuable for huge public events wherein individuals with chronic conditions may be more susceptible, like people with asthma or epilepsy. For example, during an epilepsy or asthma attack in a crowded area, it would help the medical teams locate the affected persons and provide them with the necessary attention.

Researchers: This study is essential for researchers as it discusses integrating IoT technologies. A single-board computer (SBC) was used for a real-time crowd behavior control and monitoring system in the design and implementation process. This also sharpened software and hardware skills, giving hands-on experience with the complexities of building intelligent systems combining sensors, real-time data processing, and wireless communication. It will also hone their skills throughout the design project.

Future Researchers: The research can serve as a reference or guide for individuals, academics, and researchers needing information about the Real-time crowd behavior control and monitoring system. This has turned out to be a capacity of real-time data gathering involving crowd behavior-patterns, dimension, and unusual activities through low-cost, readily available technology like Single-Board computer (SBC), by which it lays down the ground for more study regarding crowd safety features, urban planning, and so on, while managing events. Besides, it will also be a good example for further development of more sophisticated, scalable systems for public safety and disaster management that can be aligned with strategies for making cities resilient for mass gatherings, protests, or emergencies.

Assumptions

The researchers implementing the real-time crowd behavior control and monitoring system using cameras have made the following key assumptions to guide its development:

1. The researchers assumed that the necessary infrastructure and resources for the real-time crowd behavior control and monitoring system using cameras would be available, including stable internet connectivity, sufficient power supply (e.g., 5 volts), and a consistently functioning camera.
2. The prototype will focus on a specific, manageable environment, such as a small event venue or a public square, to simulate real-world crowd dynamics on a smaller scale.
3. The prototype will implement a simplified version of the machine learning algorithms for crowd behavior analysis, capable of detecting basic crowd anomalies (e.g., overcrowding, sudden movement surges); and

4. The prototype unit is designed to work reliably throughout the week unless it encounters technical issues or needs maintenance, which might temporarily make it unavailable.

Scope and Limitations

The following sections explain the scope and limitations considered in this study.

Scope:

1. The system utilized interconnected devices and advanced machine learning to monitor real-time crowd dynamics, providing security personnel with actionable insights.

2. The study detailed the design and architecture of the IoT-based system, including the selection and integration of sensors, particularly cameras and other IoT devices. The architecture was designed to ensure scalability, reliability, and performance. This comprehensive design approach aimed to create a robust system capable of effectively handling various crowd management scenarios.

3. Advanced video processing and machine learning algorithms were used to detect anomalies, potential threats, and issue alerts if necessary. These technologies enabled the system to analyze crowd behavior accurately and in real-time. By leveraging these advanced analytical tools, the system provided timely and precise information to enhance crowd safety and management.

4. The system provided real-time data through sensors and cameras to the NVIDIA Jetson Nano J1010 SBC, the central edge device for data processing and analysis. The system continuously monitored crowd behavior by leveraging advanced camera modules and detected real-time anomalies. It was trained using machine learning to enhance its capabilities to handle complex movements accurately, ensuring it understands and responds appropriately to various behaviors. This decision support functionality empowered security personnel with the information needed to make informed and effective decisions, improving overall safety and efficiency. Additionally, there will be a level flagging system:

   - Flag 1: Violent and unruly behavior.
   - Flag 2: Medical emergency
   - Flag 3: Severe panic.

Limitation

1. The device's function is limited in the event of a medical situation within the crowd. While the system is designed to monitor crowd behavior and detect unruly behavior, it cannot provide medical assistance.
2. The system might mistakenly flag benign actions as aggressive behavior. For instance, a person raising their hand as part of a dance or gesture could be incorrectly identified as exhibiting aggressive behavior, leading to false flags and unnecessary interventions. If there is a particular trend, like a mob dance,

it will be challenging to discern whether it is an emergency or a trend. The activity may need to be turned off temporarily to prevent false information.

Definition of Terms

The following terms are used operationally in the study.

3D-CNN – is an algorithm for processing three-dimensional data like images or videos. It is used for object detection, image processing, and the detection of crowd behaviors and patterns.

Algorithm - A pattern or step-by-step instruction that the proposed device or machine follows to detect and monitor the crowd and their behavior.

Behavior - is how individuals interact, move, and react within a crowd. It includes actions, emotions, and patterns cameras can observe and analyze in real time.

Camera – It can capture videos by converting light into digital or electrical signals. They are used to monitor crowd behavior.

Computer Vision - The proposed device can comprehend and interpret visual information from videos or video clips of people in public spaces.

Crowd – is a group gathered in a public space, exhibiting collective behavior influenced by density, movement, and individual emotions.

Crowd Behavior – refers to individuals' collective actions, interactions, and patterns within a specific space. It encompasses various behaviors, including movement patterns, density, emotional states, group dynamics, and anomalies.

Deep Learning – It is a subset of artificial intelligence that employs artificial neural networks with multiple layers to process and analyze complex data. It can efficiently process video data, recognize abnormal behaviors, predict potential risks, and optimize resource allocation, enhancing the overall effectiveness of crowd management systems.

IoT (Internet of Things) - It can be interconnected, like cameras and sensors, to form a network that collects and shares data about the crowd. This data can then be analyzed to understand crowd behavior and identify potential risks.

Machine Learning – It can process data collected from IoT devices. These algorithms can learn to recognize patterns in crowd behavior, such as unusual movements or density fluctuations, that may indicate potential threats.

Monitoring - This is the process where the system continuously monitors the crowd using cameras and other IoT devices, collecting data in real time. This data is then analyzed using machine learning to identify abnormal behaviors or potential risks.

Real-time - In this case, the system must process and analyze data in real time to enable timely interventions. This means that the system should be able to detect and respond to potential threats as they occur rather than after the fact.

Chapter II

RESEARCH-RELATED LITERATURE

This chapter discusses the research-related literature of the study.

News and Journal

People tend to gather in a place for an event or to celebrate something, but sometimes, even with security personnel in the venue, accidents and issues arise. This is due to the large crowds gathered in place, making it impossible for all personnel to monitor everyone [4].

Incident such as allegedly drunk youths that cause riot at Negros fiesta reported by GMA NEWS, where a fiesta is being held in their covered court where it degenerated into a brawl and attacking each other without regards to the surrounding people

Even public places are not that different, it can still be a place where dispute could happen just like in the report of GMA NEWS about the scuffle at public plaza of Leon in Iloilo, where female youths had a scuffle with each other possibly due to their social media activities that triggered this behavior [5].

Recently, science and industries have become invested in deep learning techniques, especially in Convolutional Neural Network techniques applied to, for example, voice recognition and image classification. This comes where Albattah et al. [6] proposed a system that uses CNN as a model to classify crowd density in managing the crowd during pilgrimage. The study emphasizes utilizing deep learning techniques to analyze crowd behavior and making informed decisions during critical moments of the pilgrimage.

The study, Design of the Network Security Architecture for Smart Campus in the Philippines, highlights the critical role of a secure network infrastructure in supporting real-time crowd monitoring systems. Ensuring robust network security is essential for the continuous and reliable operation of surveillance technologies that monitor crowd behavior and detect anomalies. The architecture can protect sensitive data and maintain the integrity of real-time monitoring processes by implementing advanced security measures, such as encryption and intrusion detection systems. This secure framework is fundamental to the effectiveness of smart campuses in managing crowd behavior and ensuring public safety [7].

Public Safety Strategies are also increasing with the advances in our technology. In a Blog post, Mark Dorn [8] argues that a more robust approach to crowd monitoring can be achieved by deploying real-time data visualization and using AI or Machine Learning to process this data. This enables security and law enforcement to react faster, predict potential threats, and manage the crowd effectively.

Survey and Review

The rapid and automated detection of abnormal behaviors in crowded settings is highly effective for enhancing public security. Traditionally, recognizing these abnormalities on the Web of Things (WoT) platform involves monitoring activities and analyzing crowd characteristics such as density, trajectory, and motion patterns from visual data. Integrating real-time security monitoring with the WoT platform and machine learning algorithms can significantly improve the detection of abnormal crowd behaviors. This paper explores various automatic and real-time surveillance techniques for detecting abnormal events, aimed at understanding dynamic crowd behavior in security contexts. Monitoring these officially designated locations manually is almost impossible because they are chaotic and difficult to deal with due to the unpredictability of likely threats in very complex crowds. Detecting abnormalities with algorithms aims to increase efficiency, improve resistance to pixel occlusions, increase generalizability over time, and increase computational ease and execution speed. Based on the state-of-the-art techniques for analyzing abnormal behavior in crowded scenes, we classify these methods into different types: tracking, using handcrafted features, employing deep learning models, and mixed approaches [9].

The review Deep Learning in Smart Video Surveillance for Crowd Management examines how deep learning techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) improve video surveillance for managing crowds. These models can accurately detect and analyze crowd behavior, making surveillance more efficient and responsive. The study also highlights the importance of integrating these technologies into existing surveillance systems to enhance public safety and swiftly respond to potential threats. Overall, the review underscores the significant potential of deep Learning in revolutionizing crowd management practices [10].

Real-time crowd analysis has become a key research area in computer vision and scene analysis. Over the past decade, various real-time crowd management methods have attracted significant attention due to their broad applications, such as people counting, managing public events, disaster response, and safety monitoring. Despite developing advanced algorithms to tackle these tasks, effectively managing crowds in real-time, especially in unpredictable or uncontrolled environments, remains a challenging issue that has not been fully resolved [11].

Real-time behavior monitoring systems are essential for maintaining crowd safety. These systems utilize AI and machine learning to recognize potential hazards and avert incidents. These technologies can identify anomalies in crowd behavior, prompting timely alerts to authorities. For example, in the tragic event in Antananarivo, Madagascar, where a human crush resulted in 16 deaths and 101 injuries at the Mahamasina Municipal Stadium, efficient real-time monitoring could have detected early warning signs and helped prevent the disaster" [2].

Crowd behavior detection is widely applied for monitoring and maintaining surveillance at public venues like sports events, markets, and religious or political gatherings. It also enables the automatic identification of riots and abnormal crowd behaviors. Effective crowd management and monitoring are critical for ensuring public safety and remain a key focus of research. Developing a comprehensive crowd monitoring system (CMS) presents significant challenges, including handling variations in crowd density, irregular object distribution, occlusions, and pose estimation. Large gatherings, such as those at hospitals, parks, stadiums, airports, and cultural or religious sites, are often monitored using Closed-Circuit Television (CCTV) cameras. However, addressing these challenges requires advanced systems capable of overcoming the inherent limitations of traditional CCTV technologies [12].

CCTV footage has emerged as a valuable tool for studying real-life emergencies, particularly in the Philippines. While it has been effectively used to analyze bystander responses in public assaults and commercial robberies, its application to crowd emergencies and evacuation scenarios remains relatively limited.

Understanding evacuee behavior in such contexts is crucial for enhancing public safety and improving emergency response strategies.

[13] A study used CCTV footage to analyze passenger behavior during a subway train emergency. Their findings offer valuable insights into crowd behavior in emergencies. While the study was conducted in a different context, it provides a foundation for understanding potential patterns and behaviors that might be observed in local emergencies.

[13], Passengers exhibited various behaviors, including freezing, observing, retrieving belongings, and engaging in prosocial actions like helping others. Antisocial behavior, such as pushing and prioritizing oneself, was less common. Running behavior was observed in clusters, and factors like proximity and perceived safety influenced exit choices. These findings challenge the traditional notion of "panic" in crowd emergencies and highlight the complexity of human behavior in such contexts.

Below is the research-related literature that pertains to using Machine Learning in the study of the crowd

Machine Learning

The study Crowd Estimation of the Black Nazarene Procession in Manila, Philippines, explores methods for accurately estimating crowd sizes during large-scale events. The research provides insights into crowd dynamics and density variations by analyzing video footage and employing advanced algorithms. These findings are crucial for developing real-time monitoring systems that can effectively manage and ensure the safety of large gatherings. The study highlights the importance of accurate crowd estimation in public safety planning and the potential application of these techniques in intelligent surveillance systems [14].

In many areas today, overcrowding leads to congested conditions. The analysis of crowd activity is an emerging area of research. It is widely recognized that mob behavior can serve as a predictor of potential events during gatherings. The ability to anticipate situations such as riots, mass lynchings, traffic jams, accidents, and stampedes could significantly enhance effective crowd management. This paper introduces a novel technique based on a multicolumn convolutional neural network (MCNN) for predicting mob behavior [15].

Pedestrian and abnormal behavior detection involve using computer algorithms to analyze images and videos to identify pedestrians and assess their expected behavior. Pedestrian detection is the foundation for various applications, including pedestrian tracking, behavior analysis, gait analysis, and identity recognition. An effective pedestrian detection algorithm is crucial for supporting these subsequent processes. The primary objective of this project is to explore various data mining techniques to enhance the accuracy of detecting abnormal behaviors in video crowds. Addressing the limitations of the user behavior anomaly detection model proposed by Lane et al., a new intrusion detection system (IDS) anomaly detection model is introduced. This model enhances the representation of user behavior patterns and profiles while implementing a novel similarity assignment method. Experiments conducted on Unix user shell command data demonstrate that the proposed detection model offers improved performance [16]

Real-time systems for monitoring behavior use technologies such as AI and computer vision to observe and analyze activities as they occur. These systems are deployed in various environments like schools, workplaces, and public spaces to enhance safety and efficiency. By providing immediate data, they enable quick responses to issues. For example, in educational settings, they assist teachers in identifying disengaged students or behavioral problems for timely interventions. These systems detect unusual crowd movements or potential threats in public areas, facilitating rapid action to prevent incidents [1].

This research aimed to improve crowd monitoring using machine learning and deep learning techniques for real-time people counting, density estimation, and motion analysis. It also provided autonomous surveillance solutions to detect potential dangers in crowded environments [17].

Closed-circuit television (CCTV) technology was first introduced in 1942, and since then, it has continuously evolved. Initially, it served as a basic visual and audio recording tool for security personnel. However, with technological advancements, particularly in artificial intelligence and deep Learning, CCTV systems have transformed into intelligent surveillance systems. These systems can now monitor, record, and analyze situations in real time. For example, modern systems can detect suspicious activities such as fights, identify abandoned objects like airport suitcases, recognize weapons, and even track thieves' movements or detect other abnormal behaviors [18].

Below are studies and literature on research using Deep Learning in observing and monitoring crowds.

Deep Learning

Image processing forms the backbone of modern crowd behavior analysis systems. It involves converting images into digital form to perform operations to enhance images or extract valuable information. Image processing treats images as two-dimensional signals and applies signal processing methods to them. The process generally includes importing images, manipulating them through techniques like data compression and pattern recognition, and generating outputs through enhanced images or analytical reports. Although expecting image processing techniques to replicate human observation capabilities entirely is unrealistic, studying how humans process images can help select practical algorithms for tasks like crowd behavior analysis. The technology is rapidly expanding and plays a crucial role in business applications as well as research in engineering and computer science [19].

While significant progress has been made in crowd behavior detection, several areas require further research. These include improving accuracy in extremely dense crowds, developing more robust algorithms for handling occlusions, enhancing real-time processing capabilities for immediate response, integrating multi-modal data (e.g., video, audio, social media) for comprehensive analysis, and addressing ethical concerns through privacy-preserving techniques. The widespread use of crowd monitoring technologies raises important ethical and privacy concerns, such as ensuring security.

In the Philippines, the Light Rail Transit (LRT) Line 1 faces overcrowding and delays due to a shortage of trains, particularly during peak hours. A manual Passenger Limit Per Platform (PLPP) system is currently used, but it is labor-intensive and error-prone to manage platform congestion. This study proposes an automated system combining embedded technology and software applications to intelligently manage crowds at LRT1 stations. A simulation tool was developed to generate station operational data, and tests confirmed that the system functions accurately and meets design specifications. Respondents rated the system as highly functional and reliable [20].

[21] demonstrates a study on creating Crowd Surge, a user-friendly web and mobile app designed to help monitor crowd density through intelligent video surveillance. The system provides real-time updates, generates easy-to-understand reports, and alerts staff when taking action and managing or dispersing a crowd. With the web app, admins can easily monitor live video feeds, see how many people are in a room, and get a clear view of how crowded different areas are at any moment.

Crowd analysis has gained significant attention in the field of computer vision. The automated examination of crowd activities through surveillance footage is crucial for public safety, as it aids in identifying potential threats and tracking their movements. Crowds often pose various challenges; for instance, in our country, terrorists have been known to detonate bombs in crowded areas, resulting in numerous injuries. Thieves also tend to operate in such environments to exploit the chaos. Therefore, crowd analysis is essential. This paper introduces a deep learning architecture designed to monitor crowd behavior, helping to prevent violence and other harmful incidents linked to large gatherings. We propose a system that detects abnormal crowd behavior using advanced deep learning techniques.[22]

Crowd behavior analysis is a developing research area, and due to its newness, there is currently no established taxonomy to categorize its various sub-tasks. This paper presents a proposed framework for organizing existing research along a pipeline, where later stages benefit from the results of earlier ones. It thoroughly reviews models utilizing Deep Learning for crowd anomaly detection, one of the key stages outlined. Additionally, it highlights the few studies that explore the emotional dimensions of crowd behavior. The paper emphasizes the importance of incorporating emotional aspects into crowd behavior research and the need for challenging, real-world datasets to enhance existing solutions. It also suggests ways to integrate these models into existing video analytics systems.[23]

[24] The system aims to improve public safety by classifying social distancing compliance in crowded areas. CNNs extract spatial details from visual data, allowing the system to detect whether individuals follow social distancing rules. RNNs, on the other hand, enhance the system's ability to track movement patterns over time, identifying instances where social distancing is violated.

[25] This research develops a low-cost CNN-based system for real-time violence detection, achieving 92.05% accuracy on a Raspberry Pi, with a warning system to predict and prevent violent acts in crowded and non-crowded environments.

The study uses advanced tech to explore new ways to monitor large crowds in real time. It focuses on deep learning algorithms to improve our monitoring and management of crowds. Techniques like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks help identify unusual behavior, making places safer. This method allows for constant watching and quick action if something seems off. Combining machine learning with real-time data creates a strong crowd control and awareness system, aiming to use artificial intelligence to boost security [26].

Real-time crowd behavior control and monitoring systems have become increasingly important in public safety due to the growing demand for intelligent security solutions. This research proposes a novel approach that utilizes spatio-temporal cuboids and a deep learning network to detect and classify abnormal crowd behavior in real-time. By extracting local feature tracks and foreground blocks from video streams, the system can efficiently remove irrelevant background information and focus on analyzing crowd dynamics. The STFD descriptor captures crowds' individual and collective behavior, enabling accurate detection of potential threats. The proposed model demonstrates superior performance in terms of accuracy and efficiency, making it a valuable tool for enhancing public safety and security.[27]

Several studies have explored methods for detecting abnormal crowd behavior.[28] Propose a framework that combines movement and emotion descriptors to achieve effective feature extraction and precise identification of abnormal behaviors in complex crowds. Their approach utilizes a convolutional neural network to extract spatiotemporal features from video data. These features are combined with emotion descriptors, potentially derived from facial expressions or crowd sounds, to understand crowd behavior better. This multi-modal approach aims to improve anomaly detection accuracy compared to methods that rely solely on movement characteristics.

[29] Proposed an Air-CAD, an edge-assisted multi-drone network for real-time crowd anomaly detection (CAD). This system addresses the limitations of existing drone-based CAD solutions, particularly low accuracy and high latency caused by dynamic shooting distances and angles. Air-CAD utilizes a two-stage approach: person detection and multi-feature analysis. The system dynamically adjusts the

person detection model based on the drone's shooting distance and assigns appropriate feature analysis tasks to drones with varying angles. Additionally, edge devices connected to drones offload assigned feature analysis tasks, achieving faster processing. By leveraging edge computing, Air-CAD achieves high accuracy (95.33% AUROC) and real-time inference latency within 0.47 seconds.

[30] They constructed and showed a model that effectively analyzes video footage to identify violent actions in real-time, thus providing significant advancements and improvements in surveillance security. Their method uses spatiotemporal features with a 3D Convolutional Neural Network (3D-CNN) to detect video violence. Because of its ability to record temporal motion patterns between consecutive frames and spatial information from individual frames, the model is more successful in detecting violent activity in real-time surveillance systems. The system's ability to identify violence in dynamic surroundings is greatly enhanced by using 3D-CNN, which enables the processing of video clips as a sequence rather than isolated images. Tested on open datasets, the study's findings show improved robustness and accuracy over conventional approaches, making it a valuable tool for automated crowd monitoring and public safety applications.

[31] proposed designing and implementing a real-time crowd monitoring system that utilizes the existing public Wi-Fi infrastructure. The system is built on a three-tier architecture: the sensing layer for gathering data, the communication layer for transmitting it, and the computing layer for processing, visualizing, and analyzing the information. Wi-Fi access points act as sensors, continuously tracking crowd activity and sending the data to a central server. To ensure privacy, encryption algorithms secure the data during transmission.

[32] The article "State-of-the-art violence detection techniques in video surveillance security systems: a systematic review" from PeerJ Computer Science provides an in-depth analysis of various methodologies in detecting violent incidents within video surveillance systems. The review categorizes existing techniques into three main approaches: conventional methods, machine learning-based methods, and end-to-end deep learning-based methods. Each approach has strengths and limitations concerning accuracy, computational complexity, and adaptability to different environments.

[32] The review also emphasizes the importance of accuracy in violence detection systems, particularly in real-time applications where false positives or negatives can have significant consequences. While offering higher accuracy rates, machine learning and deep learning methods often require large annotated datasets for training and may be computationally intensive. In contrast, conventional methods might be less accurate but more efficient and easier to implement in resource-constrained environments.

Accuracy remains one of the most commonly used metrics for evaluating the performance of machine learning (ML) and artificial intelligence (AI) models. It represents the ratio of correct predictions to the total number of predictions, making it a straightforward but sometimes overly simplistic indicator of model quality. In industry settings, acceptable accuracy thresholds vary depending on the application domain and the nature of the data. Deepchecks [33], standard industry benchmarks for accuracy typically range between 70% and 90%, depending on task complexity and data quality. An 80% or higher accuracy score is often acceptable for general-purpose classification tasks with balanced datasets. However, accuracy expectations in high-stakes applications such as healthcare, finance, or autonomous systems tend to exceed 90% due to the potential consequences of incorrect predictions [33].

Synthesis and Research Gaps

An in-depth examination of related research and literature helped understand and develop efficient crowd monitoring systems. Focusing on the successful application of modern technologies like machine learning and real-time surveillance, these studies were crucial in identifying the problems and solutions required to improve safety in crowded areas.

Due to the difficulties caused by huge events, crowd surveillance has become a key concern, even though the presence of security officers may not be enough to avert incidents. The incident, according to [4], involves allegedly drunk youths who started chaos during the Negros festivities, putting bystanders in risk and starting a brawl in the covered court. Similarly, another report detailed [5] a fight among female youths in Leon, Iloilo, triggered by disputes possibly rooted in their social media activities. These incidents highlight the unpredictable behavior among people and how ineffective conventional security techniques are at controlling conflicts and guaranteeing public safety.

Technological developments in recent years present promising answers to these problems. [6] states that deep learning methods, particularly Convolutional Neural Networks (CNN), have demonstrated effectiveness in crowd analysis. To support well-informed decision-making, CNN has been used to classify crowd density during pilgrimages. In the same way, the research design of the network security architecture for smart campuses in the Philippines emphasizes how important safe network infrastructures are to the operation of real-time crowd monitoring solutions. In smart campus settings, these infrastructures improve crowd management by ensuring the security and dependability of monitoring technology through sophisticated methods like intrusion detection and encryption, as studied by [7].

As stated by [8], developments in real-time data visualization, AI-driven analytics, and knowledge also improve public safety measures. Combining these techniques with machine learning makes crowd management more effective and proactive by enabling quicker responses to possible risks and improved predictive capabilities.

Real-time systems and machine learning have greatly improved crowd behavior analysis, providing helpful solutions to improve public safety. A study by [9] states that automated methods using handmade features, deep learning models, and tracking algorithms have enhanced irregularity detection in crowds, especially by improving computing efficiency and generalizability over time. Similarly, as mentioned in the article Deep Learning in Smart Video Surveillance for Crowd Management by [10], methods such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) may precisely assess crowd behavior, increasing the effectiveness and responsiveness of surveillance systems. Despite these developments, [11] discovered that real-time crowd control in unpredictable environments is still a challenging problem.

Real-time monitoring systems play a crucial role in disaster prevention by spotting irregularities and promptly alerting authorities. The terrible accident in Madagascar, for example, which resulted in many deaths, emphasizes the urgent need for effective monitoring systems that can identify early warning indicators and prevent such tragedies, as mentioned by [2]. According to [12] and [13], CCTV systems help track and evaluate emergency crowd behavior.

About machine learning, [14] emphasized that analyzing video footage and advanced algorithms can detect and estimate crowds during large gatherings to ensure public safety. On the other hand, [15] highlighted that a multicolumn convolutional neural network (MCNN) is an effective crowd management tool for predicting mob behavior, such as accidents and stampedes. Similarly, [16] studied the intrusion detection system (IDS) in which abnormal behavior and pedestrian tracking are detected. To monitor activities and behavioral problems, [1] used real-time systems such as AI and computer vision, as they provide an immediate response to unusual crowd movement and prevent public turmoil. In the study of [18], CCTV was used to monitor real-life situations, suspicious behavior, and activities.

Numerous studies have been conducted related to deep Learning. [19] Image processing has various functions, such as providing essential information and public crowd behavior when converted and enhanced. Meanwhile, to detect crowd congestion, [20] used passenger limit per platform (PLPP), which is rated highly functional and reliable. In the study of [21], he used a web and mobile app called Crowd Surge to monitor the crowd's density as it performs intelligent video surveillance. Similarly, [22] and [23] both mentioned crowd analysis in their study as they used it to monitor chaos, crowd behavior, and prevent riots in public. [24], [25], [28] added that CNNs and RNNs are essential in managing crowd behavior, showing whether people follow and violate public rules. About this, [26] also highlighted CNNs and long short-term memory (LSTM) in identifying unusual crowd behavior. In the [27] study, STFD was utilized to ensure public safety and monitor real-time crowd behavior, as both individual and crowd behavior can be detected with STFD. Moreover, [29] proposed Air-CAD with characteristics like person detection and multi-feature analysis that can detect crowd anomalies. [30] discussed that a 3D Convolutional Neural Network (3DCNN) can effectively detect video violence, an essential tool for crowd behavior management.

Despite modern society's advancements, accurate identification in extremely crowded settings is hampered by dense crowd occlusions and overlapping movements. Since these systems collect sensitive data, ethical issues like data security and privacy must also be considered. Furthermore, existing models' ability to adapt to various cultural and behavioral contexts is still restricted, underscoring the necessity for additional localization and improvement.

Scalability and cost-effectiveness of such systems are essential for their broad adoption and for tackling these issues. Researchers are investigating cutting-edge strategies to increase system efficiency and save operating costs, including edge computing and cloud integration. Additionally, these technologies are becoming more usable for emergency responders, law enforcement, and event planners thanks to developments in visualization tools like intuitive dashboards and real-time notifications.

Crowd surveillance has become a significant concern, especially during large events where even the presence of security officers might not be enough to prevent incidents. As highlighted by Omarov et al. [32], chaotic incidents, such as disturbances during festivities or fights triggered by social media disputes, underscore the unpredictable nature of crowd behavior and the limitations of conventional security methods. These real-world events emphasize how traditional techniques fail to ensure public safety and manage conflicts. In response to these concerns, technological advancements offer promising solutions, including intense Learning and machine learning.

Research by Omarov et al. [32] on violence detection within video surveillance systems highlights the effectiveness of modern approaches like Convolutional Neural Networks (CNNs) and other deep learning models. CNNs, in particular, have demonstrated strong accuracy rates in violence detection, showcasing their ability to address complex behaviors in real-time systems. The literature further emphasizes that higher accuracy rates, typically between 70% and 90%, are achievable with machine learning and deep Learning. However, these models often require large, annotated datasets and substantial computational power [33]. This accuracy threshold aligns with industry standards, where 80% or higher is acceptable for many general classification tasks. However, higher expectations arise in more critical applications like healthcare or public safety, where accuracy requirements often exceed 90%.

In addition to enhancing anomaly identification and real-time monitoring, these systems offer insightful information for long-term planning and decision-making. Developing and implementing intelligent crowd control technologies will be essential to maintaining public safety and operational effectiveness as urbanization and large-scale events continue to increase. Integrating these technologies into contemporary crowd management tactics is both feasible and essential, as demonstrated by foundational research like the CNN-based crowd management system.

Chapter III

RESEARCH METHODOLOGY

This chapter details the research methodology used in this study for collecting and assessing relevant data, methods, and tools. This chapter includes descriptions of the research design, project development, operational, testing procedures, evaluation procedures, instruments and techniques utilized, and the limitations encountered throughout the study.

Research Design

A machine learning workflow methodology systematically guides practitioners through every project phase, from defining the problem to deploying the final solution. This process involves developing, training, evaluating, and implementing machine learning models, ensuring that each step builds towards an effective and practical outcome [32]. This methodology emphasized iterative refinement and evaluation to achieve optimal performance and scalability for real-world applications. In this study, the machine learning workflow was chosen to support the design, development, and implementation of a real-time crowd behavior control and monitoring system. This approach provided a structured and scalable framework for integrating 3D-Convolutional Neural Networks (3D-CNN) to detect and classify crowd behavior, ensuring accuracy and practicality in dynamic environments. By adhering to this workflow, the study aimed to create a robust system that addresses the research objectives and meets technical and practical considerations.

Project Development

The researchers aimed to develop a real-time monitoring system that detects and analyzes crowd behaviors using a 3D-CNN model. The study's primary objective is to detect and manage crowd behaviors by highlighting the risk of unruly behaviors or health-related incidents. The system integrated several components, including a camera module for real-time video capture and an NVIDIA Jetson Nano J1010 single-board computer as the edge device for local processing and analysis. Video data was processed directly on the Jetson Nano using trained deep learning models, enabling fast, on-site behavioral assessment without reliance on external servers. The system operated over a local network to provide real-time updates and support proactive decision-making in crowd management scenarios.

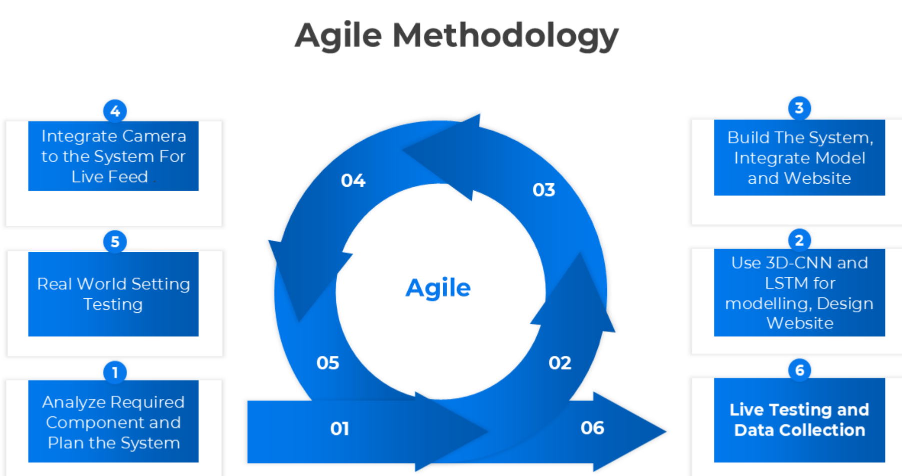


Figure 2

Agile Development Methodology

The researchers utilized Agile Development Methodology to ensure flexibility, iterative progress, and continuous feedback. This plan focuses on each step's specific objectives.

In the first phase, the researchers searched and selected a camera based on availability, cost, and technical specifications that at least captures 30 frames per second to allow seamless integration with the system. The researcher chose Jetson Nano reComputer J1010 as an edge device. This phase aims to choose components and test them to see if they are working fine with each other.

The plan's second phase is to use 3D-CNN and Long Short-term Memory in modelling using the TensorFlow framework. The model would be trained in detecting crowd behavior using videos containing a brawl (fight), a medical issue (fainting), and a few controlled video footages made by the researchers to increase the collected data sample. Most of the data used was collected from open-source data bank websites such as Kaggle and YouTube, then preprocessed by the researchers into short clips.

The third phase of agile development involves integrating the model and the system with IoT components. Implementing the model to enable a real-time analysis of video feeds involves developing and integrating the User Interface (UI) with the system. The User Interface has a color-coded alert system: orange for panic, red for violence, then blue for panic, and displays the analyzed video in real-time for live updates. This phase ended after fully integrating the model and the system, enabling a live video feed analysis.

The fourth phase is where testing and optimization happen. After integrating the 3D-CNN model, IoT components, and UI, the researchers tested the system in various scenarios with sparse to high density (5, 10, 50, 100, 500, 1000) crowds. Optimize the system to minimize the latency of video processing and transmission, and increase the model's accuracy.

The fifth phase focused on reviewing system performance, functionality, and usability. Researchers gathered feedback, analyzed results from testing, and evaluated if project goals were met. This review guided final refinements before deployment.

The last phase is deploying the project prototype in a controlled environment, such as the school cafeteria, at least 2 times during the school flag ceremony, and if possible, in the event hall when an event is held. While in deployment, the researchers collected valuable insights and feedback from users (event organizers, security, etc.) to identify areas for refinement.

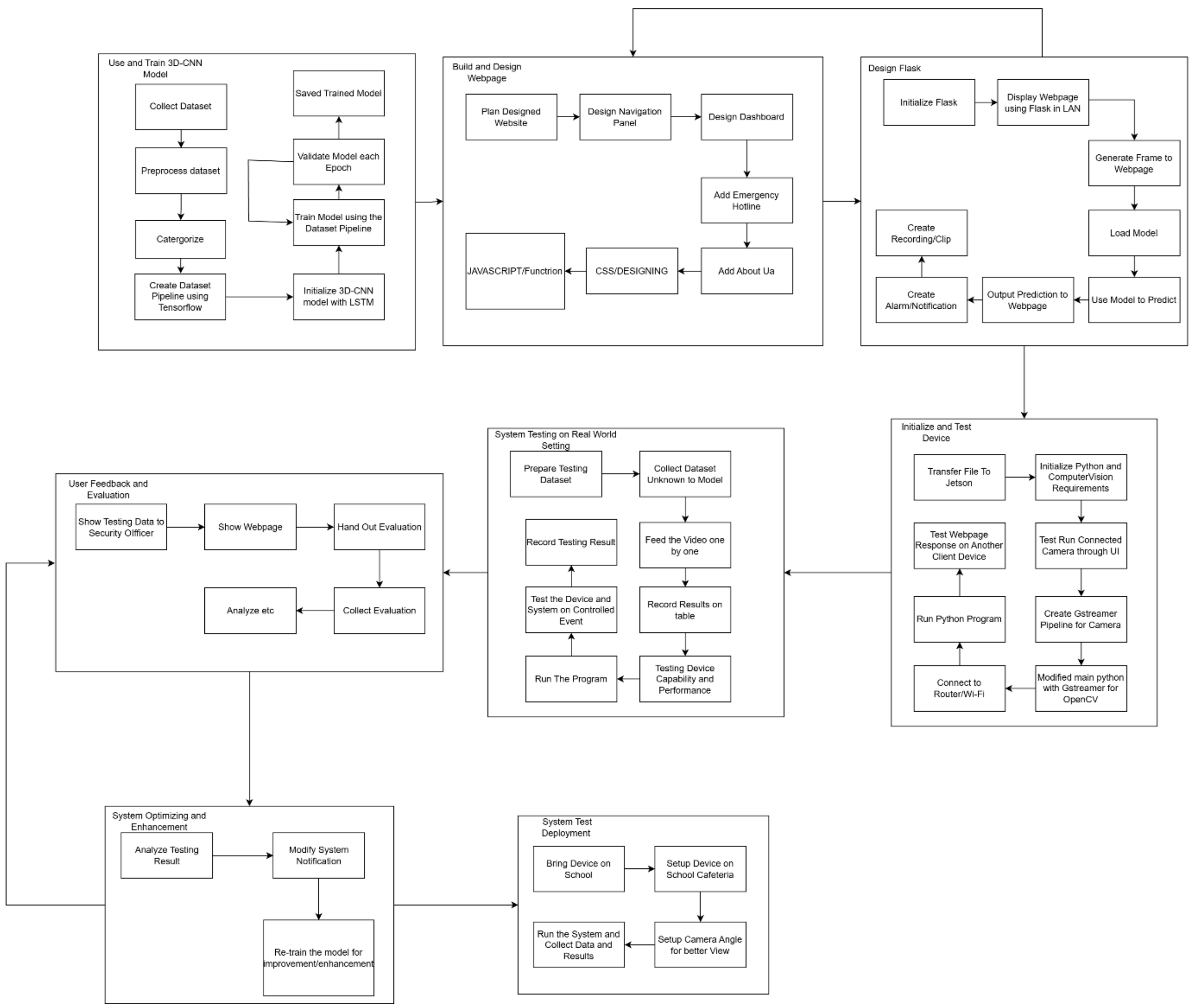


Figure 3

Methodology Workflow

Figure 3 outlines a structured and multi-phase approach that begins with training and implementing an existing machine learning model and concludes with system deployment and evaluation. The process starts with the Use and Train 3D-

CNN Model section, where a dataset is collected, preprocessed, and categorized. A TensorFlow-based dataset pipeline is created to train a 3D-CNN model enhanced with Long Short-Term Memory (LSTM) layers. This model is validated after each epoch and saved for future use. The next phase, Build and Design Webpage, focuses on designing the user interface, which includes a navigation panel, dashboard, emergency hotline, and about section, all integrated with CSS and JavaScript functionalities.

Following this, the Design Flask section initializes a Flask server for local area network (LAN) deployment, enabling real-time video frame generation, model loading, and prediction display on the webpage. Alarm and notification systems are also incorporated for real-time alerts. The Initialize and Test Device section details the setup process for the physical hardware, specifically transferring the application to a Jetson device, setting up OpenCV and GStreamer for camera input, and ensuring Wi-Fi connectivity. The model is tested via a user interface to confirm proper integration.

Once the system is functionally ready, System Testing in a Real-World Setting uses datasets unknown to the model. Each video is tested individually, and results are systematically recorded to assess performance. In the System Test Deployment phase, the device is deployed in a real environment, such as a school cafeteria, where it is configured for optimal camera angles and data is collected for evaluation. The collected data is then used in the System Optimizing and Enhancement stage to analyze results, improve notifications, and retrain the model for better accuracy. Finally, the User Feedback and Evaluation phase involves showing testing results to security officers, collecting evaluation forms, and analyzing feedback to refine the system. This cyclical and iterative methodology ensures the system is robust and practical for real-time crowd behavior monitoring and control.

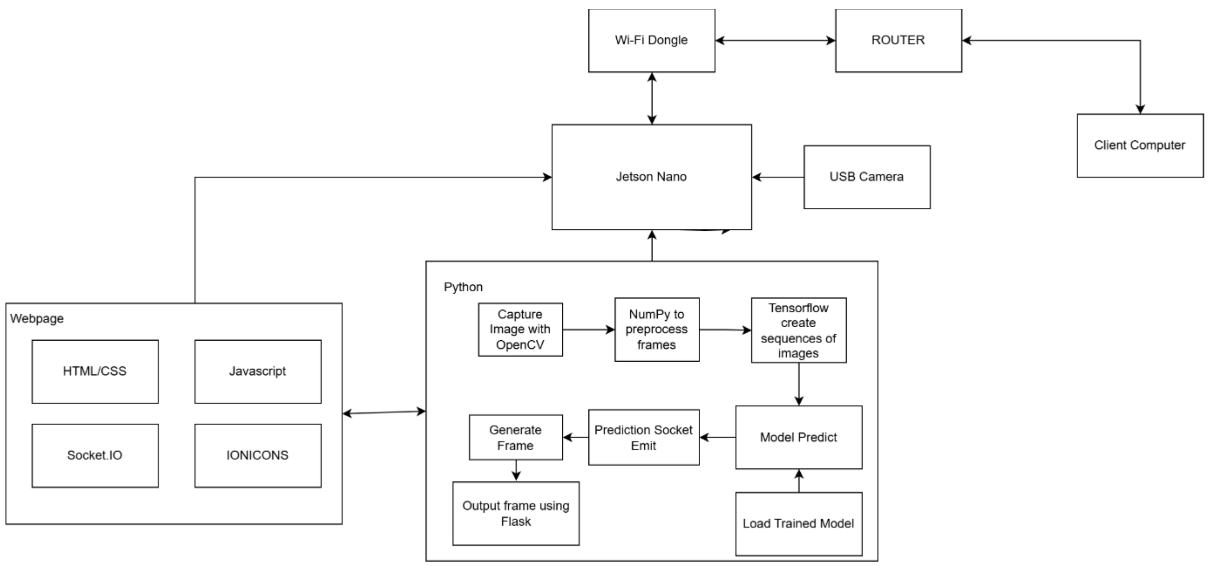


Figure 4

System Architecture

In Figure 4, the Jetson Nano is a compact edge computing device that captures real-time footage using a USB camera connected to the device. The image is first captured through OpenCV, then NumPy is used to preprocess the frame into a format that TensorFlow can interpret. A sequence of frames is created, and the pre-trained model is loaded onto the Jetson Nano to make predictions. This prediction, which classifies the situation as normal or abnormal (such as a brawl or fainting), is then emitted via a socket and returned to the system front-end. Meanwhile, a new frame is continuously generated and output via Flask, providing a live video stream embedded with behavior predictions. The Webpage Interface comprises front-end technologies like HTML/CSS, JavaScript, Socket.IO, and IONICONS. This webpage is responsible for receiving real-time video frames and displaying them to the user along with color-coded indicators: orange for panic, red for violence, blue for medical emergency, and default for normal. Socket.IO enables real-time communication between the client and the Jetson Nano, ensuring that video feed updates and behavioral alerts are instantly pushed to the user interface. For communication and data transmission, a Wi-Fi dongle connected to the Jetson Nano links it with a router connected to a client computer running the webpage. This network setup facilitates real-time data exchange between edge computing and the client interface.

1. Research and Planning

1.1 Conduct a literature review on AI-driven surveillance systems and their challenges.

1.2 Analyze existing methods for detecting and analyzing brawl events.

1.3. Identify gaps and define specific research objectives.

1.4. Planning a timetable of the proposed design project using a Gantt Chart.

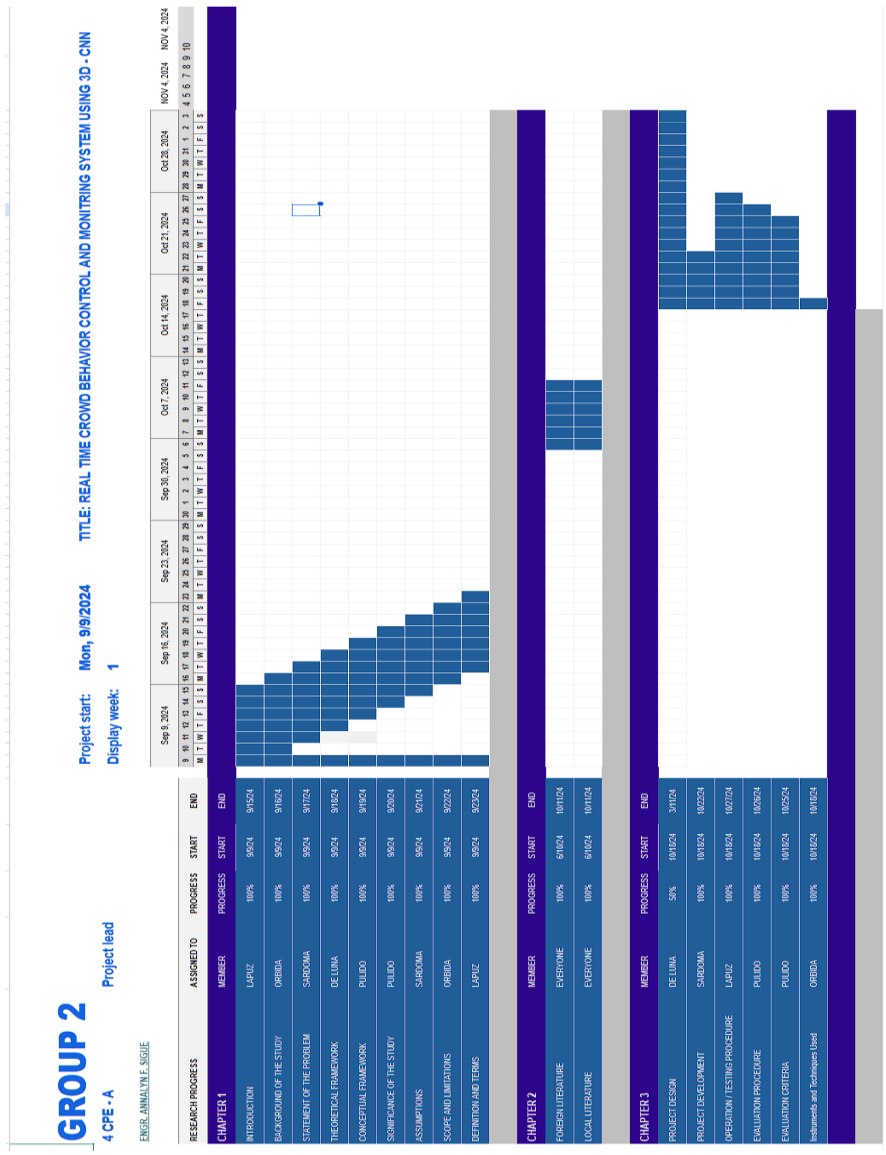


Figure 5

Gantt Chart

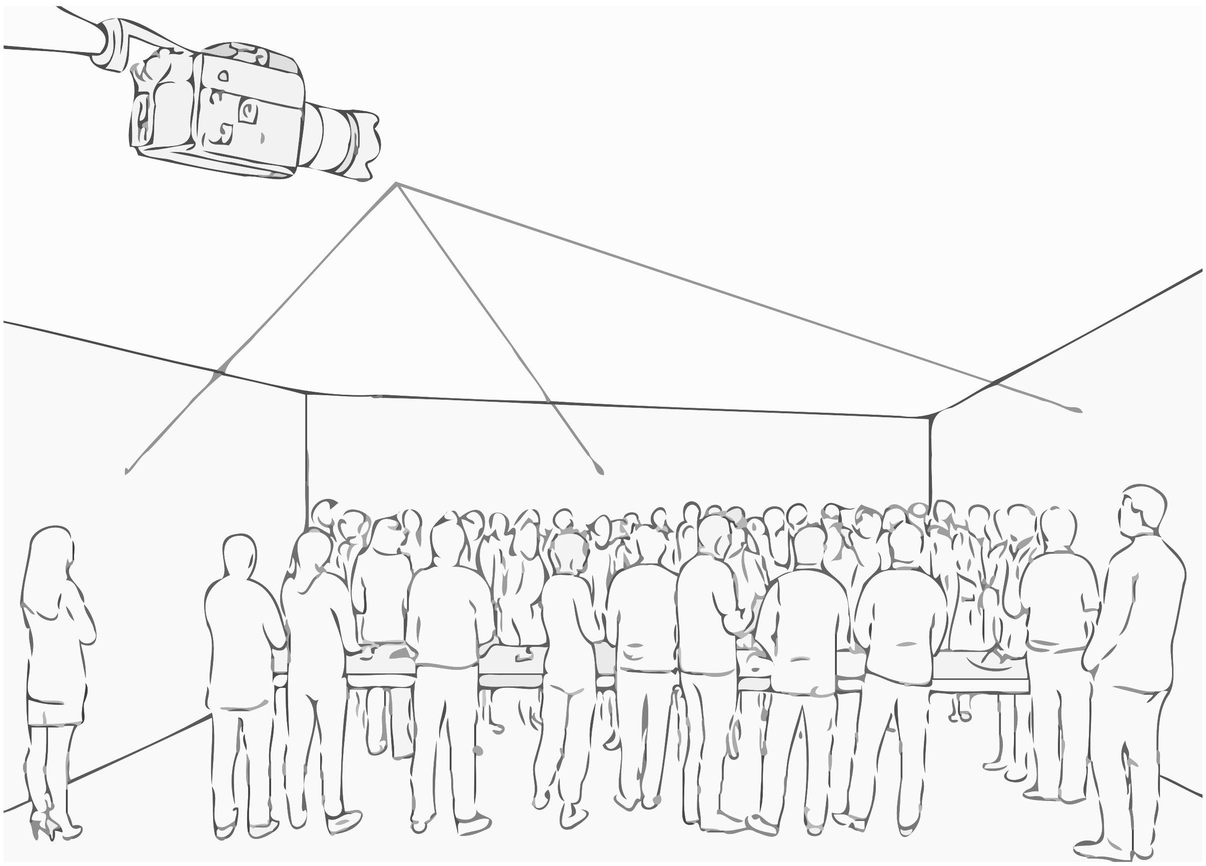


Figure 6

Prototype Camera Placement for Crowd Behavior Monitoring

Figure 6 shows the prototype installed and mounted at the top of the wall or ceiling, angled to capture clear, real-time video of the crowd below. This setup allows the camera to detect anomalies or unruly behaviors among the crowd, ensuring accurate and real-time detection for processing and alerts. The angle is estimated to be around 75 degrees downwards from the wall relative to the horizontal plane, and the height where the camera is mounted is around 2-3 meters from the ground. This ensures the camera captures the crowd effectively, neither close nor too far, and with enough range.

Hardware

- Camera: This component captures a live video feed of the crowd. It must be capable of providing high resolution to enable high accuracy and precise analysis of the 3D-CNN model.
- Jetson Nano J1010 – This AI-powered single-board computer functions as the core processing unit of the system. It receives the live video feed from the camera and processes it in real time using a 3D Convolutional Neural Network (3D-CNN) to monitor and analyze crowd behavior effectively at the edge.

Table 1

Project Prototype Components

COMPONENTS	DESCRIPTION	PRICE RANGE
Jetson j1010 reComputer	Single-Board Computer	P15,000 – P20,000
Hikvision DS-2CD2385G1-I (8MP)	Camera	P4,000 – P7,000

As shown in Table 1, the prototype utilizes a single Jetson Nano J1010 as the central processing unit, eliminating the need for separate microcontrollers. The Jetson Nano handles real-time data processing and network communication (e.g., via LAN or Wi-Fi), making the setup more efficient and compact. The camera captures live video footage of the monitored area, which is then analyzed by the Jetson Nano using a 3D-CNN model.

Table 2

Alternative Components for Project Prototype

COMPONENTS	DESCRIPTION	PRICE RANGE
NVIDIA Jetson Orin Nano	Single-Board Computer	P15,000 – P30,000+
Webcam HD 1080P	Camera	P500 – P1,000

Table 2 shows different components that can be alternatives for the Prototype components. The components in the table give different advantages and disadvantages. Using different microcontrollers to ensure performance or cheaper ones that give minimal expected performance is possible.

Software

- Ubuntu (Operating System): A Linux-based OS installed on the Jetson Nano J1010, providing a stable and flexible platform for development, AI inference, and system integration.
- Python Environment: The primary programming environment to develop, train, and deploy the 3D-CNN model. Python libraries such as TensorFlow and OpenCV are utilized for machine learning and computer vision tasks.
- Visual Studio Code (IDE): A lightweight, user-friendly integrated development environment for writing and debugging Python scripts, managing files, and monitoring the development workflow remotely or directly on the Jetson Nano.

- NVIDIA SDK Manager: A tool to flash the Jetson Nano with the appropriate Jetpack SDK, install required dependencies, and manage drivers and system libraries essential for AI and edge computing tasks.

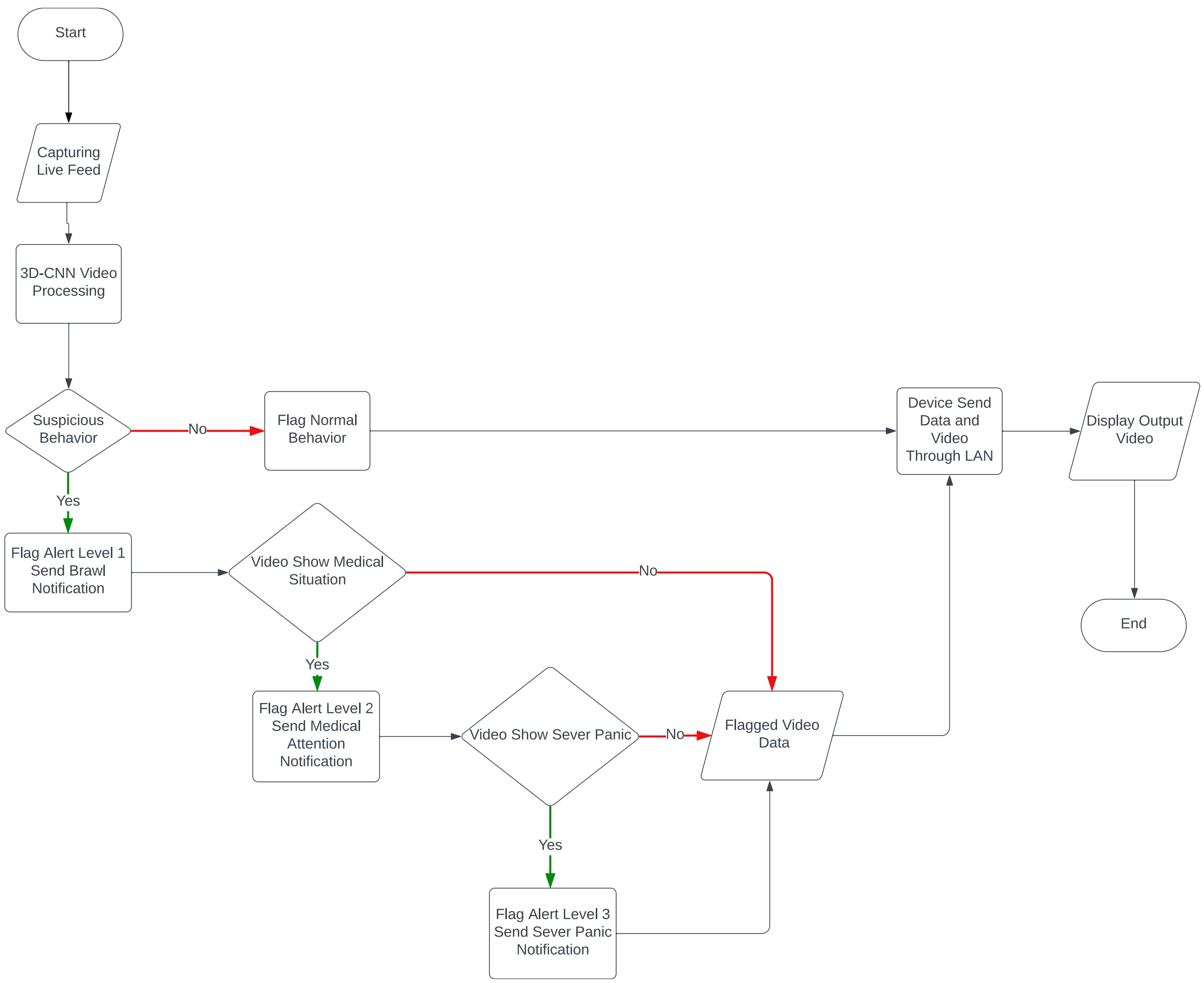


Figure 7

Software Operation Flowchart

In Figure 7, the flow of the prototype process is illustrated. The camera initially captures live video footage, which is then transmitted to the Jetson Nano J1010, where the embedded 3D-CNN model processes the data in real time. The Jetson Nano, acting as the edge computing device, then prepares the analyzed output for transmission to connected systems such as a user interface or monitoring dashboard via a local network or wireless communication protocol.

A simple User Interface (UI) was designed and implemented as part of the project development. It was used to visualize and display the processed data from the 3D-CNN model for the crowd behavior control and monitoring system. The UI was developed using Python-based libraries and the Flask Framework, ensuring compatibility with necessary functions. The primary objective of the UI is to display the real-time data processed by the system visually and interactively.

During the UI development, the user experience for the security officer who used the system was prioritized to ensure a responsive and user-friendly interface. Elements such as colored coded alerts, real-time updates, and a dashboard were incorporated to help the users quickly interpret the data and respond to any issues detected by the system.

Operation/Testing Procedure:

The operation and testing procedure provided a step-by-step guide for running the prototype. This process included researchers verifying specific criteria to ensure the device is thoroughly tested and meets its intended purpose.

Operation Procedure

The researchers developed a step-by-step process outlined below to ensure the design project works effectively and reliably before it is used.

1. **System Setup and Configuration:**

1.1 Hardware Installation:

It is essential to place the camera with its modules in key areas to provide a clear, complete view of the entire venue.

1.2 Software Installation:

Install machine learning libraries (TensorFlow, OpenCV), a database management system, and a user interface application.

2. **Data Collection and Processing:**

2.1 The camera will be activated to capture live video feeds and transmit them to the processing unit for analysis; and

2.2 Using 3D Convolutional Neural Networks (3D-CNN), the system will analyze crowd density and movement patterns, classifying behaviors as usual, suspicious, or hazardous.

3. **Risk Detection and Alert System:**

3.1 Utilize the user interface to detect anomalies; and

3.2 The system will be designed to raise alerts for potential threats such as overcrowding or panic:

- **Flag 1:** Violent and unruly behavior.

- **Flag 2:** Medical emergency.
- **Flag 3:** Severe panic.

4. **Data Tracking and Feedback:**

4.1 After the event, collect and analyze all data for trends and patterns in crowd behavior;

4.2 Generate reports summarizing key findings, which helps refine the algorithms, leading to improved accuracy and efficiency in the system over time; and

4.3 Use insights to improve future event planning and crowd management strategies.

Testing Procedure

In testing, the designed project operated as intended by following these procedures:

1. Test each component individually to confirm that all hardware parts function correctly and are appropriately connected. Verify that the necessary software and algorithms are installed and updated.
2. Ensure cameras transmit live video feeds to the processing unit without interruptions.
3. Test the performance by assessing the system's ability to monitor behavior under different crowd densities, and evaluate its detection capabilities and response time in controlled threat events.

4. Test system performance under extreme crowd conditions, assess adaptability across different event environments (e.g., concerts, festivals);
5. Involve users (event organizers, security) to test usability, gather insights, and improve user experience; and
6. Review collected data and alerts generated during testing to evaluate the system's accuracy and reliability, and identify any issues or areas for improvement based on test results and user feedback.

Evaluation Procedure

This part of the research evaluates the functionality, accuracy, and reliability of the prototype system's software and hardware components. The procedures were carried out to ensure the system operates effectively and meets the expected performance criteria. The evaluation includes the following:

1. Software Testing

1. Verify Programming Framework: Confirm that the development framework and 3D-CNN integration are appropriate for the system's needs.
2. Determine Software Limitations: Identify the limitations of the software, especially in real-time crowd behavior recognition, through rigorous testing.
3. Test System Functions: Verify all software functions and ensure the expected outputs are achieved under different scenarios.

4. Assess Program Accuracy: Confirm the accuracy of the 3D-CNN model in detecting crowd anomalies, such as fainting and abnormal behaviors.
5. Test Notification System: Test the SMS and emergency alert system to ensure they are sent on time.

2. Hardware Testing

1. Sensor Real-time Capabilities: Test sensors for collecting real-time data and syncing with the software.
2. Sensor Detection Accuracy: Assess whether sensors can effectively detect crowd dynamics and health-related anomalies.
3. Latency Testing: Measure latency from sensor data collection to system response.
4. Battery Life Test: Verify the battery life under conditions that guarantee extended workability in the real world.
5. Notification when Low Battery: Ensure the system automatically issues notifications when the battery is low.
6. Subsystems Reliability: To determine the durability and sustainability of the components of the system parts, impact scenarios come in handy.
7. Module Integrity: Withstand physical impacts, external stresses, and forces without breaking any of its wiring and connections.
8. Self-Diagnostics: Test the System's capability to detect and alert malfunctioning components or sensors.

Evaluation Criteria

Table 3

Evaluation Criteria for The System

CRITERIA	INDICATOR
ACCURACY	Behavior Detection Accuracy -Precision: Accurately identifies abnormal behaviors, such as panic attacks and aggression. -Recall: Accurately recognizes typical actions (e.g., standing, walking). Sensitivity to Changes in the Crowd -Early Detection: Predicts possible crowd problems in advance so that they can be addressed. -Environmental Sensitivity: How well a camera performs in different lighting conditions. Rates of False Positives and Negatives -FPR: The percentage of typical behaviors that are mistakenly reported as abnormal -The rate of missed aberrant behaviors is known as FNR.

	Important Performance Measures -Flag 1 (Violence): Accurately identifies altercations or hostility. -Flag 2 (medical emergency) is sensitivity to seizures or fainting. -Flag 3 (Panic): Accurately identifies panic attacks. Overall Matrix -F1 Score: Balances accuracy by combining recall and precision. -Latency: Response time under two seconds. Environmental Sensitivity -Angle and Lighting: System performance in various scenarios.
RELIABILITY	Robustness in Handling Crowd Scenarios -Performance Consistency: Preserves consistent performance under various lighting scenarios, camera angles, and crowd density. -Density Handling: Accuracy in sparse and dense crowds.

	-Lighting Sensitivity: The ability to function in different lighting scenarios (such as glare or low light). -Camera Angle: Accuracy of detection at various camera angles. -Occlusion and Noise Management: Handles occlusion (block views) and noise (motion blue, and static) in video -Occlusion Handling: Identifies individuals even when they are partially hidden. -Noise Robustness: Maintains accuracy despite video noise. Real-Time Processing -Prompt Alerting: Sends out notifications in less than two seconds when abnormal activity is recognized. -Alert Response Time: Time (≤ 2 seconds) between detection and alert. -Low Latency: Fast alert delivery and frame processing. -Frame processing latency: Each frame's processing time -Latency of alarm Transmission: The duration of the detection and alarm.
FUNCTIONALITY	Comprehensive crowd behavior analysis:

	-Detection of Abnormal Behavior: Accuracy in recognizing panic attacks, violent crimes, and medical crises. -Crowd Density Estimation: Real-time density change detection accuracy. -Flow analysis is the capacity to track and examine individual and group movement patterns. Effective Crowd Control and Management -Timely Alerts: When the system detects unusual activity, it sends alerts within two seconds. -System Integration: Interoperability with third-party crowd control devices, such as barriers or speaker systems. User-Friendly Interface -Visualization Tools: Clear graphical depictions of crowd behavior and events that have been flagged -Control Panel: Intuitive design allows system operators to monitor and control occurrences effectively.

PERFORMANCE EFFICIENCY	Real-time Processing Capabilities: -Detection Latency: The time it takes to identify and react to crowd occurrences (target ≤ 2 seconds) -Processing Speed: Frame processing rate, or speed measured in frames per second (fps). Low Computation Overhead: -Algorithm Optimization: The 3D-CNN's effectiveness for Inference in real time. -Resource Usage: Utilization of GPU/CPU during system Operation. Low Power Consumption: -Power Efficiency: Watts/hour of energy used by battery-operated gadgets. -Edge Computing Suitability: System performance on edge devices with low power consumption.

Instruments and Techniques Used

In this study, the researchers utilized a combination of Surveys, observations, and questionnaires to gather comprehensive data on the study. These instruments provided qualitative and quantitative insights, allowing us to analyze crowd behavior from multiple perspectives.

- **Surveillance Cameras** – A high-definition camera that can be positioned strategically to track and capture video footage of the crowds. These cameras provide detailed visual data, enabling the analysis of crowd movement patterns and potential security threats.
- **Sensors** – Devices designed to detect and measure various aspects of crowd behavior, movement, and density. These sensors can include motion sensors that track the movement of individuals. By collecting this data, sensors provided real-time insights into crowd dynamics.
- **Flowcharts** – Visual diagrams that outline the step-by-step process of real-time data handling. It also helped understand and organize, ensuring clarity and efficiency in the research.
- **Gantt charts** – The researchers used Gantt charts, visual tools used in project management to track progress, deadlines, and dependencies for various tasks. It displays a timeline for providing a clear overview of project schedules and milestones, ensuring that all parts of the implementation stay on track and will be completed on time.
- **Unified Modeling Language (UML)** – UML tools were used to help visualize how different components of the systems interact.

Surveys

The researchers collected the data on individuals' perceptions and experiences in crowd environments. Using semi-structured questions, the researchers got a wide range of responses regarding safety and comfort during different crowd scenarios. This data helped the researchers understand people's subjective experiences within crowds, contributing to a more precise analysis.

Observations

The researchers gathered data by using Real-time video surveillance to monitor crowd behavior. This method allowed us to capture and track the movement patterns, identify the potential anomalies, and detect unruly behavior. The continuous observation of crowd behavior provided valuable information on how the crowd behaves under various conditions.

Questionnaires

The researchers gathered detailed information on specific behavior and perceptions of the crowd. These questionnaires are designed to elicit in-depth responses from the security guard. The insight gained from these questionnaires is valuable in providing a comprehensive understanding of crowd behavior.

By integrating these research instruments, we gained valuable data. This method was used to ensure the reliability and validity of our findings and enhance the effectiveness of the real-time monitoring system. The combined survey, observation, and questionnaire answers allowed the researchers to develop a robust framework for further understanding and managing crowd behavior.

Likert Scale Interpretation

Interpretation	Weighted Mean
Very Poor	1-00 – 1.80
Poor	1.80 – 2.60
Fair	2.61 – 3.40
Good	3.41 – 4.20
Very Good	4.21 – 5.00

Weighted Mean

The formula for weighted mean measures the results of user and expert evaluations.

Weighted Average Formula

The weighted average formula is as follows:

$$\text{Weighted Average} = \frac{\sum(x_i \times w_i)}{\sum w_i}$$

Where:

- x_i = each individual value in the dataset
- w_i = the weight of each value
- $\sum$ = summation symbol, representing the sum of the products and weights

Accuracy

The researcher used the formula for accuracy to correctly classify the instances (normal, brawl, panic, faint, or not detected) over the total instances.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + TP + FP + FN}$$

Where:
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

Execution Time

The formula for Execution Time measures how long the algorithm takes to process a single frame or a batch of video frames.

$$\text{Execution Time} = \text{End Time} - \text{Start Time}$$

Precision

The formula for precision measures the proportion of true positive predictions among all positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Where:
TP = TRUE POSITIVE
FP = FALSE POSITIVE

Accuracy Evaluation

Accuracy Range %	Interpretation
0% to 50%	Poor/ Very Poor
51% to 70%	Fair
71% to 85%	Good
86% to 95%	Very Good
>95%	Excellent

The accuracy interpretation table is a practical framework for evaluating the performance levels of machine learning and artificial intelligence models, particularly in violence detection systems. As the literature outlines, accuracy remains one of the most widely used performance metrics, representing the ratio of correct predictions to total predictions. Omarov et al. emphasize the critical role of accuracy in real-time violence detection applications, where incorrect predictions—either false positives or false negatives—can have serious consequences [33].In this context, the interpretation table categorizes accuracy scores from 0% to over 95% into qualitative levels: "Poor" (0–50%), "Fair" (51–70%), "Good" (71–85%), "Very Good" (86–95%), and "Excellent" (>95%). These classifications align well with industry benchmarks discussed by Deep checks [34], suggesting that 70–90% accuracy is commonly accepted in many ML applications. In comparison, accuracy above 90% is typically expected in high-stakes environments such as healthcare, finance, or surveillance. In the reviewed literature, conventional methods often fall into the "Fair" to "Good" range due to their simplicity and lower computational demands, while machine-learning and deep learning models frequently achieve "Very Good" to "Excellent" accuracy when trained on high-quality data. Therefore, the table provides a justified and literature-supported basis for evaluating model performance and setting meaningful thresholds in academic or practical applications.

Chapter IV

DISCUSSION AND RESULTS

This chapter comprehensively analyzes the data gathered and analyzes and interprets the concerns about the project design. It includes the technical information for developing the project prototype and evaluating each objective using tables and narratives. The collected data were interpreted using a review of related literature and studies to support the research findings. The chapter discusses all the information collected from the survey or evaluation, providing valuable insights into the design projects' prototypes, schematics, and test evaluations.

This study used data gathered from the literature review and study, as well as responses collected through the survey. This chapter discusses all the information collected from the survey results in evaluating the project and justifying the technical descriptions of the study, which can be valuable for understanding the entire design project. It also includes the project structure, schematics, and test evaluations. This chapter will answer all the study objectives presented in the earlier part.

Project Technical Description

The device, V.I.S.I.O.N., is a real-time crowd behavior control and monitoring system using a 3D-Convulational Neural Network designed to improve public safety and well-being via cutting-edge crowd surveillance technologies. This technology uses a 3D-Convolutional Neural Network, or 3D-CNN, to study crowd behavior in real time. This allows for the detection of health problems like Fainting and seizures, as well as potential dangers like violent behavior. The device and its related parts are integrated into a smooth monitoring system that enables prompt action and notifies the authorities or medical personnel. The primary objectives of this device are to provide a proactive and automated solution for monitoring large groups of people, such as public events like concerts, crowded spaces, or high-risk environments. By implementing cutting-edge AI-based techniques, the device can detect anomalous behaviors and health-related issues within crowds, ensuring that necessary actions can be taken when an issue happens once the system detects it. The integration of 3D-CNNs for visual data analysis enables accurate recognition of complex human behaviors, such as violent actions and health-related issues, which would be challenging to monitor manually, so we integrate the 3D-CNN to detect the violent behavior and health issues in the crowd.

Table 4

Hardware Components

HARDWARE	QUANTITY	DESCRIPTION
Jetson J1010 reComputer	1	AI edge computing device for real-time processing of crowd behavior using 3D-CNN.
Webcam HD 1080P	1	Captures real-time video feed for crowd behavior detection.
Mouse	1	It is used to interact with the system.

Keyboard	1	is used to input.
Wi-Fi Dongle	1	enables wireless connectivity for data transmission.
Laptop	1	acts as a CPU for model training and system management.
Monitor	1	It displays the output for crowd monitoring.
USB cable (Type C)	1	Used to transfer data between computers or within the computers.

Table 4 illustrates the required hardware components in the real-time crowd control and monitoring system using a 3D-Convolutional Neural Network (3D-CNN). The reComputer Jetson J1010 is the central processing device with an NVIDIA GPU to process the real-time video data efficiently. The device plays a crucial role in executing the AI models to analyze crowd dynamics and identify outliers. Webcam HD 1080P feeds live video feeds, offering a high-resolution input to the system. It ensures proper detection and tracking of a person amidst a crowd. The laptop performs model training, data preprocessing, and system maintenance, enabling model optimization before deployment. For user interaction, a mouse and keyboard enable system control and setup, while a monitor shows real-time information, insights generated by AI, and system logs. A WIFI dongle allows wireless connection, enabling remote monitoring and data transfer to a central system. Finally, a USB cable provides a consistent power supply and secure data transfer between parts, keeping the system running and efficient. These hardware elements combine to build an AI-based monitoring system to analyze and control crowd behavior in real time.

Table 5

Software Components

SOFTWARE	DESCRIPTION
Operating system: Windows and Ubuntu (Linux)	It is a system for running AI models, development tools, and system operations.
Python Environment	Used to develop and run 3D–CNN models for real-time crowd behavior detection.
Visual Studio Code	is used for debugging, writing, managing AI-related scripts, and creating an HTML website.
Nvidia SDK/Manager	It gives the necessary drivers, libraries, and tools for setting up and optimizing the Jetson device.

Table 5 illustrates the essential software components for the real-time crowd control and monitoring system using a 3D convolutional Neural Network (3D-CNN). Windows and Ubuntu (Linux), the operating systems, host the AI model and run hardware devices smoothly. Deep learning tasks favor Ubuntu because they can easily access the NVIDIA driver and machine learning packages.

The Python Environment is crucial for model development and deployment of AI models. It consists of libraries like TensorFlow, PyTorch, and OpenCV, which are employed for deep learning, image processing, and real-time video analysis. The environment allows the deployment of the 3D-CNN model for crowd behavior analysis and anomaly detection. Visual Studio Code (VS Code) is the main code editor for coding and debugging the AI software. It offers a user-friendly interface, Python development extensions, and utilities for effective coding and error checking. The NVIDIA SDK Manager manages and installs required drivers, software development kits (SDKs), and machine learning tools for Jetson devices. It ensures that the hardware runs at its best and facilitates AI processing efficiently.

These software elements collaborate to provide the real-time monitoring system, enabling smooth AI model execution, data analysis, and system management.

Project Structure/Organization

The project is developed and managed by a team of researchers with specific roles and responsibilities:

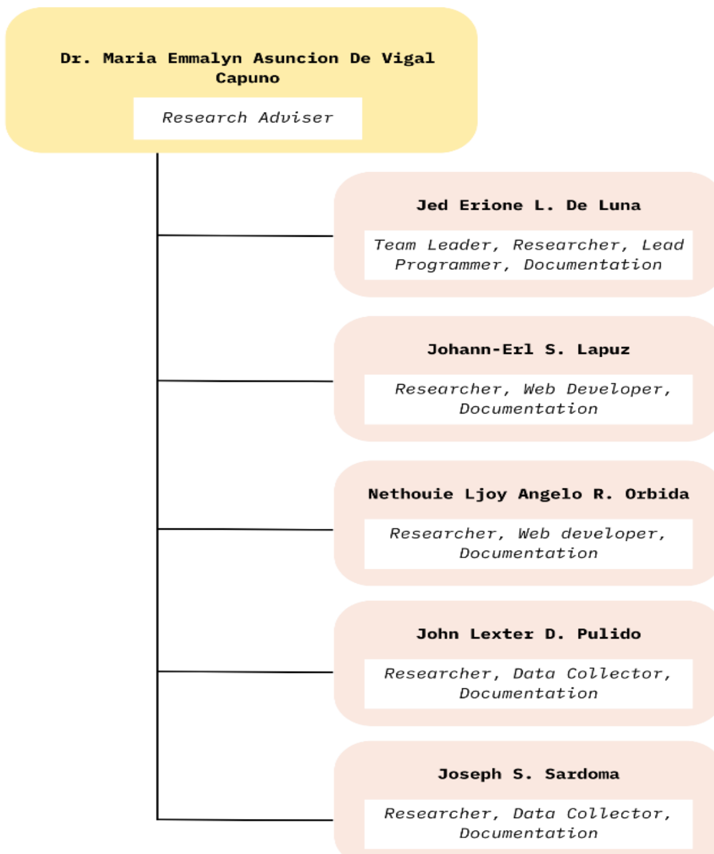


Figure 8

Project Organizational Chart

Figure 8 defines the research team's roles, responsibilities, and workflow in developing the Real-Time Crowd Behavior Control and Monitoring System Using 3D-

Convolutional Neural Network. It ensures efficient collaboration, task distribution, and goal alignment among team members. The Research Adviser provides guidance, ensuring the project meets academic and technical standards while helping refine system development and troubleshooting. The researchers led the study by conducting experiments, analyzing results, and validating system performance. Data collectors gather real-world crowd behavior data, compare outputs with actual scenarios, and enhance system accuracy. Web developers design and maintain the Vision monitoring webpage, integrating real-time data visualization and alerts for effective monitoring. The researchers documented the system design, implementation, and evaluation throughout the process to ensure a well-structured and reliable study.

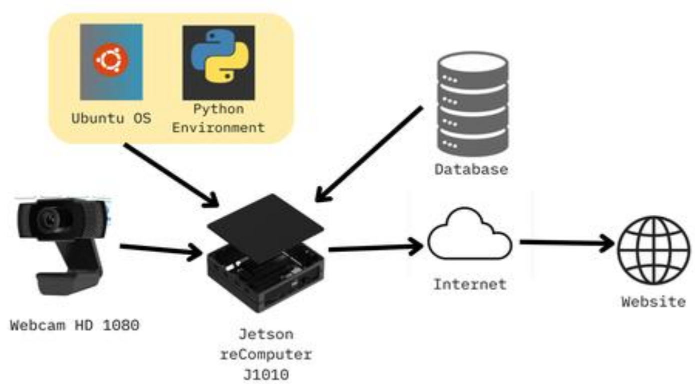


Figure 9

Architecture Diagram of the Design Project

The main goal of this system is to capture, process, and transmit video data using a combination of hardware and software components. At the core of the system is the Jetson reComputer J1010, which functions as the central processing unit. This device operates on an Ubuntu OS environment and utilizes a Python-based software stack to manage and process incoming data.

The HD Webcam 1080 captures video, which is then fed into the Jetson reComputer J1010 for processing. The Jetson device, equipped with powerful GPU capabilities, enables efficient video analysis, making it an ideal choice for AI-based applications. Integrating the camera with the Jetson device ensures seamless video acquisition, enabling real-time processing for various use cases.

Once the videos are processed, they are sent to a database stored for easy access and future analysis. This database acts like a well-organized digital storage space, making it simple for other systems or apps to find and use the video data when needed, whether for further processing or creating visuals. Keeping everything organized makes it easy to manage, ensuring that old and new video footage can be accessed whenever needed for deeper insights.

The Jetson reComputer J1010 is connected to the internet, enabling smooth data transmission to cloud services or remote servers. Through this internet connection, the processed data is also made available on a website, allowing users to access real-time information. This web-based access enhances the system's usability, providing a user-friendly interface for monitoring and analysis.

With Ubuntu OS and Python, the researchers can customize and add various features, like machine learning, computer vision, and automation. The system is built to run smoothly, ensuring that data flows easily from the camera to the Jetson device, then to the database, and finally to the website. This setup allows users to interact with the data in real-time, providing an effortless experience for monitoring and analysis.

By integrating powerful hardware and software, this system offers an efficient, scalable, and automated way to capture, process, save, and visualize video data. The setup is designed to be reliable and high-performing, making it ideal for applications like real-time crowd behavior monitoring, control, and AI-driven analysis using 3D-Convolutional Neural Networks.

Web Content

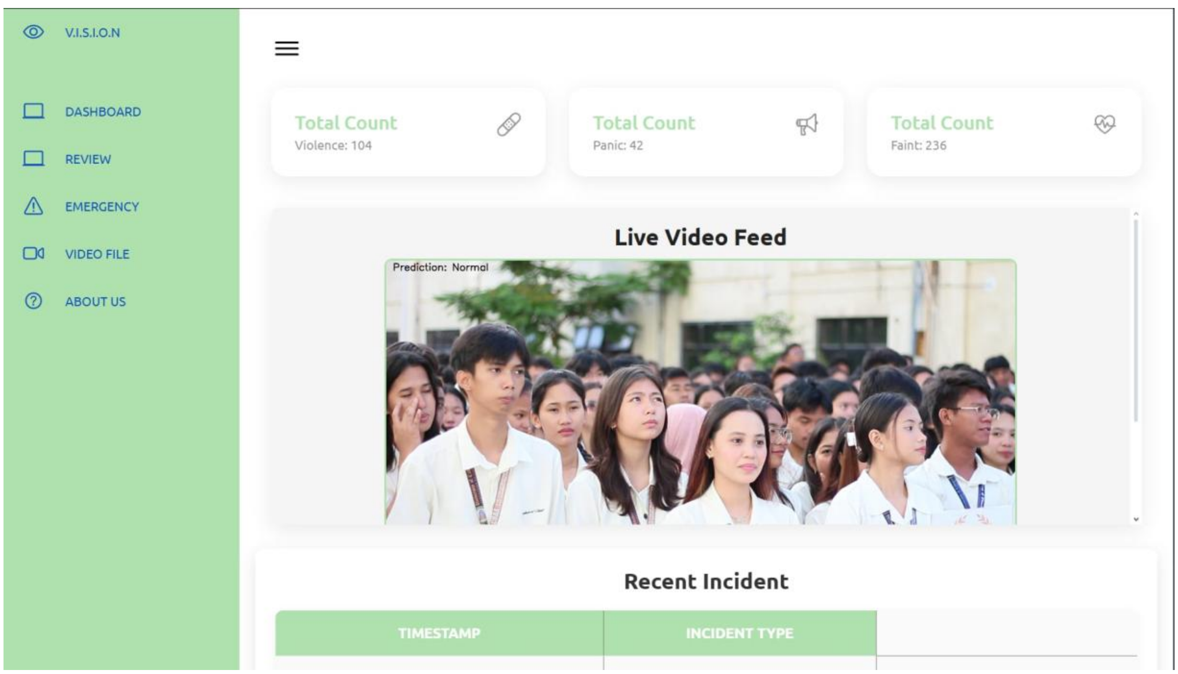


Figure 10

V.I.S.I.O.N Dashboard Interface

Figure 10 shows the V.I.S.I.O.N dashboard interface for security monitoring. On the left is a sidebar with easy-to-access navigation options like Dashboard, Review, Emergency, Video File, and About Us. The main area displays the live video feed, which shows the real-time video. The interface is designed for user access to monitoring features, enabling navigation to different functionalities for real-time surveillance and crowd behavior analysis..

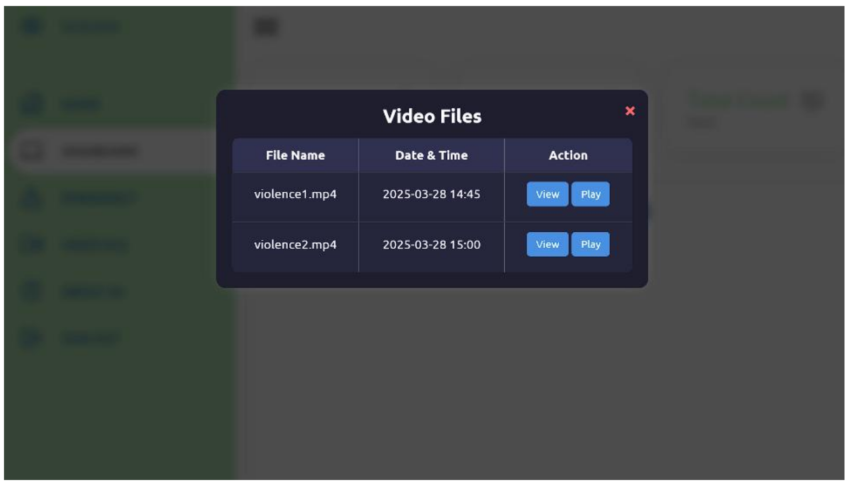


Figure 11.1

Video File Storage and Management Interface

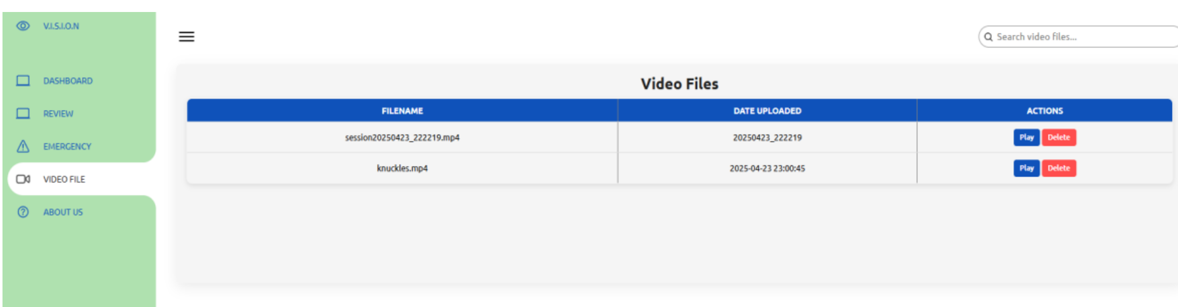


Figure 11.2

Video File Storage and Management Interface

Figure 11 shows the recorded video files in a user-friendly format. The system provides a file management interface that displays recorded incidents in a table form. This table includes the file name, date, and time of recorded events. Users can perform actions like viewing or deleting files for better management. This feature allows administrators to efficiently review footage of incidents such as brawling and other unusual behaviors. The real-time crowd behavior monitoring system includes a feature that records detected activities. This feature captures and stores data such as the file name, date, and time of recorded events. It also keeps track of incidents such as brawling and other unusual behaviors.

Figure 12

Final Prototype

Figure 12 presents the final prototype built by the proponents. This system is designed to monitor and manage crowd behavior in real time. It analyzes crowd behavior using a 3D convolutional Neural Network (3D-CNN) model, detects movement patterns, and identifies anomalies as they occur. The processed data is then stored in a database for further analysis and transmitted through the Internet to V.I.S.I.O.N, a web-based platform that enables remote monitoring and management.

Through V.I.S.I.O.N, users can visualize real-time data, review previous activity records, and make informed decisions to optimize crowd control. This system informs users about real-time crowd movements, effectively managing crowds across various environments.

Project Limitations and Capabilities

This stage establishes the prototype's functionality boundaries, outlining its operational capabilities and inherent limitations.

Capabilities

The project's capabilities, as established in the final design by the developers, are as follows:

1. The dashboard overviews system activity, including a live video feed and total counts for violence, Panic, and fainting incidents. Users can also click on each category to view all related video files based on the system's predictions.
2. The video file table allows users to view, play, and delete video files as needed.
3. The emergency feature displays the appropriate departments to contact in case of specific accidents.
4. The video file management feature lists all stored video files, allowing users to view, play, and delete them as needed.

Limitations

The following limitations are identified based on the researchers' final design:

1. The device relies solely on visual data, making it unable to detect verbal altercations or distress calls, which may reduce accuracy.
2. The system requires adequate lighting for optimal performance, as low-light conditions can hinder behavior detection.
3. The system's effectiveness depends on camera placement, which may create blind spots where specific actions go unnoticed.
4. The device may misinterpret actions, leading to incorrect classifications or missed incidents.
5. A stable internet connection is necessary for real-time analysis if cloud-based processing is used.
6. The device may require regular data management to prevent storage overload due to continuous video recording.
7. High-resolution video processing may cause delays, particularly on lower-end hardware.

Project Evaluation

This section reviews the hardware and software chosen by the proponent to ensure they meet the required standards. It also presents the results and discussion of the machine learning algorithms used in the system.

Hardware Testing

Table 6

Test	**Component**	**Assessment**	**Problem Encountered**	**Solution**
1.	HD Webcam 1080	The Accuracy and Functionality of the Camera	None	None
2.	J1010 reComputer	Assess the capability to run an AI model and perform processing.	Allocation of memory resources while running the model. The problem is corruption after initial testing and removing specific libraries from	Instead of TensorFlow, we used TensorRT, which is more suitable for edge devices with limited capabilities than computers.

			tutorials on YouTube and other tutorial sites.	Installing Ubuntu OS on a laptop and reflashing the OS on the J1010 reComputer from Seeed Studio using Nvidia SDK Manager.

Software Testing

Table 7

Test	Component	Assessment	Problem Encountered	Solution
1.	Operating System: Windows and Ubuntu (Linux)	System Compatibility with AI Models	Since the project folder was built in Windows, there are naturally incompatibilities between the libraries used for the two operating systems. Notably, the Ubuntu OS on the Jetson Nano runs on an ARM64 architecture, whereas the computer uses an x86_64 architecture.	Creating an environment directly inside the J1010 reComputer and installing and rebuilding the necessary libraries required by the initial program..

2.	Python Environment	Execution of Machine Learning Algorithms	To resolve potential issues caused by incompatibilities between these programs, due to the default Python version 2.7 on the J1010 reComputer, we installed the highest Python version supported by the J1010 system	The computer where the programs are developed and the AI model is built and trained has the latest version of Python, 3.12.

3.	Nvidia SDK Manager	Jetson Board Configuration	Unable to find the supported JetPack version for the Jetson Nano	Running the SDK Manager with the '--archived-versions'

				flag means it will run older versions of the SDK Manager, allowing us to access the JetPack system that supports Jetson Nano devices.

Table 7 presents the software testing process, which ensures system components function correctly and efficiently. The process evaluates compatibility, performance, and potential issues, implementing solutions to optimize execution. It helps identify and resolve software-related challenges, ensuring smooth integration and operation of the system.

Initial Development

On the initial development stage of our Artificial Intelligence Model, the researchers used four convolutional layers with kernel filters of [8, 16, 32, 64] for the first layer until the fourth layer, respectively, and flattened and condensed the output from all layers to 128 neurons. The first model was built with the standard architecture of 3D-CNN with a dropout of 0.5 and no regularizers. The training process shows underfitting of the model, meaning that the current architecture of the model is unable to learn progressively on each epoch. The result of the training process can be seen in the figures below.

```
Epoch 1/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 36s 201ms/step - accuracy: 0.5630 - loss: 15.8210 - val_accuracy: 0.5252 - val_loss: 15.5417
Epoch 2/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 34s 203ms/step - accuracy: 0.6068 - loss: 1.2627 - val_accuracy: 0.5223 - val_loss: 8.8724
Epoch 3/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 33s 196ms/step - accuracy: 0.6158 - loss: 1.1363 - val_accuracy: 0.4629 - val_loss: 2.0580
Epoch 4/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 33s 195ms/step - accuracy: 0.5914 - loss: 1.1258 - val_accuracy: 0.5312 - val_loss: 1.1674
Epoch 5/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 33s 197ms/step - accuracy: 0.5681 - loss: 1.1756 - val_accuracy: 0.5430 - val_loss: 1.4272
Epoch 6/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 33s 197ms/step - accuracy: 0.5962 - loss: 1.0266 - val_accuracy: 0.5935 - val_loss: 1.3785
Epoch 7/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 35s 206ms/step - accuracy: 0.5569 - loss: 1.0930 - val_accuracy: 0.5460 - val_loss: 1.6619
Epoch 8/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 34s 199ms/step - accuracy: 0.5750 - loss: 1.0040 - val_accuracy: 0.5371 - val_loss: 1.5243
Epoch 9/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 33s 197ms/step - accuracy: 0.5421 - loss: 1.3939 - val_accuracy: 0.5430 - val_loss: 1.2109
Epoch 10/10
169/169 ━━━━━━━━━━━━━━━━━━━━ 34s 199ms/step - accuracy: 0.5813 - loss: 0.9538 - val_accuracy: 0.5430 - val_loss: 1.3726
```

Figure 13.1

Initial Development of 3D-CNN Model Results

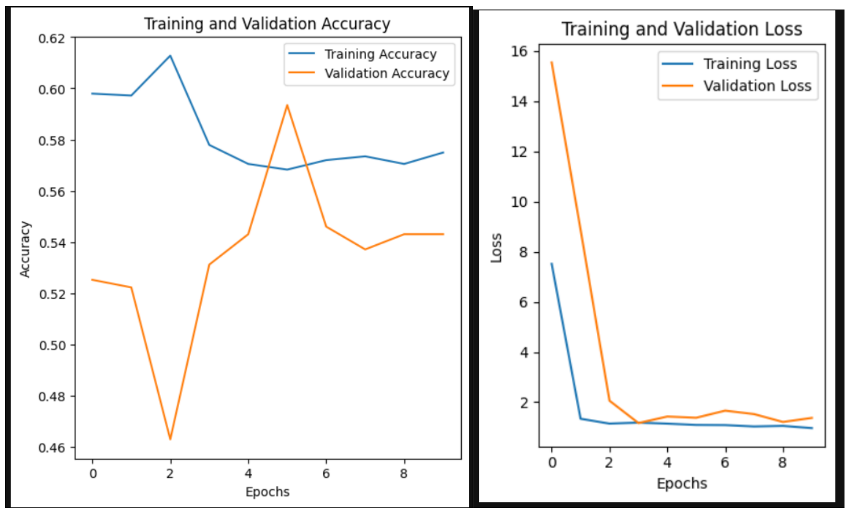


Figure 13.2

Initial Development of 3D-CNN Model Results

The development continues to try to increase the kernel filter of the model to the increased convolutional layer while still increasing the kernel filters per layer. After setting up six convolutional layers with a kernel filter of [8, 32, 64, 64, 128, 256] respectively and flattening and condensing the output from all layers to 512 neurons, researchers saw an increase in accuracy during the training process, achieving 90% to 98%, which is good.

Figure 14

Graph Result of Training 3D-CNN with 6 Convolutional Layers

The graph in Figure 14, above, shows the training accuracy of almost 100% and the validation accuracy of 100%. Higher accuracy was good, but this graph shows otherwise; the model developed is overfitting, thus leading to biased classification. To fix the model's overfitting, the researchers applied weighted regularizers ranging from 0.001 to 0.005 and configured the random dropping of neurons from 0.1 to 0.3. The researchers cleaned the data again, removing unnecessary parts of each video in the dataset and focusing on the sequential relationship between frames. For example, videos in Brawl usually start after 5-10 seconds, and sometimes they have unnecessary frame transitions. The frame transition was edited out and enhanced by having 1-2 seconds before it breaks, within 5 seconds of total time length. Researchers also include the actual brawl action until it ends within 5-10 seconds to challenge the model. With this in mind, researchers experimented with two classifications of behaviors, namely Normal and Brawl(violence)

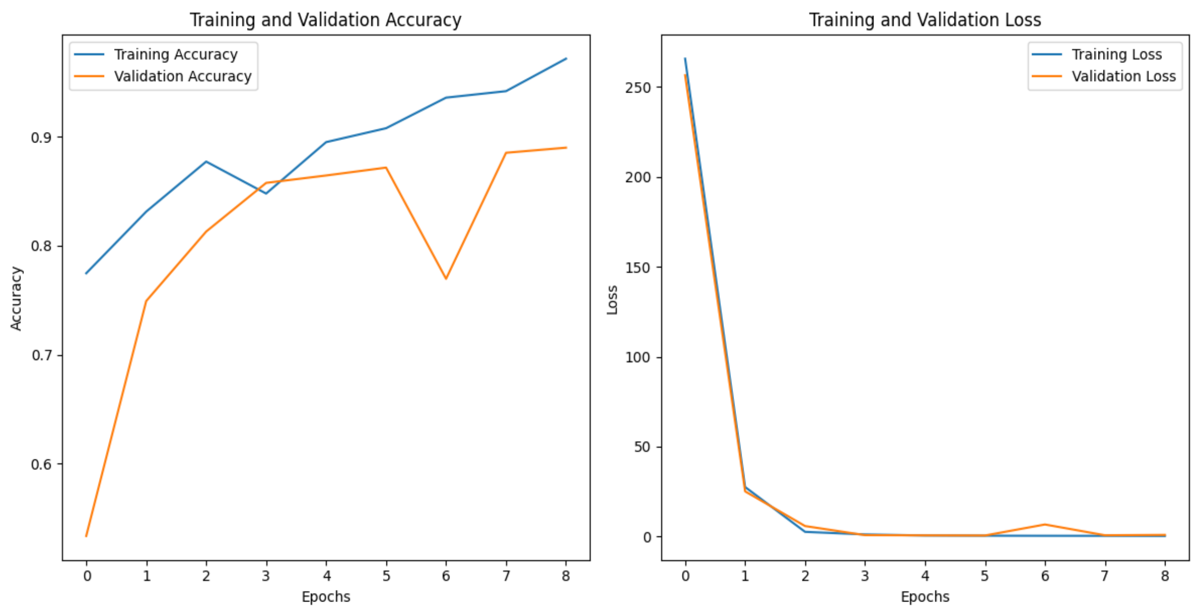


Figure 15

Training and Validation Result with 2 Class Labels of 3D-CNN and Thorough Data Cleaning

Figure 15 above improves the training and validation accuracy, showing a curve showing how the accuracy in both increased over each epoch. This states that the model learned every epoch, even though it sometimes dropped for some epochs.

Final Development

For hardware, the system's components worked smoothly together. The HD Webcam 1080 and Jetson Nano were checked for accuracy, performance, and how well they handled real-time processing. The researchers ran into issues like the model taking too much memory and slowing things down. To fix this, researchers used TensorRT to make the AI run more efficiently. Setting up Ubuntu OS and configuring the SDK properly helped the Jetson Nano process AI tasks more smoothly.

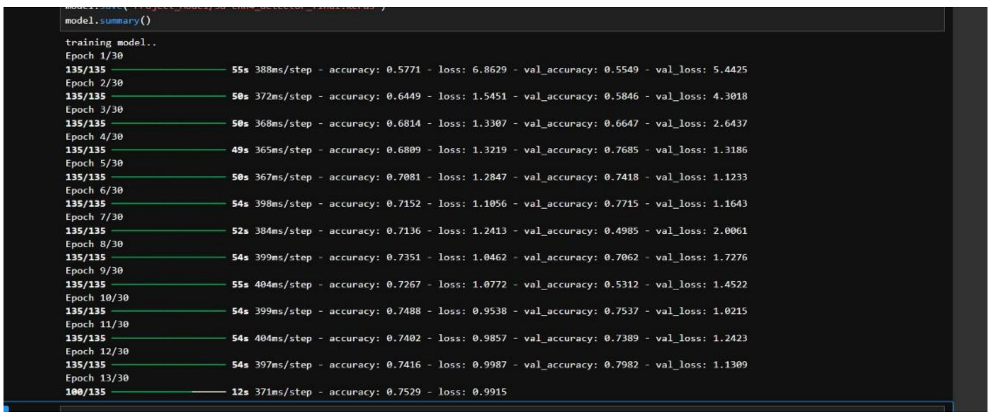
For software, the researchers tested it thoroughly to ensure smooth operation across different operating systems, programming environments, and machine learning libraries. They encountered issues with some files and tools not working the same on Windows and Ubuntu. To fix this, they ensured all the necessary files were compatible and set up separate work environments on the Jetson Nano to avoid conflicts. Python was updated to the latest version to keep everything running smoothly and efficiently.

The result will be evaluated to determine if the prototype has significant changes.

```
Epoch 1/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 57s 407ms/step - accuracy: 0.5713 - loss: 4.8485 - val_accuracy: 0.1246 - val_loss: 10.4785
Epoch 2/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 54s 397ms/step - accuracy: 0.7254 - loss: 2.1792 - val_accuracy: 0.2552 - val_loss: 2.9092
Epoch 3/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 54s 401ms/step - accuracy: 0.7875 - loss: 1.7450 - val_accuracy: 0.5252 - val_loss: 2.2923
Epoch 4/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 55s 409ms/step - accuracy: 0.8167 - loss: 1.5601 - val_accuracy: 0.8427 - val_loss: 1.4884
Epoch 5/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 55s 406ms/step - accuracy: 0.8399 - loss: 1.3955 - val_accuracy: 0.8487 - val_loss: 1.4393
Epoch 6/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 58s 427ms/step - accuracy: 0.8498 - loss: 1.3625 - val_accuracy: 0.8665 - val_loss: 1.5342
Epoch 7/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 58s 428ms/step - accuracy: 0.8746 - loss: 1.1623 - val_accuracy: 0.6677 - val_loss: 2.5695
Epoch 8/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 58s 426ms/step - accuracy: 0.7819 - loss: 1.4334 - val_accuracy: 0.7626 - val_loss: 2.1716
Epoch 9/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 56s 414ms/step - accuracy: 0.8062 - loss: 1.3561 - val_accuracy: 0.8220 - val_loss: 1.5024
Epoch 10/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 57s 420ms/step - accuracy: 0.8421 - loss: 1.2572 - val_accuracy: 0.8160 - val_loss: 1.2538
Epoch 11/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 57s 421ms/step - accuracy: 0.8359 - loss: 1.1513 - val_accuracy: 0.8754 - val_loss: 1.2182
Epoch 12/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 57s 419ms/step - accuracy: 0.8738 - loss: 1.0364 - val_accuracy: 0.8665 - val_loss: 1.0345
Epoch 13/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 56s 413ms/step - accuracy: 0.8816 - loss: 0.9073 - val_accuracy: 0.8427 - val_loss: 1.3214
Epoch 14/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 55s 409ms/step - accuracy: 0.8836 - loss: 0.9133 - val_accuracy: 0.8427 - val_loss: 1.5572
Epoch 15/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 57s 419ms/step - accuracy: 0.8542 - loss: 1.0724 - val_accuracy: 0.6884 - val_loss: 7.0866
Epoch 16/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 56s 418ms/step - accuracy: 0.8195 - loss: 1.3026 - val_accuracy: 0.8042 - val_loss: 1.4013
Epoch 17/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 56s 413ms/step - accuracy: 0.8508 - loss: 1.0939 - val_accuracy: 0.7151 - val_loss: 1.4534
Epoch 18/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 56s 415ms/step - accuracy: 0.8316 - loss: 1.1358 - val_accuracy: 0.6973 - val_loss: 2.0410
Epoch 19/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 55s 411ms/step - accuracy: 0.8698 - loss: 0.9944 - val_accuracy: 0.8694 - val_loss: 1.0967
```

Figure 16.1

Training Accuracy and Validation Performance Over Epochs



```
model.summary()

training model..
Epoch 1/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 55s 388ms/step - accuracy: 0.5771 - loss: 6.8629 - val_accuracy: 0.5549 - val_loss: 5.4425
Epoch 2/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 50s 372ms/step - accuracy: 0.6449 - loss: 1.5451 - val_accuracy: 0.5846 - val_loss: 4.3018
Epoch 3/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 50s 368ms/step - accuracy: 0.6814 - loss: 1.3307 - val_accuracy: 0.6647 - val_loss: 2.6437
Epoch 4/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 49s 365ms/step - accuracy: 0.6809 - loss: 1.3219 - val_accuracy: 0.7685 - val_loss: 1.3186
Epoch 5/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 50s 367ms/step - accuracy: 0.7081 - loss: 1.2847 - val_accuracy: 0.7418 - val_loss: 1.1233
Epoch 6/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 54s 398ms/step - accuracy: 0.7152 - loss: 1.1056 - val_accuracy: 0.7715 - val_loss: 1.1643
Epoch 7/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 52s 384ms/step - accuracy: 0.7136 - loss: 1.2413 - val_accuracy: 0.4985 - val_loss: 2.0061
Epoch 8/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 54s 399ms/step - accuracy: 0.7351 - loss: 1.0462 - val_accuracy: 0.7062 - val_loss: 1.7276
Epoch 9/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 55s 404ms/step - accuracy: 0.7267 - loss: 1.0772 - val_accuracy: 0.5312 - val_loss: 1.4522
Epoch 10/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 54s 399ms/step - accuracy: 0.7488 - loss: 0.9538 - val_accuracy: 0.7537 - val_loss: 1.0215
Epoch 11/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 54s 404ms/step - accuracy: 0.7402 - loss: 0.9857 - val_accuracy: 0.7389 - val_loss: 1.2423
Epoch 12/30
135/135 ━━━━━━━━━━━━━━━━━━━━ 54s 397ms/step - accuracy: 0.7416 - loss: 0.9987 - val_accuracy: 0.7982 - val_loss: 1.1309
Epoch 13/30
100/135 ━━━━━━━━━━━━━━━━━━━━ 12s 371ms/step - accuracy: 0.7529 - loss: 0.9915
```

Figure 16.2

Training Accuracy and Validation Performance Over Epochs

Figure 16 shows how the model's performance improved as it was trained. The model did not do very well, but learned from the data over time and improved. The accuracy ranged between 89% and 91%, meaning the model had learned the essential patterns and performed well. The validation accuracy goes up and down between 83% and 89%, which means the model's performance on new, unseen data is unstable. This could be because the model is paying too much attention to specific details in the training data, making it less reliable when tested on different data, where it performs well on training data but struggles to generalize fully. The validation loss is high (10.47), but decreases as the training progresses. Although the loss generally decreases, there are times when it spikes a little. In some parts of the training, the model might focus too much on the details of the training data and not do as well when handling new, unseen data. If the model does not have enough layers, it might have trouble learning the more complex patterns in the data. This can make it more sensitive to random mistakes and prevent improving accuracy. The ups and downs in validation accuracy and loss show the importance of finding the right balance between making the model deep enough and using techniques to prevent it from overfitting, so it can perform well on new data.

Layer (type)	Output Shape	Param #
conv3d_12 (Conv3D)	(None, 16, 112, 112, 8)	656
batch_normalization_12 (BatchNormalization)	(None, 16, 112, 112, 8)	32
max_pooling3d_12 (MaxPooling3D)	(None, 16, 56, 56, 8)	0
conv3d_13 (Conv3D)	(None, 16, 56, 56, 32)	6,944
batch_normalization_13 (BatchNormalization)	(None, 16, 56, 56, 32)	128
max_pooling3d_13 (MaxPooling3D)	(None, 16, 28, 28, 32)	0
conv3d_14 (Conv3D)	(None, 16, 28, 28, 64)	55,360
batch_normalization_14 (BatchNormalization)	(None, 16, 28, 28, 64)	256
max_pooling3d_14 (MaxPooling3D)	(None, 16, 14, 14, 64)	0
conv3d_15 (Conv3D)	(None, 16, 14, 14, 64)	110,656
batch_normalization_15 (BatchNormalization)	(None, 16, 14, 14, 64)	256
max_pooling3d_15 (MaxPooling3D)	(None, 16, 7, 7, 64)	0
conv3d_16 (Conv3D)	(None, 16, 7, 7, 128)	221,312
batch_normalization_16 (BatchNormalization)	(None, 16, 7, 7, 128)	512
max_pooling3d_16 (MaxPooling3D)	(None, 16, 3, 3, 128)	0
conv3d_17 (Conv3D)	(None, 16, 3, 3, 256)	884,992
batch_normalization_17 (BatchNormalization)	(None, 16, 3, 3, 256)	1,024
max_pooling3d_17 (MaxPooling3D)	(None, 16, 1, 1, 256)	0
flatten_3 (Flatten)	(None, 4096)	0
dense_6 (Dense)	(None, 512)	2,097,664
dropout_3 (Dropout)	(None, 512)	0
dense_7 (Dense)	(None, 5)	2,565

Figure 17

3D-CNN Model Architecture

Figure 17 presents the architecture and parameter summary of the 3D Convolutional Neural Network (3D-CNN) used for real-time crowd behavior monitoring and control. The model consists of multiple layers, including 3D convolutional layers, batch normalization, max-pooling layers, flattening, dense layers, and dropout, all contributing to processing and understanding spatial and temporal features from crowd movement data.

The Conv3D layers apply 3D filters to detect essential patterns in space (such as movement structures) and time (such as behavioral changes). The prototype uses fewer filters (8) and progressively increases the count (up to 256) to capture finer details. Batch Normalization stabilizes learning by normalizing activations, making training faster and more efficient. Max-Pooling layers progressively reduce the spatial dimensions of the data while preserving significant information, improving computational efficiency. Finally, fully connected (Dense) and Dropout layers help in decision-making and prevent overfitting, leading to better classification of crowd behaviors.

Table 8

Parameter Breakdown of the Model

The table consists of 10,144,865 total parameters (38.70 MB), categorized as follows:

Parameter Type	**Parameter Count & Size**	**Description**
Trainable Parameters	3,381,253 (12.90 MB)	These are the parameters that the model learns during training.

		The model includes weights and biases that get updated through a process where the model learns from its errors.
Non-Trainable Parameters	1,104 (4.31 KB)	These parameters were fixed during training but have not been updated.
Optimizer Parameters	6,762,508 (25.80 MB)	The optimizer uses additional parameters to improve training efficiency by storing momentum, moving averages, and second-order moments.

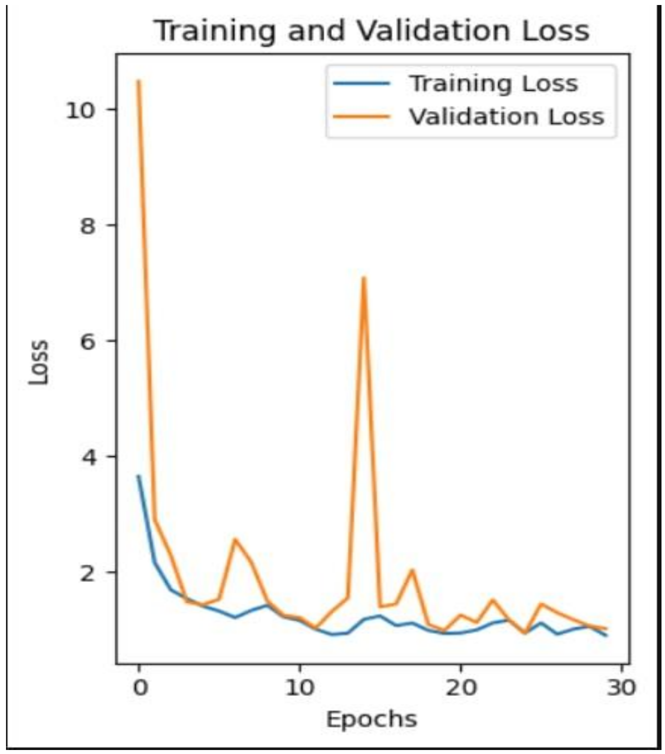


Figure 18

Training and Validation Loss Over Epochs

Figure 18 shows how the error changes over time during training. The blue line represents the training error, steadily decreasing as learning progresses. The orange line represents the validation error, which is more unpredictable, with ups and downs. This means that while performance improves, it might not be reliable when predicting new data.

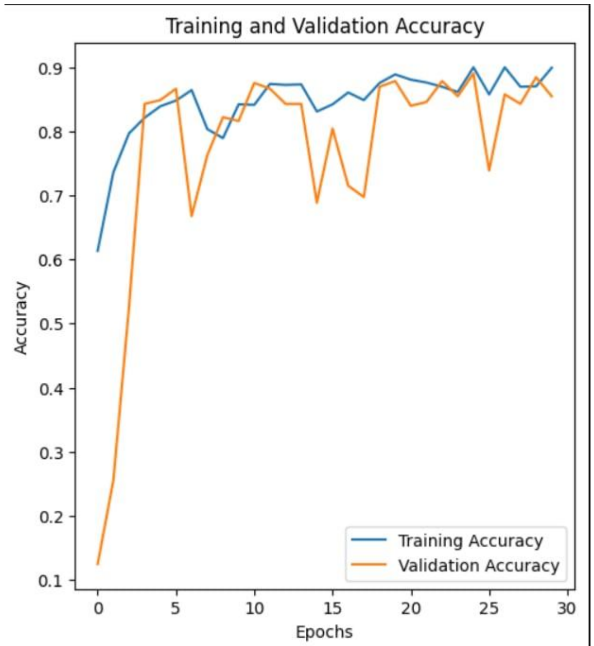


Figure 19

Training and Validation Accuracy Over Epochs

Figure 19 shows how accuracy improves over time during training. The blue line represents training accuracy, which improves as learning continues. The orange line represents validation accuracy, which goes up and down but generally improves. This means the learning process is working, but the results on new data are not always consistent, which could be a sign of overfitting.

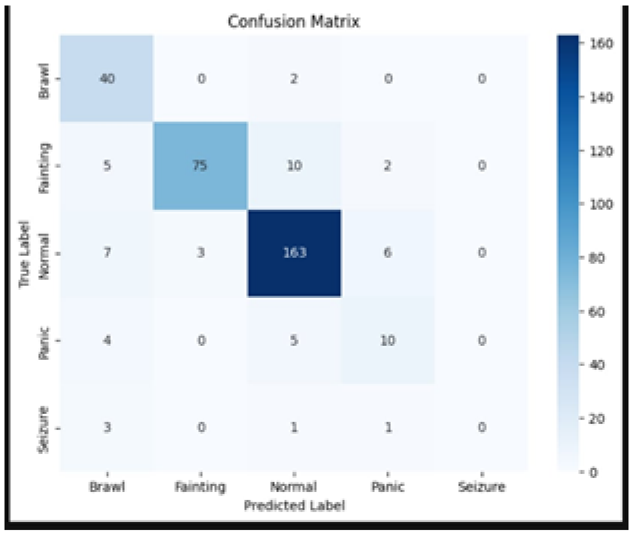


Figure 20

Confusion Matrix for Real-Time Crowd Behavior Classification using 3D-CNN

Figure 20 evaluates the performance of a real-time crowd behavior control and monitoring system using a 3D-Convolutional Neural Network (3D-CNN). The matrix shows how well the model predicts different crowd behaviors, comparing actual (accurate labels) behaviors to predicted behaviors.

The diagonal values represent correctly classified behaviors, with the highest accuracy observed for Normal behavior (163 correct predictions). Off-diagonal values indicate misclassifications, where specific behaviors were incorrectly predicted as others. For example, some instances of Fainting were misclassified as Normal, and Panic was occasionally mistaken for Brawl.

Table 9

Model: Brawl (Training 1)

	Normal		**Brawl Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Normal	True Negative	Brawl Detected	True Positive
2	Normal	True Negative	Brawl Detected	True Positive
3	Normal	True Negative	Brawl Detected	True Positive
4	Normal	True Negative	Brawl Detected	True Positive
5	Normal	True Negative	Brawl Detected	True Positive
6	Normal	True Negative	Brawl Detected	True Positive
7	Brawl Detected	False Negative	Normal	False Positive
8	Brawl Detected	False Negative	Normal	False Positive
9	Brawl Detected	False Negative	Normal	False Positive

10	Brawl Detected	False Negative	Brawl Detected	True Positive
11	Brawl Detected	False Negative	Brawl Detected	True Positive
12	Normal	True Negative	Normal	False Positive
13	Normal	True Negative	Brawl Detected	True Positive
14	Normal	True Negative	Brawl Detected	True Positive
15	Normal	True Negative	Brawl Detected	True Positive
16	Normal	True Negative	Brawl Detected	True Positive
17	Normal	True Negative	Brawl Detected	True Positive
18	Normal	True Negative	Brawl Detected	True Positive
19	Normal	True Negative	Normal	False Positive
20	Brawl Detected	False Negative	Brawl Detected	True Positive
21	Brawl Detected	False Negative	Brawl Detected	True Positive

22	Brawl Detected	False Negative	Normal	False Positive
23	Brawl Detected	False Negative	Normal	False Positive
24	Normal	True Negative	Brawl Detected	True Positive
25	Normal	True Negative	Brawl Detected	True Positive
26	Normal	True Negative	Brawl Detected	True Positive
27	Normal	True Negative	Brawl Detected	True Positive
28	Normal	True Negative	Brawl Detected	True Positive
29	Normal	True Negative	Brawl Detected	True Positive
30	Normal	True Negative	Brawl Detected	True Positive

Table 10

Tally of Model: Brawl (Training 1)

(N=30)

Metrics	**Count**
True Positives (TP)	23
True Negatives (TN)	21

False Positives (FP)	7
False Negatives (FN)	9
Accuracy	**73.33%**

Table 9 and 10 shows the results of the initial test prediction for identifying Brawl and non-brawl situations are presented in the table. The analysis involved 30 samples of test video, with the model identifying 23 brawl scenarios as True Positives and 21 non-brawl scenarios as True Negatives. However, the model also misclassified seven non-brawl situations as brawls (False Positives) and failed to detect nine actual brawls (False Negatives). These findings suggest that while the AI model is generally reliable in distinguishing between brawl and non-brawl events, it still shows some margin for error, particularly in over-predicting brawl events. The model's overall accuracy was calculated at 73.33%, indicating a reasonably strong performance with room for improvement.

Table 11

Model: Brawl (Training 2)

	Normal		**Brawl Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Normal	True Negative	Brawl Detected	False Positive
2	Normal	True Negative	Brawl Detected	True Positive

3	Normal	True Negative	Brawl Detected	True Positive
4	Normal	True Negative	Brawl Detected	True Positive
5	Normal	True Negative	Brawl Detected	True Positive
6	Normal	True Negative	Brawl Detected	True Positive
7	Normal	True Negative	Brawl Detected	True Positive
8	Normal	True Negative	Brawl Detected	True Positive
9	Normal	True Negative	Brawl Detected	True Positive
10	Normal	True Negative	Brawl Detected	True Positive
11	Brawl Detected	False Negative	Normal	False Positive
12	Normal	True Negative	Brawl Detected	True Positive
13	Normal	True Negative	Brawl Detected	True Positive
14	Normal	True Negative	Brawl Detected	True Positive

15	Normal	True Negative	Brawl Detected	True Positive
16	Normal	True Negative	Brawl Detected	True Positive
17	Normal	True Negative	Brawl Detected	True Positive
18	Normal	True Negative	Normal	False Positive
19	Normal	True Negative	Normal	False Positive
20	Normal	True Negative	Brawl Detected	True Positive
21	Normal	True Negative	Brawl Detected	True Positive
22	Brawl Detected	False Negative	Normal	False Positive
23	Normal	True Negative	Brawl Detected	True Positive
24	Brawl Detected	False Negative	Brawl Detected	True Positive
25	Normal	True Negative	Brawl Detected	True Positive
26	Normal	True Negative	Brawl Detected	True Positive

27	Normal	True Negative	Brawl Detected	True Positive
28	Normal	True Negative	Brawl Detected	True Positive
29	Normal	True Negative	Brawl Detected	True Positive
30	Normal	True Negative	Brawl Detected	True Positive

Table 12

Tally of Model: Brawl (Training 2)

(N=30)

Metrics	**Count**
True Positives (TP)	22
True Negatives (TN)	27
False Positives (FP)	8
False Negatives (FN)	3
Accuracy	**81.67%**

Table 11 and 12 shows the results of the second test prediction for identifying Brawl and non-brawl situations are presented in the table. The evaluation included 30 test video samples, with the model successfully identifying 22 brawl scenarios as True Positives and 27 non-brawl scenarios as True Negatives. However, it recorded 8 False Positives where non-brawl events were incorrectly classified as brawls, and 3 False Negatives where actual brawls were missed. The model achieved an accuracy of

81.67%, indicating strong performance in distinguishing brawl incidents from everyday scenarios, though a few misclassifications were still present.

Table 13

Model: Brawl (Training 3)

Testing Video	**Normal**		**Brawl Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Normal	True Negative	Brawl Detected	True Positive
2	Normal	True Negative	Brawl Detected	True Positive
3	Normal	True Negative	Brawl Detected	True Positive
4	Normal	True Negative	Brawl Detected	True Positive
5	Normal	True Negative	Brawl Detected	True Positive
6	Normal	True Negative	Brawl Detected	True Positive
7	Normal	True Negative	Brawl Detected	True Positive

8	Normal	True Negative	Brawl Detected	True Positive
9	Normal	True Negative	Brawl Detected	True Positive
10	Normal	True Negative	Brawl Detected	True Positive
11	Brawl Detected	False Negative	Brawl Detected	True Positive
12	Normal	True Negative	Normal	False Positive
13	Normal	True Negative	Brawl Detected	True Positive
14	Brawl Detected	False Negative	Brawl Detected	True Positive
15	Normal	True Negative	Normal	False Positive
16	Normal	True Negative	Brawl Detected	True Positive
17	Normal	True Negative	Brawl Detected	True Positive
18	Normal	True Negative	Brawl Detected	True Positive
19	Normal	True Negative	Brawl Detected	True Positive

20	Normal	True Negative	Brawl Detected	True Positive
21	Normal	True Negative	Brawl Detected	True Positive
22	Normal	True Negative	Brawl Detected	True Positive
23	Normal	True Negative	Normal	False Positive
24	Normal	True Negative	Brawl Detected	True Positive
25	Normal	True Negative	Brawl Detected	True Positive
26	Normal	True Negative	Brawl Detected	True Positive
27	Brawl Detected	False Negative	Brawl Detected	True Positive
28	Brawl Detected	False Negative	Brawl Detected	True Positive
29	Normal	True Negative	Brawl Detected	True Positive
30	Normal	True Negative	Brawl Detected	True Positive

Table 14

Tally of Model: Brawl (Training 3)

(N=30)

Metric	**Count**
True Positive (TP)	27
True Negative (TN)	26
False Positive (FP)	3
False Negative (FN)	4
Accuracy (%)	**88.33%**

Table 13 and 14 shows the results of the third test prediction for identifying Brawl and non-brawl situations are presented in the table. The analysis involved 30 test video samples, with the AI model accurately identifying 27 brawl scenarios as True Positives and 26 non-brawl scenarios as True Negatives. The model made 3 False Positive predictions, incorrectly labeling everyday situations as brawls, and 4 False Negatives, missing actual brawl events. Achieving an accuracy of 88.33%, this model demonstrates a high level of precision in distinguishing between brawl and non-brawl scenarios, while allowing room for slight improvements in reducing false predictions.

Table 15

Model: Brawl (Training 4)

Testing Video	**Normal**		**Brawl** **Prediction**	

	Prediction	Verdict	**Prediction**	Verdict
1	Normal	True Negative	Brawl Detected	True Positive
2	Normal	True Negative	Brawl Detected	True Positive
3	Normal	True Negative	Brawl Detected	True Positive
4	Normal	True Negative	Brawl Detected	True Positive
5	Normal	True Negative	Brawl Detected	True Positive
6	Normal	True Negative	Brawl Detected	True Positive
7	Normal	True Negative	Brawl Detected	True Positive
8	Normal	True Negative	Brawl Detected	True Positive
9	Normal	True Negative	Brawl Detected	True Positive
10	Normal	True Negative	Brawl Detected	True Positive
11	Normal	True Negative	Brawl Detected	True Positive
12	Normal	True Negative	Brawl Detected	True Positive

13	Normal	True Negative	Brawl Detected	True Positive
14	Normal	True Negative	Brawl Detected	True Positive
15	Normal	True Negative	Brawl Detected	True Positive
16	Normal	True Negative	Brawl Detected	True Positive
17	Normal	True Negative	Normal	False Positive
18	Normal	True Negative	Normal	False Positive
19	Normal	True Negative	Brawl Detected	True Positive
20	Normal	True Negative	Brawl Detected	True Positive
21	Normal	True Negative	Brawl Detected	True Positive
22	Brawl Detected	False Negative	Normal	False Positive
23	Normal	True Negative	Brawl Detected	True Positive
24	Brawl Detected	False Negative	Brawl Detected	True Positive

25	Normal	True Negative	Brawl Detected	True Positive
26	Normal	True Negative	Brawl Detected	True Positive
27	Normal	True Negative	Brawl Detected	True Positive
28	Normal	True Negative	Brawl Detected	True Positive
29	Normal	True Negative	Brawl Detected	True Positive
30	Normal	True Negative	Brawl Detected	True Positive

Table 16

Tally of Model: Brawl (Training 4)

(N=30)

Metrics	**Count**
True Positives (TP)	27
True Negatives (TN)	28
False Positives (FP)	3
False Negatives (FN)	2
Accuracy	**91.67%**

Tables 15 and 16 show the results of the fourth test prediction for identifying Brawl and non-brawl situations. The analysis involved 30 test video samples, with the AI model accurately identifying 27 brawl scenarios as True Positives and 28 non-brawl scenarios as True Negatives. The model made 3 False Positive predictions, incorrectly labeling a normal situation as a brawl, and 2 False Negative predictions, missing actual brawl events. Achieving an accuracy of 91.67%, this model demonstrates strong performance in distinguishing brawl scenarios, with minimal misclassifications.

Table 17

Model: Fainting (Training 1)

	Normal		**Fainting Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Fainting Detected	False Negative	Fainting Detected	True Positive
2	Normal	True Negative	Fainting Detected	True Positive
3	Fainting Detected	False Negative	Normal	False Positive
4	Normal	True Negative	Fainting Detected	True Positive
5	Normal	True Negative	Fainting Detected	True Positive

6	Normal	True Negative	Fainting Detected	True Positive
7	Fainting Detected	False Negative	Normal	False Positive
8	Normal	True Negative	Fainting Detected	True Positive
9	Normal	True Negative	Fainting Detected	True Positive
10	Fainting Detected	False Negative	Normal	False Positive
11	Fainting Detected	False Negative	Fainting Detected	True Positive
12	Normal	True Negative	Fainting Detected	True Positive
13	Normal	True Negative	Fainting Detected	True Positive
14	Fainting Detected	False Negative	Normal	False Positive
15	Normal	True Negative	Fainting Detected	True Positive
16	Fainting Detected	False Negative	Normal	False Positive
17	Fainting Detected	False Negative	Fainting Detected	True Positive

18	Fainting Detected	False Negative	Normal	False Positive
19	Normal	True Negative	Fainting Detected	True Positive
20	Fainting Detected	False Negative	Fainting Detected	True Positive
21	Fainting Detected	False Negative	Normal	False Positive
22	Normal	True Negative	Fainting Detected	True Positive
23	Normal	True Negative	Fainting Detected	True Positive
24	Fainting Detected	False Negative	Normal	False Positive
25	Fainting Detected	False Negative	Fainting Detected	True Positive
26	Normal	True Negative	Fainting Detected	True Positive
27	Normal	True Negative	Fainting Detected	True Positive
28	Fainting Detected	False Negative	Normal	False Positive
29	Fainting Detected	False Negative	Normal	False Positive

30	Normal	True Negative	Fainting Detected	True Positive

Table 18

Tally of Model: Fainting (Training 1)

(N=30)

Metrics	**Count**
True Positives (TP)	20
True Negatives (TN)	15
False Positives (FP)	10
False Negatives (FN)	15
Accuracy	**58.33%**

Tables 17 and 18 show the results of the initial test prediction for identifying threatening and non-fainting situations. The analysis involved 30 samples of test video, where the model accurately identified 20 fainting scenarios as True Positives and 15 non-fainting scenarios as True Negatives. However, it also recorded 10 False Positives, where non-fainting instances were mistakenly detected as Fainting, and 15 False Negatives, where actual fainting cases were not detected. The model achieved an accuracy of 58.33%, suggesting a relatively low performance in correctly distinguishing between Fainting and non-fainting events, with significant room for improvement in minimizing misclassifications.

Table 19

Model: Fainting (Training 2)

	Normal		**Fainting Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Normal	True Negative	Fainting Detected	False Negative
2	Normal	True Negative	Fainting Detected	False Negative
3	Normal	True Negative	Fainting Detected	True Positive
4	Normal	False Positive	Fainting Detected	True Positive
5	Normal	True Negative	Fainting Detected	True Positive
6	Normal	True Negative	Fainting Detected	True Positive
7	Normal	True Negative	Fainting Detected	True Positive
8	Normal	False Positive	Fainting Detected	True Positive
9	Normal	True Negative	Fainting Detected	True Positive
10	Normal	True Negative	Fainting Detected	False Negative
11	Normal	True Negative	Fainting Detected	True Positive
12	Normal	True Negative	Fainting Detected	False Negative
13	Normal	True Negative	Fainting Detected	True Positive
14	Normal	True Negative	Fainting Detected	True Positive
15	Normal	True Negative	Fainting Detected	True Positive

16	Normal	True Negative	Fainting Detected	False Negative
17	Normal	True Negative	Fainting Detected	False Negative
18	Normal	False Positive	Fainting Detected	False Negative
19	Normal	False Positive	Fainting Detected	True Positive
20	Normal	True Negative	Fainting Detected	True Positive
21	Normal	True Negative	Fainting Detected	True Positive
22	Normal	True Negative	Fainting Detected	True Positive
23	Normal	True Negative	Fainting Detected	True Positive
24	Normal	False Positive	Fainting Detected	True Positive
25	Normal	False Positive	Fainting Detected	True Positive
26	Normal	True Negative	Fainting Detected	True Positive
27	Normal	False Positive	Fainting Detected	True Positive
28	Normal	True Negative	Fainting Detected	True Positive
29	Normal	False Positive	Fainting Detected	False Negative
30	Fainting Detected	False Negative	Fainting Detected	True Positive

Table 20

Tally of Model: Fainting (Training 2)

(N=30)

Metric	Count
True Positive (TP)	22
True Negative (TN)	21
False Positive (FP)	8
False Negative (FN)	9
Accuracy (%)	**71.67%**

Tables 19 and 20 show the results of the second test prediction for identifying fainting and non-fainting situations. The model was tested on 30 samples, accurately detecting 22 fainting cases as True Positives and correctly identifying 21 non-fainting cases as True Negatives. However, it also recorded 8 False Positives, incorrectly detecting fainting in everyday scenarios, and 9 False Negatives, failing to identify actual fainting events. The model demonstrates moderate effectiveness with an accuracy of 70.00%, though some refinement may be needed to reduce misclassifications.

Table 21

Model: Fainting (Training 3)

	Normal		**Fainting Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Normal	True Negative	Fainting Detected	True Positive
2	Normal	True Negative	Fainting Detected	True Positive
3	Normal	True Negative	Fainting Detected	True Positive
4	Normal	True Negative	Normal	True Positive

5	Normal	True Negative	Normal	True Positive
6	Normal	True Negative	Normal	True Positive
7	Normal	True Negative	Normal	True Positive
8	Normal	True Negative	Fainting Detected	True Positive
9	Normal	True Negative	Fainting Detected	True Positive
10	Fainting Detected	False Negative	Fainting Detected	True Positive
11	Normal	True Negative	Fainting Detected	True Positive
12	Normal	True Negative	Normal	False Positive
13	Normal	True Negative	Fainting Detected	True Positive
14	Normal	True Negative	Fainting Detected	True Positive
15	Fainting Detected	False Negative	Fainting Detected	True Positive
16	Fainting Detected	False Negative	Normal	True Positive
17	Normal	True Negative	Normal	True Positive
18	Fainting Detected	False Negative	Normal	True Positive
19	Fainting Detected	False Negative	Normal	True Positive
20	Normal	True Negative	Fainting Detected	True Positive
21	Normal	True Negative	Fainting Detected	True Positive
22	Fainting Detected	False Negative	Fainting Detected	True Positive

23	Normal	True Negative	Normal	False Positive
24	Fainting Detected	False Negative	Normal	False Positive
25	Normal	True Negative	Fainting Detected	True Positive
26	Normal	True Negative	Fainting Detected	True Positive
27	Normal	True Negative	Fainting Detected	True Positive
28	Normal	True Negative	Fainting Detected	True Positive
29	Fainting Detected	False Negative	Normal	False Positive
30	Fainting Detected	False Negative	Fainting Detected	True Positive

Table 22

Tally of Model: Fainting (Training 3)

(N=30)

Metric	**Count**
True Positive (TP)	24
True Negative (TN)	21
False Positive (FP)	6
False Negative (FN)	9
Accuracy (%)	**75.0%**

Tables 21 and 22 show the results of the third test prediction for identifying fainting and non-fainting situations. The analysis involved 30 test video samples, with the AI model accurately identifying 24 fainting scenarios as True Positives and 21 non-fainting scenarios as True Negatives. The model made six false-positive predictions, incorrectly labeling everyday situations as fainting, and 9 False Negatives, missing actual fainting events. Achieving an accuracy of 75.00%, this model performs well in detecting fainting scenarios, with room for improvement in reducing false positives and false negatives.

Table 23

Model: Fainting (Training 4)

	Normal		**Fainting Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Normal	True Negative	Fainting Detected	True Positive
2	Normal	True Negative	Fainting Detected	True Positive
3	Fainting Detected	False Negative	Fainting Detected	True Positive
4	Normal	True Negative	Fainting Detected	True Positive
5	Fainting Detected	False Negative	Fainting Detected	True Positive
6	Normal	True Negative	Fainting Detected	True Positive
7	Normal	True Negative	Fainting Detected	True Positive
8	Normal	True Negative	Fainting Detected	True Positive
9	Normal	True Negative	Fainting Detected	True Positive
10	Normal	True Negative	Fainting Detected	True Positive
11	Normal	True Negative	Fainting Detected	True Positive
12	Normal	True Negative	Normal	False Positive
13	Normal	True Negative	Fainting Detected	True Positive

14	Normal	True Negative	Fainting Detected	True Positive
15	Fainting Detected	False Negative	Fainting Detected	True Positive
16	Fainting Detected	False Negative	Fainting Detected	True Positive
17	Normal	True Negative	Fainting Detected	True Positive
18	Normal	True Negative	Fainting Detected	True Positive
19	Normal	True Negative	Fainting Detected	True Positive
20	Normal	True Negative	Fainting Detected	True Positive
21	Normal	True Negative	Fainting Detected	True Positive
22	Fainting Detected	False Negative	Fainting Detected	True Positive
23	Normal	True Negative	Fainting Detected	True Positive
24	Normal	True Negative	Normal	False Positive
25	Normal	True Negative	Fainting Detected	True Positive
26	Normal	True Negative	Fainting Detected	True Positive
27	Normal	True Negative	Fainting Detected	True Positive
28	Normal	True Negative	Fainting Detected	True Positive
29	Fainting Detected	False Negative	Fainting Detected	True Positive
30	Fainting Detected	False Negative	Fainting Detected	True Positive

Table 24

Tally of Model: Fainting (Training 4)

(N=30)

Metrics	**Count**
True Positives (TP)	28
True Negatives (TN)	23
False Positives (FP)	2
False Negatives (FN)	7
Accuracy	**85%**

Tables 23 and 24 show the results of the fourth test prediction for identifying fainting and non-fainting situations. The analysis involved 30 test video samples, with the AI model accurately identifying 28 fainting scenarios as True Positives and 23 non-fainting scenarios as True Negatives. The model made two false-positive predictions, incorrectly labeling everyday situations as fainting, and 7 False Negatives, missing actual fainting events. Achieving an accuracy of 85%, this model demonstrates moderate reliability in detecting fainting scenarios, with potential for improvement, especially in minimizing missed cases.

Table 25

Model: Panic (Training 1)

	Normal		**Panic Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Panic Detected	False Negative	Panic Detected	True Positive
2	Normal	True Negative	Panic Detected	True Positive
3	Panic Detected	False Negative	Normal	False Positive

4	Normal	True Negative	Normal	False Positive
5	Panic Detected	False Negative	Normal	False Positive
6	Panic Detected	False Negative	Normal	False Positive
7	Normal	True Negative	Normal	False Positive
8	Normal	True Negative	Normal	False Positive
9	Panic Detected	False Negative	Panic Detected	True Positive
10	Panic Detected	False Negative	Panic Detected	True Positive
11	Normal	False Negative	Panic Detected	True Positive
12	Normal	True Negative	Normal	False Positive
13	Panic Detected	False Negative	Panic Detected	True Positive
14	Panic Detected	False Negative	Normal	False Positive
15	Panic Detected	False Negative	Normal	False Positive
16	Panic Detected	False Negative	Panic Detected	True Positive
17	Panic Detected	False Negative	Panic Detected	True Positive
18	Panic Detected	False Negative	Normal	False Positive
19	Panic Detected	False Negative	Normal	False Positive
20	Normal	True Negative	Panic Detected	True Positive
21	Panic Detected	False Negative	Panic Detected	True Positive

22	Panic Detected	False Negative	Panic Detected	True Positive
23	Panic Detected	False Negative	Panic Detected	True Positive
24	Panic Detected	False Negative	Panic Detected	True Positive
25	Normal	True Negative	Normal	False Positive
26	Normal	True Negative	Panic Detected	True Positive
27	Panic Detected	False Negative	Panic Detected	True Positive
28	Panic Detected	False Negative	Panic Detected	True Positive
29	Panic Detected	False Negative	Panic Detected	True Positive
30	Normal	True Negative	Panic Detected	True Positive

Table 26

Tally of Model: Panic (Training 1)

(N=30)

Metrics	**Count**
True Positives (TP)	18
True Negatives (TN)	19
False Positives (FP)	12
False Negatives (FN)	11
Accuracy	**61.67%**

Table 25 and 26 shows the results of the initial test prediction for identifying panic and non-panic situations are presented in the table. The analysis involved 30 samples of test video, where the model identified 18 panic scenarios as True Positives and 19 non-panic scenarios as True Negatives. However, it misclassified 12 non-panic instances as panic (False Positives) and failed to detect 11 actual panic cases (False Negatives). These outcomes highlight that the AI model struggles with distinguishing panic events, showing a notable number of incorrect classifications. The model's overall accuracy was 61.67%, indicating a moderate performance and suggesting further refinement to enhance detection reliability.

Table 27

Model: Panic (Training 2)

	Normal		**Panic Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Normal	True Negative	Normal	False Positive
2	Normal	True Negative	Panic Detected	True Positive
3	Panic Detected	False Negative	Normal	False Positive
4	Normal	True Negative	Normal	False Positive
5	Normal	True Negative	Panic Detected	True Positive
6	Normal	True Negative	Panic Detected	True Positive
7	Normal	True Negative	Panic Detected	True Positive
8	Normal	True Negative	Panic Detected	True Positive
9	Normal	True Negative	Normal	False Positive
10	Normal	True Negative	Panic Detected	True Positive
11	Normal	True Negative	Panic Detected	True Positive
12	Panic Detected	False Negative	Panic Detected	True Positive

13	Normal	True Negative	Panic Detected	True Positive
14	Normal	True Negative	Panic Detected	True Positive
15	Normal	True Negative	Panic Detected	True Positive
16	Normal	True Negative	Panic Detected	True Positive
17	Panic Detected	False Negative	Panic Detected	True Positive
18	Normal	True Negative	Panic Detected	True Positive
19	Panic Detected	False Negative	Panic Detected	True Positive
20	Panic Detected	False Negative	Panic Detected	True Positive
21	Panic Detected	False Negative	Panic Detected	True Positive
22	Normal	True Negative	Panic Detected	True Positive
23	Normal	True Negative	Panic Detected	True Positive
24	Normal	True Negative	Panic Detected	True Positive
25	Normal	True Negative	Panic Detected	True Positive
26	Panic Detected	False Negative	Panic Detected	True Positive
27	Normal	True Negative	Panic Detected	True Positive
28	Panic Detected	False Negative	Normal	False Positive
29	Normal	True Negative	Panic Detected	True Positive
30	Normal	True Negative	Normal	False Positive

Table 28

Tally Model: Panic (Training 2)

Metric	**Count**
True Positive (TP)	24
True Negative (TN)	22
False Positive (FP)	6
False Negative (FN)	8
Accuracy (%)	**76.67%**

Table 27 and 28 shows the results of the second test prediction for identifying panic and non-panic situations are presented in the table. This evaluation involved 30 samples, where the model accurately detected 24 panic incidents as True Positives and 22 non-panic cases as True Negatives. Despite its overall solid performance, the model recorded 6 False Positives, everyday scenarios incorrectly flagged as panic, and 8 False Negatives, missed panic incidents. With an accuracy of 76.67%, the model demonstrates competent capability in detecting panic events while maintaining a relatively low error rate.

Table 29

Model: Panic (Training 3)

	Normal		**Panic Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Panic Detected	False Negative	Panic Detected	True Positive
2	Normal	True Negative	Panic Detected	True Positive
3	Normal	True Negative	Panic Detected	True Positive

4	Normal	True Negative	Panic Detected	True Positive
5	Panic Detected	False Negative	Panic Detected	True Positive
6	Normal	True Negative	Panic Detected	True Positive
7	Panic Detected	False Negative	Panic Detected	True Positive
8	Normal	True Negative	Panic Detected	True Positive
9	Normal	True Negative	Panic Detected	True Positive
10	Normal	True Negative	Panic Detected	True Positive
11	Normal	True Negative	Normal	False Positive
12	Normal	True Negative	Panic Detected	True Positive
13	Panic Detected	False Negative	Panic Detected	True Positive
14	Normal	True Negative	Panic Detected	True Positive
15	Panic Detected	False Negative	Normal	False Positive
16	Panic Detected	False Negative	Panic Detected	True Positive
17	Normal	True Negative	Panic Detected	True Positive
18	Panic Detected	False Negative	Normal	False Positive
19	Normal	True Negative	Panic Detected	True Positive
20	Normal	True Negative	Panic Detected	True Positive
21	Normal	True Negative	Panic Detected	True Positive

22	Panic Detected	False Negative	Panic Detected	True Positive
23	Normal	True Negative	Panic Detected	True Positive
24	Normal	True Negative	Normal	False Positive
25	Normal	True Negative	Panic Detected	True Positive
26	Panic Detected	False Negative	Panic Detected	True Positive
27	Panic Detected	False Negative	Panic Detected	True Positive
28	Panic Detected	False Negative	Panic Detected	True Positive
29	Normal	True Negative	Panic Detected	True Positive
30	Normal	True Negative	Panic Detected	True Positive

Table 30

Tally of Model: Panic (Training 3)

(N=30)

Metrics	**Count**
True Positives (TP)	23
True Negatives (TN)	24
False Positives (FP)	7
False Negatives (FN)	6
Accuracy	**78.33%**

Tables 29 and 30 show the results of the third test prediction for identifying panic and non-panic situations. The analysis involved 30 test video samples, with the AI model accurately identifying 23 panic scenarios as True Positives and 24 non-panic scenarios as True Negatives. The model made seven false-positive predictions, incorrectly labeling everyday situations as panic, and 6 False Negatives, missing actual panic events. Achieving an accuracy of 78.33%, this model shows fair performance in distinguishing panic from non-panic scenarios, though improvements in minimizing false predictions are still needed.

Table 31

Model: Panic (Training 4)

	Normal		**Panic Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Panic Detected	False Negative	Panic Detected	True Positive
2	Normal	True Negative	Panic Detected	True Positive
3	Panic Detected	False Negative	Panic Detected	True Positive
4	Normal	True Negative	Panic Detected	True Positive
5	Normal	True Negative	Panic Detected	True Positive
6	Normal	True Negative	Panic Detected	True Positive
7	Normal	True Negative	Panic Detected	True Positive
8	Normal	True Negative	Panic Detected	True Positive
9	Normal	True Negative	Panic Detected	True Positive
10	Normal	True Negative	Panic Detected	True Positive
11	Normal	True Negative	Panic Detected	True Positive

12	Normal	True Negative	Normal	False Positive
13	Normal	True Negative	Panic Detected	True Positive
14	Normal	True Negative	Normal	False Positive
15	Panic Detected	False Negative	Panic Detected	True Positive
16	Normal	True Negative	Panic Detected	True Positive
17	Normal	True Negative	Panic Detected	True Positive
18	Normal	True Negative	Panic Detected	True Positive
19	Normal	True Negative	Panic Detected	True Positive
20	Normal	True Negative	Panic Detected	True Positive
21	Normal	True Negative	Panic Detected	True Positive
22	Normal	True Negative	Panic Detected	True Positive
23	Normal	True Negative	Normal	False Positive
24	Panic Detected	True Positive	Panic Detected	True Positive
25	Normal	True Negative	Normal	False Positive
26	Normal	True Negative	Panic Detected	True Positive
27	Panic Detected	False Negative	Panic Detected	True Positive
28	Panic Detected	False Negative	Panic Detected	True Positive
29	Normal	True Negative	Panic Detected	True Positive
30	Normal	True Negative	Panic Detected	True Positive

Table 32

Tally of Model: Panic (Training 4)

(N=30)

Verdict Type	**Count**
True Positive (TP)	27
True Negative (TN)	24
False Positive (FP)	3
False Negative (FN)	6
Accuracy	**85%**

Tables 31 and 32 show the results of the fourth test prediction for identifying panic and non-panic situations. The analysis involved 30 test video samples, with the AI model accurately identifying 27 panic scenarios as True Positives and 24 non-panic scenarios as True Negatives. The model made three false-positive predictions, incorrectly labeling everyday situations as panic, and 6 False Negatives, missing actual panic events. Achieving an accuracy of 85%, this model shows good performance in detecting panic scenarios, with room for improvement in reducing false alarms and missed events.

Table 33

Model: Brawl, Fainting, Panic (Training 1)

	Non - Normal		**Normal Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Non-Normal	True Negative	Normal Detected	True Positive
2	Non-Normal	True Negative	Normal Detected	True Positive

3	Normal Detected	False Negative	Normal Detected	True Positive
4	Normal Detected	False Negative	Non-Normal	False Positive
5	Non-Normal	True Negative	Non-Normal	False Positive
6	Non-Normal	True Negative	Non-Normal	False Positive
7	Non-Normal	True Negative	Normal Detected	True Positive
8	Normal Detected	False Negative	Normal Detected	True Positive
9	Non-Normal	True Negative	Normal Detected	True Positive
10	Non-Normal	True Negative	Non-Normal	False Positive
11	Normal Detected	False Negative	Normal Detected	True Positive
12	Non-Normal	True Negative	Normal Detected	True Positive
13	Non-Normal	True Negative	Normal Detected	True Positive
14	Non-Normal	True Negative	Normal Detected	True Positive
15	Non-Normal	True Negative	Normal Detected	True Positive
16	Normal Detected	False Negative	Normal Detected	True Positive
17	Non-Normal	True Negative	Normal Detected	True Positive
18	Non-Normal	True Negative	Normal Detected	True Positive
19	Non-Normal	True Negative	Non-Normal	False Positive
20	Non-Normal	True Negative	Normal Detected	True Positive

21	Non-Normal	True Negative	Normal Detected	True Positive
22	Normal Detected	False Negative	Normal Detected	True Positive
23	Non-Normal	True Negative	Normal Detected	True Positive
24	Non-Normal	True Negative	Normal Detected	True Positive
25	Non-Normal	True Negative	Normal Detected	True Positive
26	Non-Normal	True Negative	Normal Detected	True Positive
27	Normal Detected	False Negative	Normal Detected	True Positive
28	Non-Normal	True Negative	Normal Detected	True Positive
29	Non-Normal	True Negative	Normal Detected	True Positive
30	Non-Normal	True Negative	Normal Detected	True Positive

Table 34

Tally of Model: Brawl, Fainting, Panic (Training 1)

(N=30)

Metric	**Count**
True Positive (TP)	24
True Negative (TN)	23
False Positive (FP)	6
False Negative (FN)	7
Accuracy (%)	**78.33%**

Tables 33 and 34 present the results of the first test prediction for identifying everyday and non-normal situations using the standard dataset. Out of 30 test video samples, the AI model successfully identified 24 everyday scenarios as True Positives and 23 non-normal scenarios as True Negatives. However, it also made 6 False Positive predictions, misclassifying non-normal events as usual, and 7 False Negatives, where actual regular events were misclassified as non-normal. With an accuracy of 78.33%, the model demonstrates solid performance. However, the occurrence of False Negatives indicates a need for improvement in accurately identifying everyday situations, reducing the chances of missing potential typical cases.

Table 35

Model: Brawl, Fainting, Panic (Training 2)

	Non - Normal		**Normal Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Non-Normal	True Negative	Normal Detected	True Positive
2	Non-Normal	True Negative	Normal Detected	True Positive
3	Non-Normal	True Negative	Normal Detected	True Positive
4	Non-Normal	True Negative	Normal Detected	True Positive
5	Non-Normal	True Negative	Normal Detected	True Positive
6	Non-Normal	True Negative	Normal Detected	True Positive
7	Non-Normal	True Negative	Normal Detected	True Positive

8	Non-Normal	True Negative	Normal Detected	True Positive
9	Non-Normal	True Negative	Normal Detected	True Positive
10	Non-Normal	True Negative	Non-Normal	False Positive
11	Non-Normal	True Negative	Normal Detected	True Positive
12	Non-Normal	True Negative	Normal Detected	True Positive
13	Non-Normal	True Negative	Normal Detected	True Positive
14	Non-Normal	True Negative	Normal Detected	True Positive
15	Non-Normal	True Negative	Normal Detected	True Positive
16	Normal Detected	False Negative	Normal Detected	True Positive
17	Non-Normal	True Negative	Normal Detected	True Positive
18	Non-Normal	True Negative	Normal Detected	True Positive
19	Non-Normal	True Negative	Non-Normal	False Positive
20	Non-Normal	True Negative	Normal Detected	True Positive
21	Non-Normal	True Negative	Normal Detected	True Positive
22	Normal Detected	False Negative	Normal Detected	True Positive
23	Non-Normal	True Negative	Normal Detected	True Positive
24	Non-Normal	True Negative	Normal Detected	True Positive
25	Non-Normal	True Negative	Normal Detected	True Positive

26	Non-Normal	True Negative	Normal Detected	True Positive
27	Normal Detected	False Negative	Non-Normal	False Positive
28	Non-Normal	True Negative	Normal Detected	True Positive
29	Non-Normal	True Negative	Normal Detected	True Positive
30	Non-Normal	True Negative	Normal Detected	True Positive

Table 36

Tally of Model: Brawl, Fainting, Panic (Training 2)

(N=30)

Metric	**Count**
True Positives (TP)	26
True Negatives (TN)	27
False Positives (FP)	4
False Negatives (FN)	3
Accuracy (%)	**88.33%**

Tables 35 and 36 show the results of the second test prediction for identifying everyday and non-normal situations. The analysis involved 30 test video samples, with the AI model correctly identifying 26 brawl scenarios as True Positives and 27 non-brawl scenarios as True Negatives. However, the model made 4 False Positive predictions, incorrectly classifying everyday situations as non-normal, and 3 False Negatives, where a typical scenario was missed. With an accuracy of 88.33%, this model maintains a good level of performance, although the slightly higher number of false predictions suggests room for improvement in precision and recall.

Table 37

Model: Brawl, Fainting, Panic (Training 3)

	Non - Normal		**Normal Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Non-Normal	True Negative	Normal Detected	True Positive
2	Non-Normal	True Negative	Normal Detected	True Positive
3	Non-Normal	True Negative	Normal Detected	True Positive
4	Non-Normal	True Negative	Normal Detected	True Positive
5	Non-Normal	True Negative	Normal Detected	True Positive
6	Non-Normal	True Negative	Normal Detected	True Positive
7	Non-Normal	True Negative	Normal Detected	True Positive
8	Non-Normal	True Negative	Normal Detected	True Positive
9	Non-Normal	True Negative	Normal Detected	True Positive
10	Non-Normal	True Negative	Non-Normal	False Positive
11	Non-Normal	True Negative	Normal Detected	True Positive
12	Non-Normal	True Negative	Normal Detected	True Positive
13	Non-Normal	True Negative	Normal Detected	True Positive
14	Non-Normal	True Negative	Normal Detected	True Positive
15	Non-Normal	True Negative	Normal Detected	True Positive

16	Normal Detected	False Negative	Non-Normal	False Positive
17	Non-Normal	True Negative	Normal Detected	True Positive
18	Non-Normal	True Negative	Normal Detected	True Positive
19	Non-Normal	True Negative	Normal Detected	True Positive
20	Non-Normal	True Negative	Normal Detected	True Positive
21	Non-Normal	True Negative	Normal Detected	True Positive
22	Normal Detected	False Negative	Normal Detected	True Positive
23	Non-Normal	True Negative	Normal Detected	True Positive
24	Non-Normal	True Negative	Normal Detected	True Positive
25	Non-Normal	True Negative	Normal Detected	True Positive
26	Non-Normal	True Negative	Normal Detected	True Positive
27	Normal Detected	False Negative	Non-Normal	False Positive
28	Non-Normal	True Negative	Normal Detected	True Positive
29	Non-Normal	True Negative	Normal Detected	True Positive
30	Non-Normal	True Negative	Normal Detected	True Positive

Table 38

Tally of Model: Brawl, Fainting, Panic (Training 3)

(N=30)

Metric	**Count**
True Positives (TP)	24
True Negatives (TN)	27
False Positives (FP)	6
False Negatives (FN)	3
Accuracy (%)	**85.00%**

Tables 37 and 38 show the results of the third test prediction for identifying everyday and non-normal situations. The analysis involved 30 test video samples, with the AI model accurately identifying 24 everyday scenarios as True Positives and 27 non-normal scenarios as True Negatives. The model made 6 False Positive predictions, incorrectly labeling everyday situations as a brawl, fainting, panic, and 3 False Negatives, meaning all actual regular events were successfully detected. Achieving an accuracy of 85.00%, this model demonstrates solid performance in detecting everyday situations, though with a slightly higher rate of false alarms than the previous test.

Table 39

Model: Brawl, Fainting, Panic (Training 4)

	Non - Normal		**Normal Prediction**	
	Prediction	Verdict	**Prediction**	Verdict
1	Non-Normal	True Negative	Normal Detected	True Positive
2	Non-Normal	True Negative	Normal Detected	True Positive

3	Non-Normal	True Negative	Normal Detected	True Positive
4	Non-Normal	True Negative	Normal Detected	True Positive
5	Non-Normal	True Negative	Normal Detected	True Positive
6	Non-Normal	True Negative	Normal Detected	True Positive
7	Non-Normal	True Negative	Normal Detected	True Positive
8	Non-Normal	True Negative	Normal Detected	True Positive
9	Non-Normal	True Negative	Normal Detected	True Positive
10	Non-Normal	True Negative	Normal Detected	True Positive
11	Non-Normal	True Negative	Normal Detected	True Positive
12	Non-Normal	True Negative	Normal Detected	True Positive
13	Non-Normal	True Negative	Normal Detected	True Positive
14	Normal Detected	False Negative	Normal Detected	True Positive
15	Normal Detected	False Negative	Non-Normal	False Positive
16	Non-Normal	True Negative	Normal Detected	True Positive
17	Non-Normal	True Negative	Normal Detected	True Positive
18	Non-Normal	True Negative	Normal Detected	True Positive
19	Non-Normal	True Negative	Normal Detected	True Positive
20	Non-Normal	True Negative	Normal Detected	True Positive

21	Non-Normal	True Negative	Normal Detected	True Positive
22	Non-Normal	True Negative	Normal Detected	True Positive
23	Non-Normal	True Negative	Normal Detected	True Positive
24	Non-Normal	True Negative	Normal Detected	True Positive
25	Non-Normal	True Negative	Normal Detected	True Positive
26	Non-Normal	True Negative	Normal Detected	True Positive
27	Normal Detected	False Negative	Non-Normal	False Positive
28	Non-Normal	True Negative	Normal Detected	True Positive
29	Non-Normal	True Negative	Normal Detected	True Positive
30	Non-Normal	True Negative	Normal Detected	True Positive

Table 40

Tally of Model: Brawl, Fainting, Panic (Training 4)

Metric	**Value**
True Positives	28
False Positives	2
False Negatives	3
True Negatives	27
Accuracy	**91.67%**

Tables 39 and 40 show the results of the fourth test prediction for identifying everyday and non-normal situations. The analysis involved 30 test video samples, with the AI model accurately identifying 28 brawl scenarios as True Positives and 27 non-normal scenarios as True Negatives. The model made two false-positive predictions, incorrectly labeling everyday situations as non-normal, and 3 False Negatives, successfully identifying all actual regular events. Achieving an accuracy of 91.67%, this model demonstrates strong performance in distinguishing everyday scenarios, with minimal misclassifications.

Table 41

Overall Accuracy

Category	True Positives	True Negatives	False Positives	False Negatives	Accuracy
Brawl	27	28	3	2	91.67%
Fainting	28	23	2	7	85%
Panic	27	24	3	6	85%
Normal	28	27	2	3	91.67%
Overall	110	102	10	18	**88.33%**

Table 42

Training and Validation Metrics per Epoch (Approximate Values)

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.55	0.21	2.05	2.35
2	0.68	0.24	1.60	3.00
3	0.75	0.26	1.40	2.80
4	0.80	0.22	1.30	2.30
5	0.83	0.45	1.15	2.00
6	0.90	0.70	1.00	1.60
7	0.94	0.74	0.95	1.50
8	0.92	0.76	0.90	1.30
9	0.93	0.78	0.85	1.60
10	0.93	0.79	0.80	1.40

11	0.95	0.79	0.78	1.50
12	0.98	0.78	0.75	1.40
13	0.99	0.77	0.72	1.50
14	0.98	0.78	0.70	1.30
15	0.97	0.75	0.72	1.60
16	0.95	0.76	0.80	2.00
17	0.98	0.78	0.68	1.40

Table 42 shows how the model's performance changes over 17 training epochs. As training progresses, the model's accuracy improves and its loss decreases on the training and validation data. However, the validation loss fluctuates slightly in later epochs, which may suggest some overfitting. Overall, the model learns well and performs consistently.

Table 43

Confusion Matrix Table

True Label / Predicted Label	Brawl	Fainting	Panic	Normal
BRAWL	41	0	3	6
FAINTING	14	34	2	0
PANIC	0	1	36	3
NORMAL	10	0	4	46

Table 44

True Label: Brawl

Predicted As	**Count**
Brawl	41(correct predictions)
Fainting	0
Panic	3

Normal	6

Out of 50 actual Brawl cases, the model correctly predicted 41 and misclassified 9 (as Fainting, Normal, or Panic).

Table 45

True Label: Fainting

Predicted As	Count
Brawl	14
Fainting	34 (correct predictions)
Panic	2
Normal	0

Out of 50 actual fainting cases, the model correctly predicted 34 and misclassified 18 (as Brawl, Normal, or Panic).

Table 46

True Label: Panic

Predicted As	Count
Brawl	0
Fainting	1
Panic	36 (correct predictions)
Normal	3

Out of 40 actual Panic cases, the model correctly predicted 36 and misclassified 4 (as Brawl, Normal, or Fainting).

Table 47

True Label: Brawl, Fainting, Panic

Predicted As	Count
Brawl	0

Fainting	0
Panic	4
Normal	46 (correct predictions)

Out of 50 actual normal cases, the model correctly predicted 46 and misclassified 4 (as Brawl, Fainting, or Panic).

Table 48: Weighted Mean Evaluation Criteria

Weighted Mean Range	Interpretation
1-00 – 1.80	Very Poor
1.80 – 2.60	Poor
2.61 – 3.40	Fair
3.41 – 4.20	Good
4.21 – 5.00	Very Good

Table 49

Users' Prototype Evaluation Based on System Accuracy & Functional Suitability

System Accuracy & Functional Suitability	Weighted Mean	Interpretation
(Completeness) The set of functions covers all the specified tasks and user objectives.	4.10	Good
(Correctness) The function provides the correct results with the needed degree of precision.	4.25	Very Good
(Appropriateness) The function facilitates the	4.15	Good

accomplishment of specified tasks and objectives.		
Mean	**4.17**	**Good**

Table 49 shows the average user evaluation based on the prototype system's accuracy and functional Suitability. It measures how well the system meets user needs based on three criteria: Completeness, Correctness, and Appropriateness. The overall rating score is "Good," which may be considered acceptable.

Table 50

Users' Prototype Evaluation Based on System Reliability

System Reliability	Weighted Mean	Interpretation
(Maturity) A system, product, or component meets the requirements for reliability under normal operation.	4.30	Very Good
(Availability) A product or system is operational and accessible when required for use.	4.15	Good
(Recoverability) Data integrity is maintained without loss or corruption.	4.20	Good
(Operational) Row Edge device operates consistently without unexpected crashes or errors.	4.25	Very Good

Mean	**4.23**	**Very Good**

Table 50 shows the average result of users' evaluation based on the System Reliability of the prototype system based on four factors: Maturity, Availability, Recoverability, and Operational Consistency. There are two good results interpretations and two excellent interpretations, which result in a "Very Good" interpretation in the overall rating, which is an acceptable rating.

Table 51

Users' Prototype Evaluation Based on Overall Satisfaction

Overall Satisfaction	Weighted Mean	Interpretation
How satisfied are you with the system overall?	4.30	Very Good
Would you recommend this system to other security personnel?	4.25	Very Good
Does the system meet your expectations based on its purpose?	4.20	Very Good
Mean	**4.21**	**Very Good**

Table 51 shows the average user evaluation result based on their overall satisfaction with the prototype. Most ratings fall under "Very Good," with Overall Satisfaction, which is acceptable.

Table 52

Overall Users' Evaluation of the Prototype

Prototype Evaluation Characteristics	Weighted Mean	Interpretation
System Accuracy & Functional Suitability	4.17	Good
System Reliability	4.23	Very Good
Overall Satisfaction	4.25	Very Good
Mean	**4.21**	**Very Good**

Table 52 shows the overall evaluation results of the prototype based on user feedback. System Accuracy & Functional Suitability results in reasonable interpretation, while the two characteristics, which are the system reliability and overall satisfaction, result in perfect interpretation, which results in "Very Good" overall user evaluation.

Table 53

Expert Prototype Evaluation Based on System Accuracy & Functional Suitability

System Accuracy & Functional Suitability	Weighted Mean	Interpretation
(Completeness) The set of functions covers all the specified tasks and user objectives.	4	Good
(Correctness) The function provides the correct results with the needed degree of precision.	4.2	Good
(Appropriateness) The function facilities the accomplishment of specified tasks and objectives.	4.2	Good
Mean	**4.13**	**Good**

Table 53 shows the expert evaluation results of the prototype based on System Accuracy & Functional Suitability. All the results are reasonable interpretations, resulting in a rating of “Good”.

Table 54

Expert Prototype Evaluation Based on System Reliability

System Reliability	Weighted Mean	Interpretation
(Maturity) A system, product, or component meets the requirements for reliability under normal operation.	4	Good
(Availability) A product or system is operational and accessible when required for use.	4	Good
(Recoverability) Data integrity is maintained without loss or corruption.	4	Good
(Operational) Row Edge device operates consistently without unexpected crashes or errors.	4.4	Very Good
Mean	**4.1**	**Good**

Table 54 shows the expert evaluation results of the prototype based on System Reliability. Three results have reasonable interpretations, and one has a perfect interpretation, which is rated as "Good," which may be considered acceptable.

Table 55

Expert Prototype Evaluation Based on System Performance Efficiency

System Performance Efficiency	Weighted Mean	Interpretation
(Time-behavior) When performing its functions, the response and processing times and throughput rates of a product or system meet requirements.	4.4	Very Good
(Capacity) The maximum limits of the product or system parameter meet requirements.	4.4	Very Good
(Peak Performance) The system's performance remains stable under peak load conditions.	4.4	Very Good
(Data Efficiency) Edge device handles large volumes of data efficiently without significant delays.	4.2	Good
Mean	**4.35**	**Very Good**

Table 55 shows the expert evaluation results of the prototype based on System Performance Efficiency. Three results have excellent interpretations, and one has a reasonable interpretation. The overall result is "Very Good", an acceptable rating.

Table 56

Expert Prototype Evaluation Based on Overall Satisfaction

Overall Satisfaction	Weighted Mean	Interpretation
How satisfied are you with the system overall?	4.2	Good

Would you recommend this system to other security personnel?	4	Good
Does the system meet your expectations based on its purpose?	4.4	Very Good
Mean	**4.2**	**Good**

Table 56 shows the expert evaluation of the prototype's overall satisfaction. There are two reasonable interpretations and one perfect interpretation, which results in an overall "Good" interpretation, which is acceptable.

Table 57

Overall Expert Evaluation of the Prototype

Prototype Evaluation Characteristics	Weighted Mean	Interpretation
System Accuracy & Functional Suitability	4.13	Good
System Reliability	4.1	Good
System Performance Efficiency	4.35	Very Good
Overall Satisfaction	4.2	Good
Mean	**4.195**	**Good**

Table 57 summarizes the expert evaluation of the prototype across key characteristics. The system accuracy and functional Suitability, system reliability, and overall satisfaction are rated as “Good”, and system performance efficiency is rated as “Very Good”, resulting in a “Good Rating”, which is acceptable.

Chapter V

SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

This chapter presents the summary, conclusion, and recommendations of the design project entitled Real-Time Crowd Behavior Control and Monitoring System Using 3D-Convolutional Neural Network. All observations are gathered into conclusions, and experts and survey participants provide recommendations for addressing the issues identified during the investigation. With insights from those involved, the researcher refines the software and prototype.

Summary of Findings

The research project, titled "Real-Time Crowd Behavior Monitoring System Using 3D-Convolutional Neural Network," intends to resolve an essential public safety issue by anticipating and identifying risky crowd behaviors in real time. The system analyzes crowd video footage using 3D-Convolutional Neural Networks (3D-CNN) to detect essential behaviors, including brawls, panic, and fainting. If not identified early, these behaviors can cause significant safety issues in public places like schools, concerts, crowded events, or high-risk environments.

Early detection is the primary focus in this study conducted at Pamantasan ng Cabuyao (PNC). The objective is to anticipate and track crowd behaviors before they become more problematic so that security or medical staff can react more quickly. By identifying potential aggressive acts and health problems like fainting, the technology enables authorities to intervene swiftly, reducing danger and enhancing public safety. As part of the researchers' goal, the prototype device resolves the following:

1. The system successfully met its design goal of providing a flexible and dependable crowd behavior monitoring setup using camera input and machine learning. It achieved an accuracy rate of 87.5%, confirming it performed within the target range of 85–90% across different crowd sizes (100, 500, and 1000) and settings (school cafeteria and flag ceremony grounds). It also operated effectively during scheduled times (7:00–9:00 AM for flag ceremonies and 11:00 AM–1:00 PM for cafeteria use), from Monday to Saturday. The system could detect critical behaviors—brawl, fainting/seizure, and panic—with less than 2 seconds' latency, successfully issuing real-time alerts based on live behavioral changes.
2. The system utilized video processing and a trained 3D-CNN model to correctly identify potential threats such as brawls and health-related incidents like seizures and fainting. These were detected as they occurred, demonstrating that the machine learning algorithm effectively classified risky behaviors in real time. The system's predictions closely matched real-world observations, indicating the success of the detection method in providing timely support for immediate interventions.
3. The system was deployed and tested in different real-world settings—school cafeteria and flag ceremony areas—to evaluate its adaptability and real-time responsiveness. In both cases, it maintained stable performance and accurate behavior tracking, providing live support for safety monitoring. This showed that the system can effectively assist school officials, health responders, and security personnel during high-density events or daily routines where crowd behavior needs to be observed closely.

4. The system's performance was evaluated in various environments using the ISO/IEC 25010 software quality model, focusing on Accuracy, Reliability, Functional Suitability, and Performance Efficiency. User evaluations rated the system as Good to Very Good, with an overall mean score of 4.21, indicating consistent and acceptable performance. Expert evaluations similarly resulted in a Good overall rating with a mean of 4.195, supported by a Very Good score in Performance Efficiency. These findings confirm the system's ability to detect crowd behaviors and potential threats reliably and accurately under typical operating conditions. However, further enhancement in behavioral precision may strengthen overall system dependability.

Conclusion

Based on the implementation of our research, the following conclusions were drawn:

1. The system successfully met its design target, achieving 88.33% accuracy in detecting crowd behaviors across various sizes and locations. Its ability to issue real-time alerts with minimal latency confirms its reliability for continuous monitoring during scheduled school activities.

2. The use of a 3D-CNN model and video processing allowed the system to detect violent or health-related incidents like brawls, fainting, and panic as they happened. The system's predictions closely matched actual events, proving its effectiveness in real-time threat identification.

3. The system worked reliably in different real-world settings, such as the cafeteria and the flag ceremony area. Its consistent performance in these environments

shows its usefulness for supporting safety personnel during routine and high-density school events.

4. Based on the ISO/IEC 25010 evaluation, the system showed strong accuracy, reliability, functionality, and efficiency performance. The positive ratings from users and experts confirm that the system meets quality standards and can be used for practical crowd behavior monitoring.

Recommendation

Based on the summary of findings and the conclusions, the researchers would like to recommend the following:

1. The researchers advise continuous improvement of the 3D-CNN algorithm to improve the system's accuracy in anticipating and identifying different crowd behaviors. To increase the system's adaptability to various crowd circumstances, including expanding the dataset and training it in various behaviors.

2. Adding new features, including incorporating a sound-detecting device, is advised to increase the system's overall functionality and responsiveness. This would allow the system to recognize distress signals or loud noises, such as cries or aid calls, facilitating the early detection of possible problems and enhancing reaction times in dire circumstances.

3. Future iterations of the system should be improved to detect a broader range of other behavior issues, even though the current version concentrates on violent behavior, panic, and fainting. This would ensure thorough safety and well-being monitoring for huge groups.

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Appendices

Appendix A

Letter Request

Republic of the Philippines
University of Cabuyao
(PAMANTASAN NG CABUYAO)
College of Engineering
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

PNC:AS-LE-48
April 2, 2025

MR. COLIN B. GARCIA
Vice President for Administration and Linkages
University of Cabuyao

Thru: **MR. ALFREDO GLENN H. BEAÑO**
Head, PMGSD

Dear Mr. Garcia:

We, the **4th year students of 4CPE - A**, are conducting our research study titled **"Real-Time Crowd Behavior Control and Monitoring System Using 3D-Convolutional Neural Network."** As part of our study, we respectfully seek your permission to deploy our prototype within the school campus to test its effectiveness in detecting crowd behavior in real time.

As part of our testing process, we would also like to **request permission to film within the campus** during our testing phase. This will allow us to gather the necessary data and evaluate the performance of our edge device. To ensure a thorough assessment, we plan to conduct tests during key periods of the day **early morning, lunch break, and if possible, in the afternoon.**

Additionally, as part of our testing, we **plan to simulate specific crowd behaviors** to observe how our device reacts to different scenarios. Rest assured, we will take the necessary steps to inform the campus community in advance about these simulations to avoid any confusion or concern regarding the enactment of these controlled environments.
We sincerely appreciate your time and consideration of our request. We are more than willing to discuss any guidelines or adjustments needed to proceed with our research responsibly.

Sincerely yours,

JED ERIONE L. DE LUNA
Lead Researcher

JOHANN-ERL S. LAPUZ
Researcher

JOSEPH S. SARDOMA
Researcher

NETHOUIE LJOY ANGELO R. ORBIDA
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Noted by:

DR MA. EMMALYN DE VIGAL CAPUNO
Research Adviser / Data Privacy Officer

fw:
ENGR. ANNA-LIZA F. SIGUE
Research Professor

ENGR. ALDRIN J. SORIANO
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DR. RIZAL M. MOSQUERA
Dean, College of Engineering

DR. GEORGE V. LAMBOT
Vice President for Academics and Student Services

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RESEARCH INSTRUMENT

This study, titled **"Real-Time Crowd Behavior Control and Monitoring System Using 3D-Convolutional Neural Network,"** aims to assess the usability, accuracy, reliability, and effectiveness of our developed system in detecting and responding to various crowd behaviors. The evaluation questionnaire is designed to gather relevant feedback from users and stakeholders to ensure system effectiveness and practical application.

The instrument consists of five main sections. The first section, General Information, collects basic details about the respondents, including their name (optional) and position. This helps provide context to the feedback given, ensuring that the data gathered is interpreted within the appropriate scope of the participant's background and role.

The second section, System Usability, evaluates the ease of use and navigation of the system. It seeks to determine whether the interface is user-friendly and intuitive, ensuring that alerts and notifications are clear and easily understood. Additionally, this section examines any difficulties encountered while using the system, assesses the clarity of visual alerts and indicators, and considers the comfort level of users after an initial period of training and familiarization.

The third section, System Accuracy & Reliability, focuses on the effectiveness of the system in detecting various crowd behaviors. It assesses how accurately the system identifies incidents such as violence, panic, or fainting while also evaluating the occurrence of false alarms and missed incidents. Furthermore, this section investigates the overall reliability of the system when used over extended periods and its ability to distinguish between normal crowd behavior and actual emergencies.

The fourth section, Response Time & Effectiveness, measures the system's efficiency in generating alerts and assisting in emergency responses. This section analyzes how quickly the system detects and reports incidents, its role in improving emergency response capabilities, and its ability to integrate with existing security protocols. Additionally, it examines whether the system provides useful and detailed information about detected incidents and whether it contributes to reducing response time in critical situations.
The final section, Overall Satisfaction, gathers the general perception of respondents regarding the system's overall performance. It explores whether the users are satisfied with the system, whether they would recommend its use by security personnel, and if the system meets expectations based on its intended purpose. Furthermore, this section provides an opportunity for respondents to share their suggestions for possible improvements.
To ensure the validity and reliability of this research instrument, expert reviews and pilot testing will be conducted before full-scale implementation. This will help refine the questionnaire items to align with the study's objectives.

DATA PRIVACY NOTICE

We recognize the importance of privacy and confidentiality in research. All information provided by the respondents will be treated with the highest level of confidentiality and used strictly for academic purposes in line with our study, **"Real-Time Crowd Behavior Control and Monitoring System Using 3D-Convolutional Neural Network."** The data collected through this evaluation will be analyzed solely for the purpose of assessing the system's usability, accuracy, reliability, and effectiveness.

In compliance with the **Data Privacy Act of 2012**, all personally identifiable information will be anonymized to ensure that no individual respondent can be directly linked to specific responses. Additionally, any footage or data collected during the testing and simulation process will be securely stored and used exclusively for research validation. No part of this study, including respondent feedback and recorded data, will be shared with third parties outside of our research team without explicit consent.

By participating in this evaluation, respondents acknowledge their voluntary involvement and agree that their insights will contribute to improving the functionality of our system. Should any participant wish to withdraw their responses or require further clarifications regarding data privacy, they may reach out to the research team. We are committed to maintaining transparency and ethical research practices to ensure a responsible and secure handling of all gathered information.

Republic of the Philippines
University of Cabuyao
(PAMANTASAN NG CABUYAO)
College of Engineering
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

PNC:AS-LE-48.1
April 2, 2025

4/8/25

DR. GEORGE V. LAMBOT
Vice President for Academics and Student Services
University of Cabuyao

Thru: **MR. LUIGI KIM FLORA**
Director MISD/ Adviser, PnC Lente

Dear Dr. Lambot:

We, the 4th year students of 4CPE - A, are currently conducting our research study titled **"Real-Time Crowd Behavior Control and Monitoring System Using 3D-Convolutional Neural Network."** As part of the data-gathering phase of our research, we respectfully seek your permission to **collect and use video recordings from school events, including the flag ceremony and other gatherings held within the campus.**

These video files will serve as valuable datasets for training and evaluating our prototype, which is designed to detect and classify various crowd behaviors in real time. By using actual crowd scenarios from school activities, we aim to improve the system's accuracy and ensure that it is well-adapted to real-world conditions.

Please be assured that all collected materials will be used strictly for academic purposes and handled with the utmost care and confidentiality. If necessary, we are also willing to coordinate with relevant school personnel regarding the proper procedures for accessing and handling these video files.

We sincerely appreciate your time and consideration of our request. We are more than willing to comply with any guidelines or protocols you may set to ensure responsible and ethical data collection for our study.

Sincerely yours,

JED ERIONE L. DE LUNA
Lead Researcher

JOHANN-ERL S. LAPUZ
Researcher

JOSEPH C. SARDOMA
Researcher

NETHOUIE LJOY ANGELO R. ORBIDA
Researcher

JOHNLEXTER D. PULIDO
Researcher

Noted by:

DR MA. EMMALYN ASUNCION DE VIGAL CAPUNO
Research Adviser / Data Privacy Officer

ENGR. ANNA-LIZA F. SIGUE
Research Professor

ENGR. ALDRIN J. SORIANO
Program Chair, CpE

DR. RIZAL M. MOSQUERA
Dean, College of Engineering

jed/04012025

PNC:PRE-FO-71 rev.0 03082023

Republic of the Philippines
Pamantasan ng Cabuyao
(University of Cabuyao)
Planning, Research, and Extension Division
Research and Development Department
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

Group 2
4:54 pm
April 4, 2025

STUDENT RESEARCH RECOMMENDATION FORM

Group No.	2	Date Filed:	April 4, 2025
Researchers:	De Luna, Jed Erione L.	Lapuz, Johann-Erl S.	Orbida, Nethouie Ljoy Angelo R.
	Pulido, Johnlexter D.	Sardoma, Joseph S.	
Research Title:	Real-Time Crowd Behavior Control and Monitoring System Using 3D-Convolutional Neural Network		

This research has been thoroughly examined and is now recommended for Final Defense.

Dr. Maria Emmalyn Asuncion D. Capuno
(Signature Over Printed Name)
Adviser

Appendix B

Questionnaire

Evaluation Questionnaire for Real – Time Crowd Behavior Monitoring System Using 3D – Convolutional Neural Network

EVALUATION INSTRUMENT OF ISO 25010 FOR END USER

Section 1: General Information

1. Name (Optional): _______________

2. Position: _______________

INSTRUCTION: Please evaluate the prototype and the website by using the given scale and placing a checkmark (/) under the corresponding numerical rating.

(Mangyaring suriin ang prototype at ang website sa pamamagitan ng paggamit ng ibinigay na sukatan at paglagay ng tsek (/) sa ilalim ng kaukulang puntos.)

Numerical Rating and Equivalent

1 – Very poor (Kailangang paunlarin)	2 – Poor (Di-gaanong Mahusay)	3 – Fair (Katamtaman)	4 – Good (Mahusay)	5 – Very Good (Napakahusay)

Section 2: System Accuracy & Functional Suitability

	Question	1	2	3	4	5
Completeness	**The set of functions covers all the specified tasks and user objectives.** *(Ang buong system ay sumasaklaw sa lahat ng tinutukoy na mga Gawain at mga layunin ng gumagamit.)*					
Correctness	**The function provides the correct results with the needed degree of precision.** *(Ang system ay nagbibigay ng tamang resulta sa kinakailangang antas ng katumpakan.)*					
Appropriateness	**The function facilities the accomplishment of specified tasks and objective.** *(Ang paggamit sa sistema ay nangangasiwa sa pagtupad ng tiyakang mga gawain at layunin.)*					

Section 3: System Reliability

	Question	1	2	3	4	5
Maturity	**A system, product or component meets for reliability under normal operation.** *(Ang sistema, produkto o bahagi nito ay nakatutugon at maaasahan sa ilalim ng normal na operasyon.)*					
Availability	**A product or system is operational and accessible when required for use.** *(Ang produkto o sistema ay gumagana at maaaring makuha kapag kinakailangan para sa paggamit.)*					
Recoverability	**Data integrity is maintained without loss or corruption.** *(Ang integridad ng datos ay pinangangalagaan nang walang pagkawala o katiwalian.)*					
Operational	**Edge device operates consistently without unexpected crashes or errors.** *(Ang edge device ay tumatakbo nang tuluy-tuloy nang walang hindi inaasahang pag-crash o error.)*					

Section 5: Overall Satisfaction

Question	1	2	3	4	5
How satisfied are you with the system overall?					
Would you recommend this system to other security personnel?					
Does the system meet your expectations based on its purpose?					

Comments / Suggestions:
Mga Komento / Mga mungkahi

____

____

Signature (Optional): ______________________

Date: ______________________

Evaluation Questionnaire for Real – Time Crowd Behavior Monitoring System Using 3D – Convolutional Neural Network

EVALUATION INSTRUMENT OF ISO 25010 FOR EXPERT

Section 1: General Information

1. Name (Optional): _______________

2. Position: _______________

INSTRUCTION: Please evaluate the prototype and the website by using the given scale and placing a checkmark (/) under the corresponding numerical rating.

(Mangyaring suriin ang prototype at ang website sa pamamagitan ng paggamit ng ibinigay na sukatan at paglagay ng tsek (/) sa ilalim ng kaukulang puntos.)

Numerical Rating and Equivalent

1 – Very poor	2 – Poor	3 – Fair	4 – Good	5 – Very Good
(Kailangang paunlarin)	(Di-gaanong Mahusay)	(Katamtaman)	(Mahusay)	(Napakahusay)

	Question	1	2	3	4	5
Completeness	**The set of functions covers all the specified tasks and user objectives.** *(Ang buong system ay sumasaklaw sa lahat ng tinutukoy na mga Gawain at mga layunin ng gumagamit.)*					
Correctness	**The function provides the correct results with the needed degree of precision.** *(Ang system ay nagbibigay ng tamang resulta sa kinakailangang antas ng katumpakan.)*					
Appropriateness	**The function facilities the accomplishment of specified tasks and objective.** *(Ang paggamit sa sistema ay nangangasiwa sa pagtupad ng tiyakang mga gawain at layunin.)*					

Section 2: System Accuracy & Functional Suitability

Section 3: System Reliability

	Question	1	2	3	4	5
Maturity	**A system, product or component meets for reliability under normal operation.** *(Ang sistema, produkto o bahagi nito ay nakatutugon at maaasahan sa ilalim ng normal na operasyon.)*					
Availability	**A product or system is operational and accessible when required for use.**					

	(Ang produkto o sistema ay gumagana at maaaring makuha kapag kinakailangan para sa paggamit.)					
Recoverability	**Data integrity is maintained without loss or corruption.** *(Ang integridad ng datos ay pinangangalagaan nang walang pagkawala o katiwalian.)*					
Operational	**Edge device operates consistently without unexpected crashes or errors.** *(Ang edge device ay tumatakbo nang tuluy-tuloy nang walang hindi inaasahang pag-crash o error.)*					

Section 4: System Performance Efficiency

	Question	1	2	3	4	5
Time-behavior	**The response and processing times and throughput rates of a product or system, when performing its functions meet requirements.** *(Nakatutugon ang Sistema sa mga kinakailangang oras ng pagtugon at pagproseso at mga antas ng isang produkto o sustema kapag nakapagsasagawa ng tungkulin nito .)*					
Capacity	**The maximum limits of the product or system, parameter meet requirements.** *(Natutugunan ng pinakamataas na limitasyon o parametron ng Sistema ang mga pangangailangan.)*					
Peak Performance	**The system's performance remains stable under peak load conditions.** *(Ang pagganap ng sistema ay nananatiling matatag kahit sa ilalim ng matinding karga.)*					

Question	1	2	3	4	5
How satisfied are you with the system overall?					
Would you recommend this system to other security personnel?					
Does the system meet your expectations based on its purpose?					

Data Efficiency	**Edge device handles large volumes of data efficiently without significant delays.** *(Ang edge device ay nagpoproseso ng malaking dami ng data nang maayos nang hindi nagkakaroon ng malalaking pagkaantala.)*					

Section 5: Overall Satisfaction

Comments / Suggestions:

Mga Komento / Mga mungkahi

____

Signature: ____________________

Date: ____________________

Appendix C

Calculations And Statistical Information

Calculations and Statistical Information

The statistical tool used in the interpretation of data is weighted mean. Weighted mean was used to determine the average responses of the five options in each item namely, Very Good – 5, Good – 4, Fair – 3, Poor - 2, Very Poor – 1. This mean was used to compute the overall evaluation mean of the prototype and the system.

User Evaluation

EVALUATION SUMMARY RESULTS FOR 10 USERS	Very Poor	Poor	Fair	Good	Very Good	Weighted Mean	Interpretation
USER EVALUATION CHARACTERISTICS FOR PROTOTYPE	(1)	(2)	(3)	(4)	(5)		
System Accuracy & Functional Suitability							
(Completeness) The set of functions covers all the specified tasks and user objectives. (Ang buong system ay	0	0	3	12	5	4.10	Good

sumasaklaw sa lahat ng tinutukoy na mga Gawain at mga layunin ng gumagamit.)							
(Correctness) The function provides the correct results with the needed degree of precision. (Ang system ay nagbibigay ng tamang resulta sa kinakailangang antas ng katumpakan.)	0	0	2	11	7	4.25	Very Good
(Appropriateness) The function facilities the accomplishment of specified tasks and objective. (Ang paggamit sa sistema ay nangangasiwa sa pagtupad ng	0	0	3	11	6	4.15	Good

tiyakang mga gawain at layunin.)							

System Reliability							
(Maturity) A system, product or component meets for reliability under normal operation. (Ang sistema, produkto o bahagi nito ay nakatutugon at maaasahan sa ilalim ng normal na operasyon.)	0	0	2	10	8	4.30	Very Good
(Availability) A product or system is operational and accessible when required for use. (Ang produkto o sistema ay	0	0	3	11	6	4.15	Good

gumagana at maaaring makuha kapag kinakailangan para sa paggamit.)							
(Recoverability) Data integrity is maintained without loss or corruption. (Ang integridad ng datos ay pinangangalagaan nang walang pagkawala o katiwalian.)	0	0	2	12	6	4.20	Good
(Operational) Row Edge device operates consistently without unexpected crashes or errors. (Ang edge device ay tumatakbo nang	0	0	2	11	7	4.25	Very Good

tuluy-tuloy nang walang hindi inaasahang pag-crash o error.)							
Overall Satisfaction							
How satisfied are you with the system overall?	0	0	2	10	8	4.30	Very Good
Would you recommend this system to other security personnel?	0	0	2	11	7	4.25	Very Good
Does the system meet your expectation based on its purpose	0	0	3	10	7	4.20	Good

Overall Users' Evaluation of the Prototype

Prototype Evaluation Characteristics	Weighted Mean	Interpretation
System Accuracy & Functional Suitability	4.17	Good
System Reliability	4.23	Very Good
Overall Satisfaction	4.25	Very Good
Mean	**4.21**	**Very Good**

Expert Evaluation

EVALUATION SUMMARY RESULTS FOR 3 EXPERTS	Very Poor	Poor	Fair	Good	Very Good	Weighted Mean	Interpretation
EXPERTS EVALUATION CHARACTERISTICS FOR PROTOTYPE	(1)	(2)	(3)	(4)	(5)		
System Accuracy & Functional Suitability							

(Completeness) The set of functions covers all the specified tasks and user objectives. (Ang buong system ay sumasaklaw sa lahat ng tinutukoy na mga Gawain at mga layunin ng gumagamit.)	0	0	1	3	1	4	Good
(Correctness) The function provides the correct results with the needed degree of precision. (Ang system ay nagbibigay ng tamang resulta sa kinakailangang antas ng katumpakan.)	0	0	0	4	1	4.2	Good
(Appropriateness) The function facilities the accomplishment	0	0	0	4	1	4.2	Good

of specified tasks and objective. (Ang paggamit sa sistema ay nangangasiwa sa pagtupad ng tiyakang mga gawain at layunin.)							

System Reliability							
(Maturity) A system, product or component meets for reliability under normal operation. (Ang sistema, produkto o bahagi nito ay nakatutugon at maaasahan sa ilalim ng normal na operasyon.)	0	0	1	2	2	4	Very Good
(Availability) A product or system	0	0	1	2	2	4	Good

is operational and accessible when required for use. (Ang produkto o sistema ay gumagana at maaaring makuha kapag kinakailangan para sa paggamit.)							
(Recoverability) Data integrity is maintained without loss or corruption. (Ang integridad ng datos ay pinangangalagaan nang walang pagkawala o katiwalian.)	0	0	1	2	2	4	Good
(Operational) Row Edge device operates consistently	0	0	0	3	2	4.4	Very Good

without unexpected crashes or errors. (Ang edge device ay tumatakbo nang tuluy-tuloy nang walang hindi inaasahang pag-crash o error.)							
System Performance Efficiency							
(Time-behavior) The response and processing times and throughput rates of a product or system, when performing its functions meet requirements. (Nakatutugon ang Sistema sa mga kinakailangang oras ng pagtugon at pagproseso at	0	0	0	3	2	4.2	Good

mga antas ng isang produkto o sustema kapag nakapagsasagawa ng tungkulin nito .)							
(Capacity) The maximum limits of the product or system, parameter meet requirements. (Natutugunan ng pinakamataas na limitasyon o parametron ng Sistema ang mga pangangailangan.)	0	0	0	3	2	4.2	Good
(Peak Performance) The system's performance remains stable under peak load conditions. (Ang	0	0	0	3	2	4.2	Good

pagganap ng sistema ay nananatiling matatag kahit sa ilalim ng matinding karga.)							
(Data Efficiency) Edge device handles large volumes of data efficiently without significant delays. (Ang edge device ay nagpoproseso ng malaking dami ng data nang maayos nang hindi nagkakaroon ng malalaking pagkaantala.)ay tumatakbo nang tuluy-tuloy nang walang hindi	0	0	0	4	1	. 4.2	Good

inaasahang pag-crash o error.)							
Overall Satisfaction							
How satisfied are you with the system overall?	0	0	0	4	1	4.2	Good
Would you recommend this system to other security personnel?	0	0	1	2	2	4	Good
Does the system meet your expectations based on its purpose?	0	0	0	3	2	4.4	. Very Good

Overall Expert Evaluation of the Prototype

Prototype Evaluation Characteristics	Weighted Mean	Interpretation
System Accuracy & Functional Suitability	4.13	Good
System Reliability	4.1	Good
System Performance Efficiency	4.35	Very Good
Overall Satisfaction	4.2	Good
Mean	**4.195**	**Good**

Appendix D

Hardware Specifications

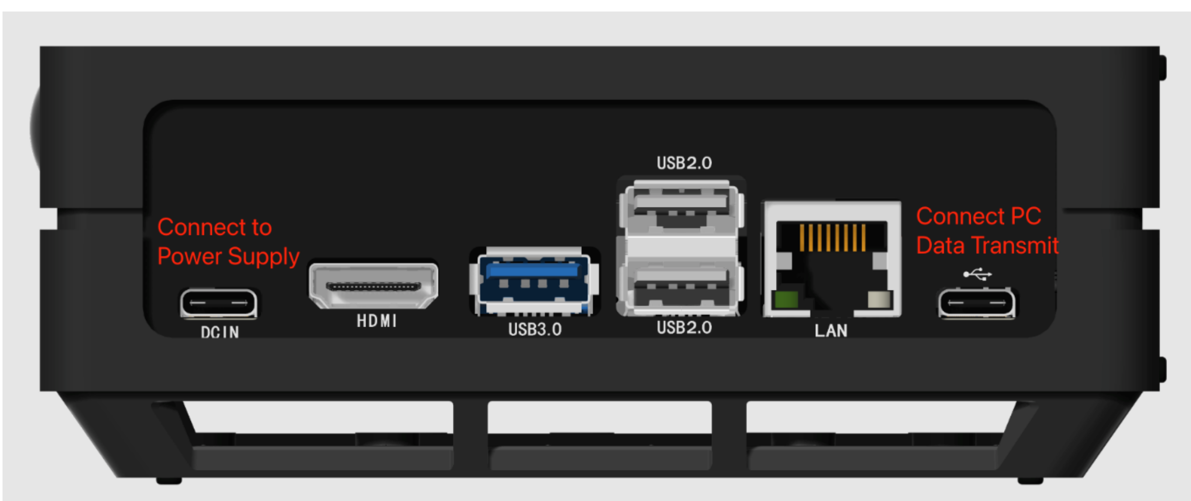
Hardware Specifications

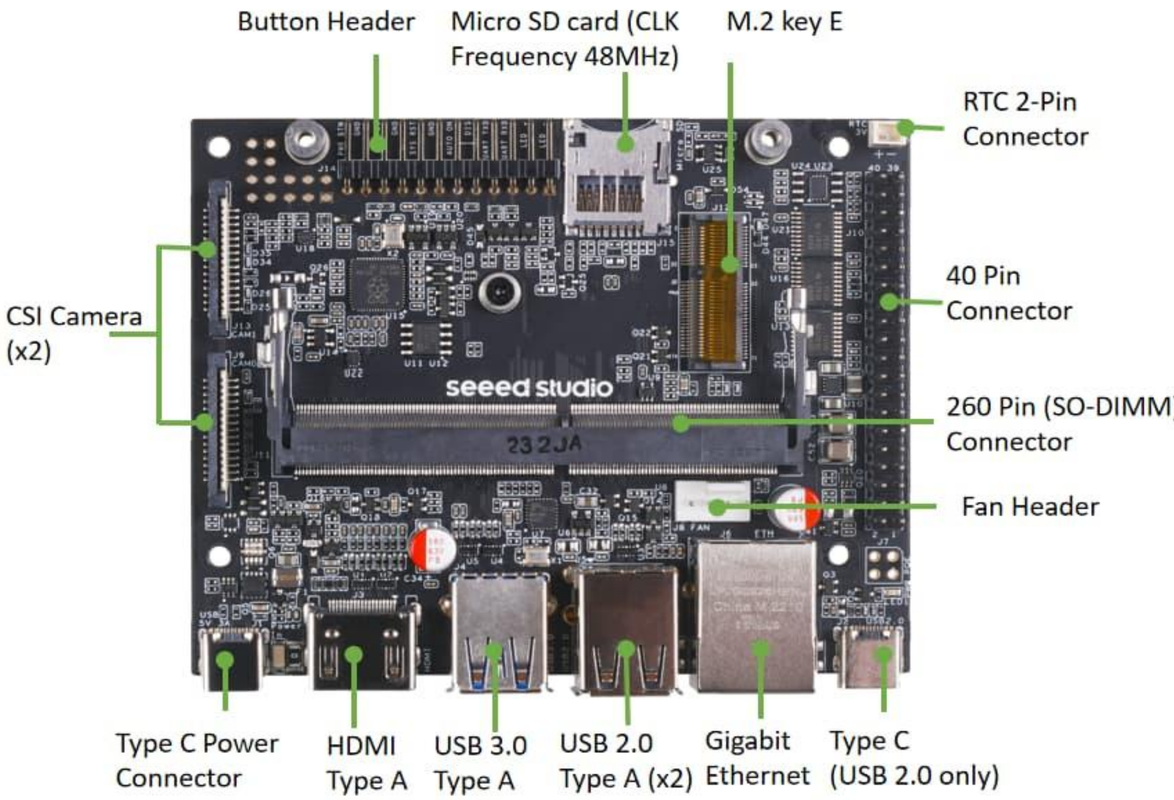
reComputer J1010 -Edge AI Computer Jetson Nano

Jetson Nano 4GB System on Module	
Ai Performance	Jetson Nano 4GB – 0.5 TOPS
GPU	NVIDIA Maxwel™ architecture with 128 NVIDIA CUDA® cores
CPU	Quad – core ARM Cortex – A57 MPCore processor
Memory	4GB 64 – bit LPDDR4 25.6 GB/s
Video Encoder	1x 4K30 | 2x1080p60 | 4x1080p30 | 4x720p60 | 9x720p30 (H.265 & H.264)
Video Decoder	1x 4K60 | 2x 4K30 | 4x 1080p60 | 8x 1080p30 | 9x 720p60 (H.265 & H.264)

Carrier Board		
Storage		1x TF_Card
Networking	**Ethernet**	1x RJ-45 Gigabit Ethernet (10/100/1000M)
	M.2 KEY E	1x M.2 Key E for WiFi/Bluetooth module
I/O	**USB**	1x USB 3.0 Type A; 2x USB 2.0 Type A;
	Camera	2x CSI

	Display	1x HDMI Type A
	Fan	1x 4 pin Fan Connector (5V PWM)
	Multifunctional Port	1x 40-Pin Expansion header1x 12-Pin Control and UART header
Power		USB-Type C 5V⎓3A
Mechanical	**Dimensions (W x D x H)**	130 mm x 120 mm x 58.5 mm (with case)
	Installation	Desk,wall mounting
Operating Temperature		0℃ ~ 60℃





Webcam

Webcam HD 1080P	
Resolution	**Resolution**
Frame Rate	**Frame Rate**
Field of View (FOV)	**Field of View (FOV)**
Focus Type	**Focus Type**
Microphone	**Microphone**
Connectivity	**Connectivity**

Operating Systems	Compatible with Windows, macOS, Linux, and Android
Mounting Options	Universal clip suitable for laptops and monitors
Additional Features	Ideal for video conferencing, online education, and live streaming

Acer Predator Helios Neo 18 (Intel i5-13th Gen, RTX 4050) Specifications

Acer Predator Helios Neo 18	
Processor	Intel Core i5-13500HX (14 cores, 20 threads, 2.5 GHz base, up to 4.7 GHz, 24MB cache)
Graphics	NVIDIA GeForce RTX 4050 (Laptop) - 115W TGP, 140W MGP, 2355MHz boost clock
Display	18.0" WUXGA (1920 x 1200) IPS, 165 Hz / QHD+ (2560 x 1600) IPS, 165 Hz / 240 Hz
Memory	16GB DDR5 SO-DIMM (Upgradeable up to 64GB)
Storage	1TB SSD (Up to 4TB supported, Two M.2 PCIe NVMe 4.0 x4 slots)
Battery	90Wh, 4-cell lithium-ion

Dimensions	404 x 312.08 x 27.15–29.15 mm (15.91" x 12.29" x 1.07")
Weight	Approx. 3.40 kg (7.5 lbs)
USB Ports	1x USB-A 3.2 Gen 1, 1x USB-A, 1x USB-A 3.2 Gen 2 (Sleep & Charge), 2x USB-C 3.2 Gen 2 (Thunderbolt 4, PD)
Other Ports	HDMI 2.1, MicroSD reader, Ethernet LAN (10/100/1000/2500 Mbit/s), 3.5mm audio jack
Wireless	Wi-Fi 6E, Bluetooth 5.3
Camera	Full HD webcam with Temporal Noise Reduction
Audio	Stereo speakers with DTS X: Ultra, Dual microphones with Acer Purified Voice
Keyboard	Optional backlit keyboard
Security	Optional fingerprint reader, Security lock slot

Appendix E

Software Specifications

Software Specifications

Windows (Operating System)

Feature	Details
Developer	Microsoft
Latest Version	Windows 11 (as of 2024)
Kernel Type	Hybrid (NT Kernel)
License	Proprietary (some open-source components)
User Interface	Graphical (GUI)
Package Manager	Microsoft Store, Windows Package Manager (winget)
Security	Windows Defender, BitLocker, Firewall
System Requirements	Minimum 4GB RAM, 64GB Storage, TPM 2.0
Software Compatibility	Supports most commercial software (MS Office, Adobe, etc.)
Customization	Limited (compared to Linux)
Updates	Automatic updates via Windows Update

Ubuntu (Operating System)

Feature	Details
Developer	Canonical Ltd.
Latest Version	Ubuntu 24.04 (as of 2024)
Kernel Type	Monolithic (Linux Kernel)
License	Mostly open-source (GNU GPL, MIT)
User Interface	Graphical (GNOME by default) & Command Line
Package Manager	APT (Advanced Package Tool), Snap
Security	AppArmor, Firewall, SELinux (optional)
System Requirements	Minimum 2GB RAM, 25GB Storage
Software Compatibility	Open-source software (LibreOffice, GIMP, etc.), Some Windows apps via Wine
Customization	Highly customizable (Desktop Environments, Themes, etc.)
Updates	Regular updates, LTS versions available

Python Environment

Feature	Details
Developer	Python Software Foundation
Latest Version	Python 3.12 (as of 2024)
License	Open-source (PSF License)
Package Manager	pip, conda (for Anaconda)
Virtual Environments	venv, virtualenv, conda environments
Supported Platforms	Windows, macOS, Linux
Common Libraries	NumPy, Pandas, TensorFlow, Flask, Django
Use Cases	Web Development, Data Science, Machine Learning, Automation

Visual Studio Code (IDE)

Feature	Details
Developer	Microsoft
Latest Version	VS Code 1.87 (as of 2024)
License	Free (MIT License) with proprietary extensions
Supported Languages	Python, JavaScript, C++, Java, many more
Extensions	Available through VS Code Marketplace
Customization	Themes, Shortcuts, Plugins

System Requirements	Minimum 4GB RAM, 2GB Storage
Debugging Support	Built-in debugger for various languages

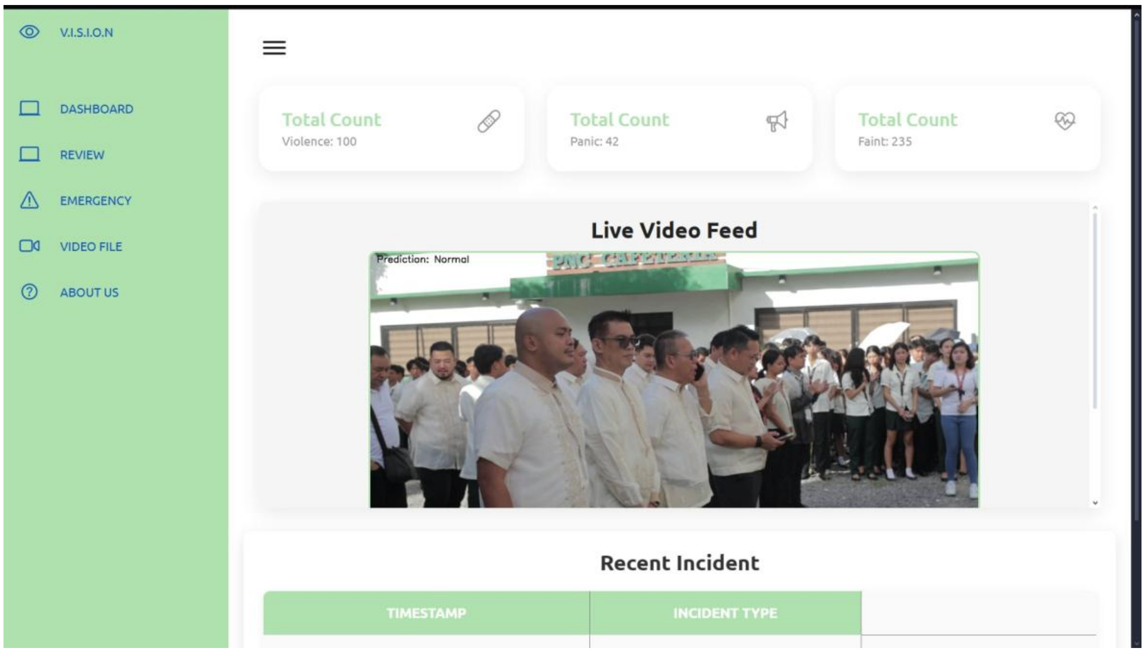
NVIDIA SDK Manager

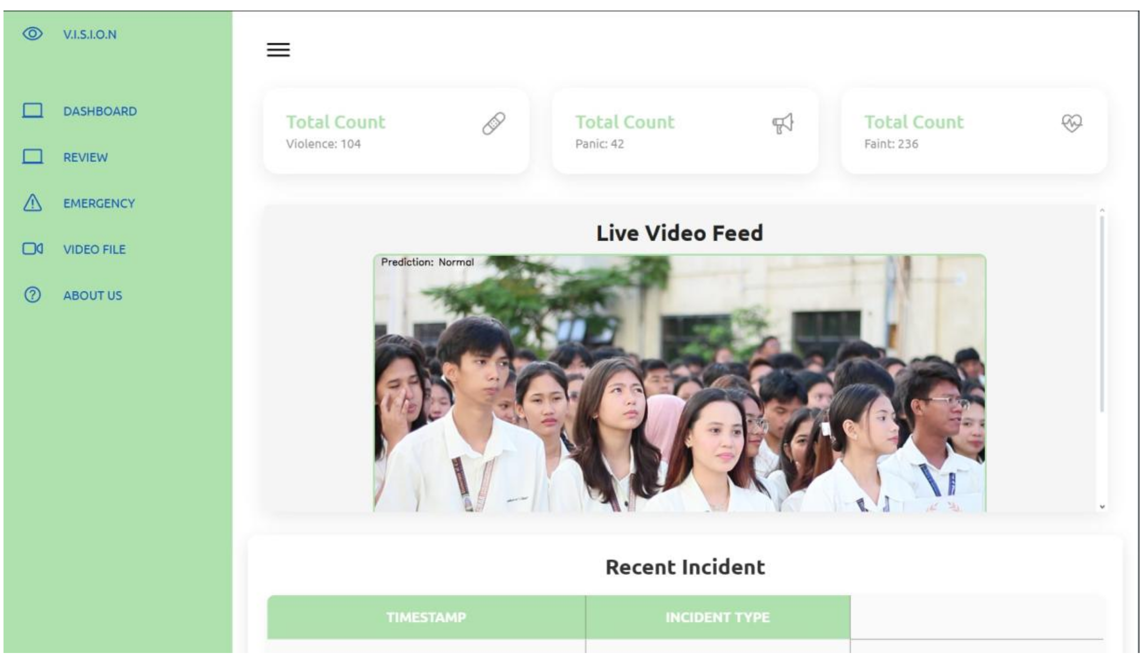
Feature	Details
Developer	NVIDIA Corporation
Latest Version	SDK Manager 1.9 (as of 2024)
License	Proprietary
Supported Platforms	Ubuntu Linux (18.04, 20.04, 22.04)
Use Case	Installing NVIDIA Jetson and DRIVE SDKs
Dependencies	Requires NVIDIA account, sudo privileges

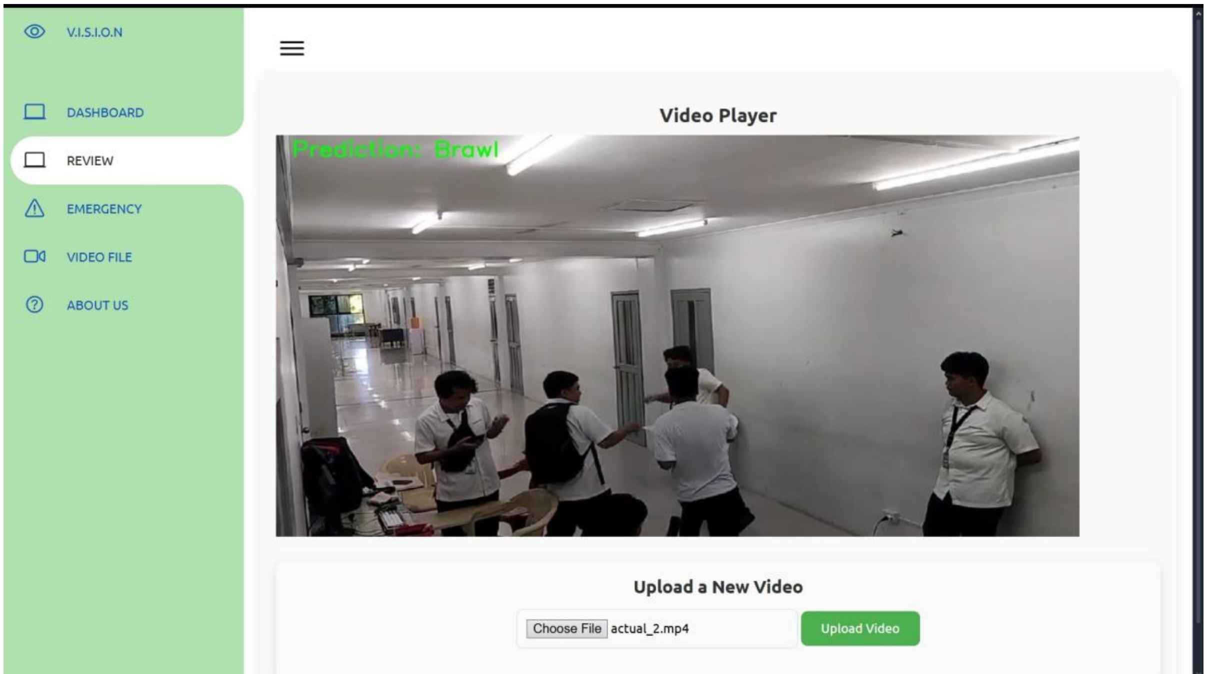
Appendix F

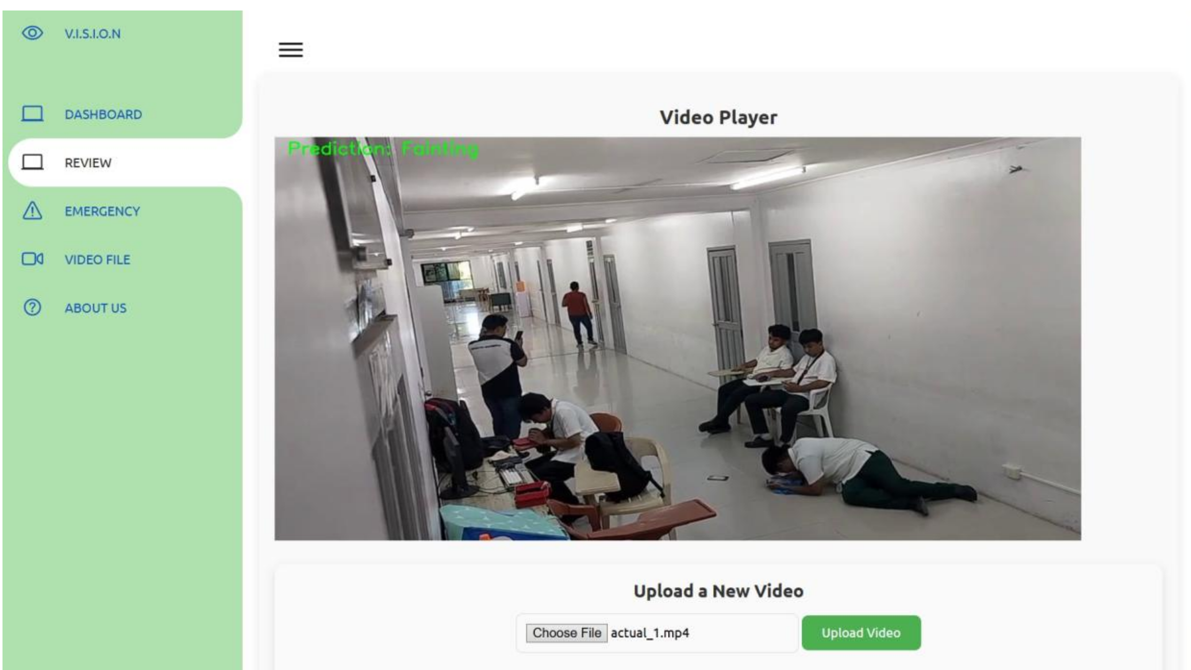
Actual Testing and Results

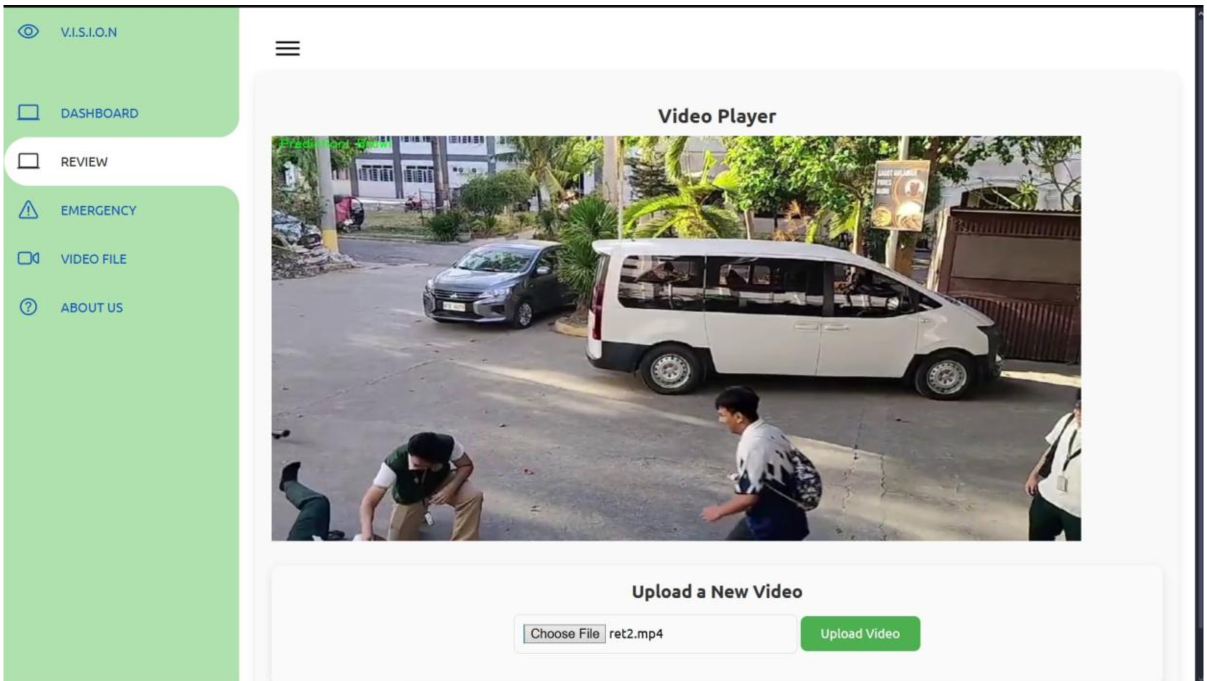
Testing and Result:





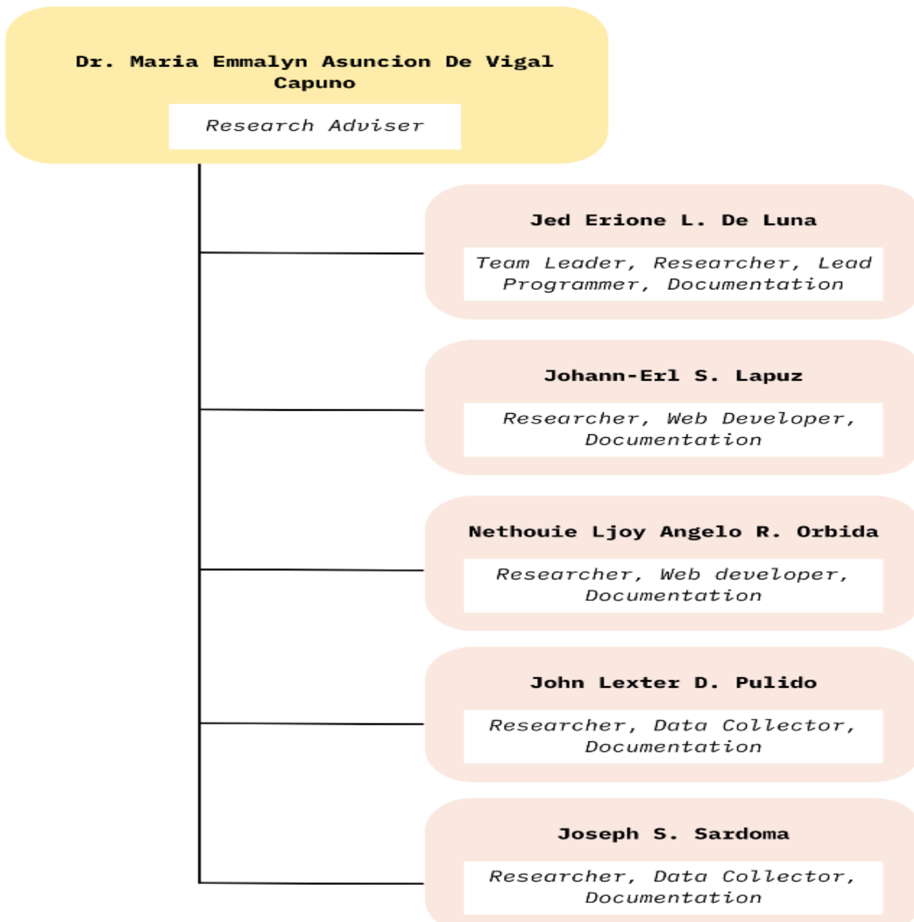

V.I.S.I.O.N
DASHBOARD
REVIEW
EMERGENCY
VIDEO FILE
ABOUT US
Video Player
Prediction: Brawl
Upload a New Video
Choose File actual_2.mp4
Upload Video


V.I.S.I.O.N
DASHBOARD
REVIEW
EMERGENCY
VIDEO FILE
ABOUT US
Video Player
Prediction: Fainting
Upload a New Video
Choose File actual_1.mp4
Upload Video


V.I.S.I.O.N
DASHBOARD
REVIEW
EMERGENCY
VIDEO FILE
ABOUT US
Video Player
Upload a New Video
Choose File
ret2.mp4
Upload Video

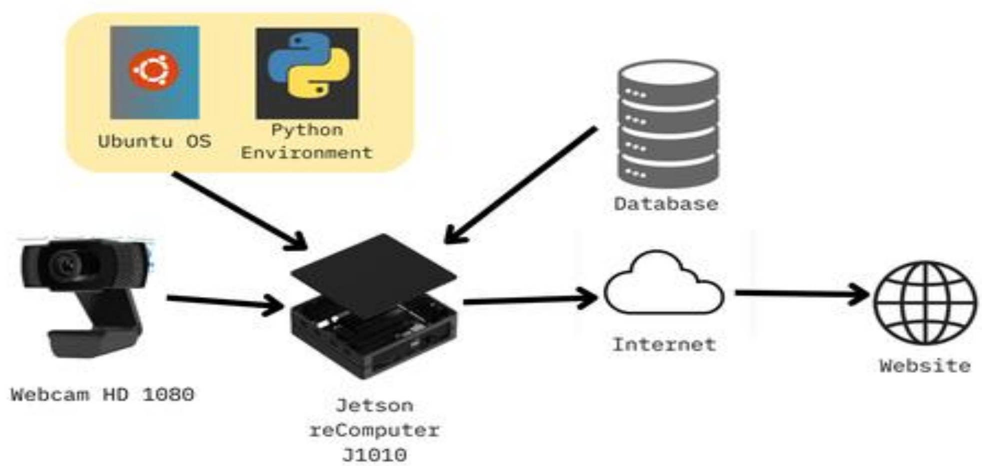
Appendix G

Project Structure and Assessment



Project Organizational Chart

Figure 6 defines the roles, responsibilities, and workflow of the research team in developing the Real-Time Crowd Behavior Control and Monitoring System Using 3D-Convolutional Neural Network. It ensures efficient collaboration, task distribution, and goal alignment among team members. The Research Adviser provides guidance, ensuring the project meets academic and technical standards while helping refine system development and troubleshooting. As researchers, we lead the study by conducting experiments, analyzing results, and validating system performance. Data collectors gather real-world crowd behavior data, compare outputs with actual scenarios, and enhance system accuracy. Web developers design and maintain the Vision monitoring webpage, integrating real-time data visualization and alerts for effective monitoring. Throughout the process, we document system design, implementation, and evaluation to ensure a well-structured and reliable study



Architecture Diagram of the Design Project

The main goal of this system is to capture, process, and transmit video data using a combination of hardware and software components. At the core of the system is the Jetson reComputer J1010, which functions as the main processing unit. This device operates on an Ubuntu OS environment and utilizes a Python-based software stack to manage and process incoming data.

The HD Webcam 1080 is responsible for capturing video, which is then fed into the Jetson reComputer J1010 for processing. The Jetson device, equipped with powerful GPU capabilities, enables efficient video analysis, making it an ideal choice for AI-based applications. The integration of the camera with the Jetson device ensures seamless video acquisition, enabling real-time processing for various use cases.

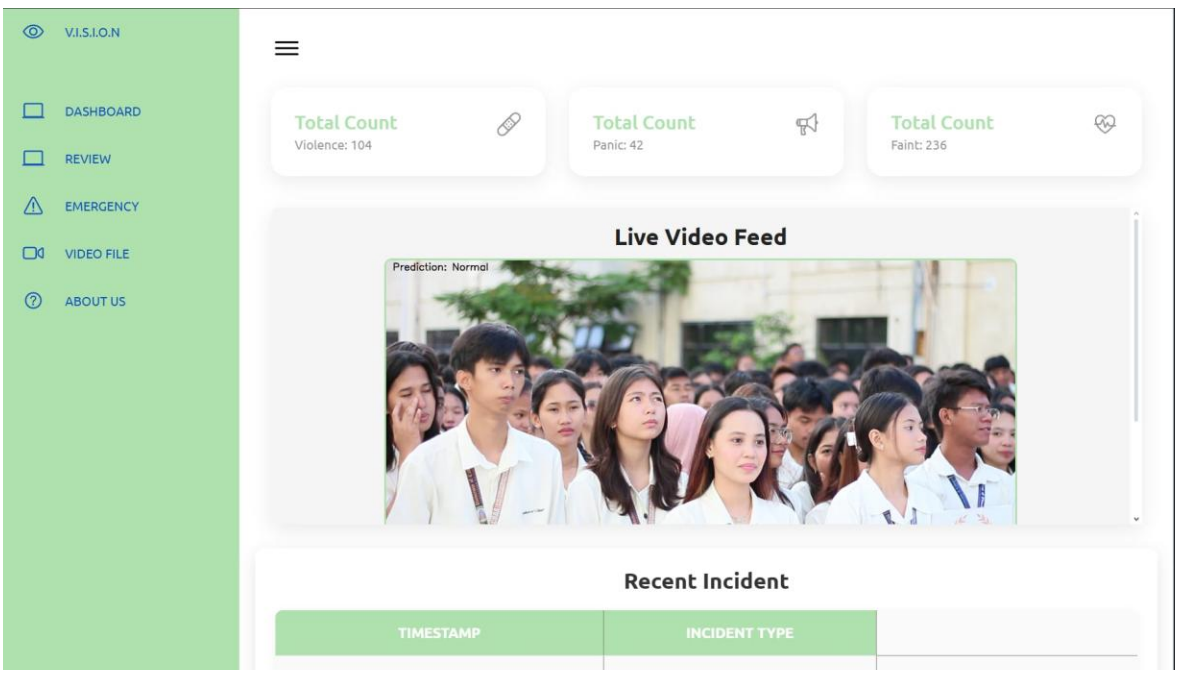
Once the videos are processed, they're sent to a database where they're stored for easy access and future analysis. This database acts like a well-organized digital storage space, making it simple for other systems or apps to find and use the video data when needed, whether for further processing or creating visuals. By keeping everything organized, it's easy to manage, ensuring that both old and new video footage can be accessed whenever needed for deeper insights.

The Jetson reComputer J1010 is connected to the internet, enabling smooth data transmission to cloud services or remote servers. Through this internet connection, the processed data is also made available on a website, allowing users to access real-time information. This web-based access enhances the usability of the system, providing a user-friendly interface for monitoring and analysis.

With Ubuntu OS and Python set up on the system, we, as researchers, have the flexibility to customize and add various features, like machine learning, computer vision, and automation. The system is built to run smoothly, ensuring that data flows easily from the camera to the Jetson device, then to the database, and finally to the website. This setup allows users to interact with the data in real-time, providing an effortless experience for monitoring and analysis.

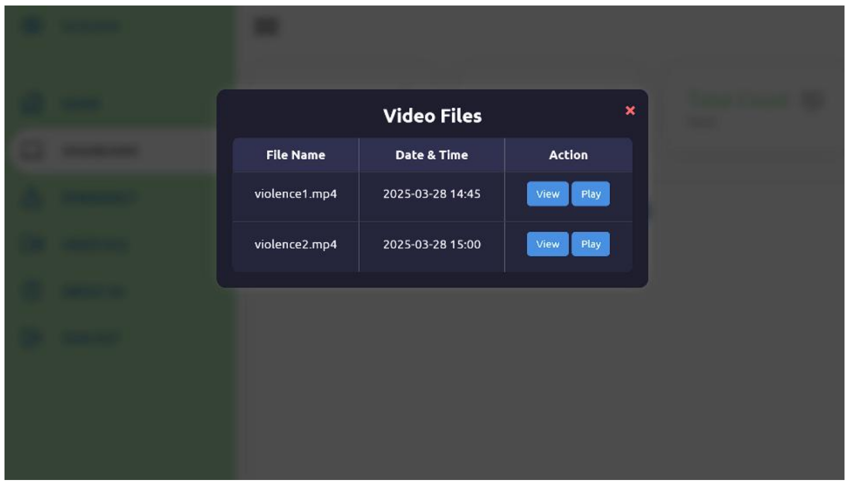
By integrating powerful hardware and software, this system offers an efficient, scalable, and automated way to capture, process, save, and visualize video data. The setup is designed to be reliable and high-performing, making it ideal for applications like real-time crowd behavior monitoring, control, and AI-driven analysis using 3D-Convolutional Neural Networks.

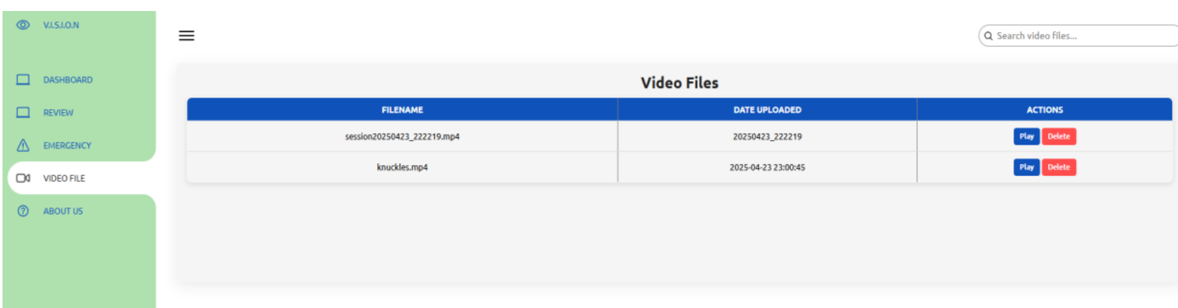
Web Content



V.I.S.I.O.N Dashboard Interface

The V.I.S.I.O.N dashboard interface for security monitoring. On the left, there's a sidebar with easy-to-access navigation options like Dashboard, Review, Emergency, Video File, and About Us. The main area displays the live video feed where it shows the real time video detecting. The interface is designed for user access to monitoring features, enabling navigation to different functionalities for real-time surveillance and crowd behavior analysis.





Video File Storage and Management Interface

The recorded video files in a user-friendly format. The system provides a file management interface that displays recorded incidents in a table form. This table includes details such as the file name, date, and time of recorded events. Users can perform actions like viewing or deleting files for better management. This feature allows administrators to efficiently review footage of incidents such as brawling and other unusual behaviors. The real-time crowd behavior monitoring system includes a feature that records detected activities. This feature captures and stores data such as the file name, date, and time of recorded events. It also keeps track of incidents such as brawling and other unusual behaviors.

Final Prototype

This figure presents the final prototype built by the proponents. This system is designed to monitor and manage crowd behavior in real time. It analyzes crowd behavior using a 3D-Convolutional Neural Network (3D-CNN) model, detects movement patterns, and identifies anomalies as they occur. The processed data is then stored in a database for further analysis and transmitted through an internet to V.I.S.I.O.N, a web-based platform that enables remote monitoring and management.

Through V.I.S.I.O.N, users can visualize real-time data, review previous activity records, and make informed decisions to optimize crowd control. This system keeps users informed about crowd movements in real time, making it easier to manage crowds effectively across various environments.

Appendix H

Source Codes

```
# Define 3D-CNN Model
def build_3d_cnn(input_shape):
    model = Sequential([
        Conv3D(8, kernel_size=(3, 3, 3), activation='relu', input_shape=input_shape,
kernel_regularizer=l2(0.005), padding='same'),
        BatchNormalization(),
        MaxPooling3D(pool_size=(1, 2, 2)),

        Conv3D(32, kernel_size=(3, 3, 3), activation='relu', kernel_regularizer=l2(0.005), padding='same'),
        BatchNormalization(),
        MaxPooling3D(pool_size=(1, 2, 2)),

        Conv3D(64, kernel_size=(3, 3, 3), activation='relu', kernel_regularizer=l2(0.002), padding='same'),
        BatchNormalization(),
        MaxPooling3D(pool_size=(1, 2, 2)),

        Conv3D(64, kernel_size=(3, 3, 3), activation='relu', kernel_regularizer=l2(0.002), padding='same'),
        BatchNormalization(),
        MaxPooling3D(pool_size=(1, 2, 2)),

        Conv3D(128, kernel_size=(3, 3, 3), activation='relu', kernel_regularizer=l2(0.005), padding='same'),
        BatchNormalization(),
        MaxPooling3D(pool_size=(1, 2, 2)),

        Conv3D(256, kernel_size=(3, 3, 3), activation='relu', kernel_regularizer=l2(0.002), padding='same'),
        BatchNormalization(),
        MaxPooling3D(pool_size=(1, 2, 2)),

        Flatten(),
```

```
        Dense(512, activation='relu'),
        Dropout(0.5),
        Dense(5, activation='softmax')  # Number of Classes to be detected
    ])

    model.compile(optimizer='adam',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model



# Training the model
video_directory = "dataset"  # Folder containing datasets
labels = ["Brawl", "Fainting", "Normal", "Panic", "Seizure"] # Folders Name as label

# Load dataset to prepare for Training
X, y = load_dataset(video_directory, labels)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) # 80% training,
20% Testing
                                                           #Introduce random state of dataset to make it
challening

# Building model
input_shape = (16, 128, 128, 3)
model = build_3d_cnn(input_shape)

print("training model..")
# Train the model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=30, batch_size=10)
```

```
# Save the model
model.save("Project_Model/3d-test1_detector_final.h5") # For Legacy
model.save("Project_Model/3d-test1_detector_final.keras") # For deployment
model.summary() # Show Model Parameters after Training
```

Appendix I

Project Costing

Project Costing of Materials

Materials	Quantity	Price (Php)
Jetson J1010	1x	P15,990
Webcam	1x	P500
3D Printing (Casing)	1x	P3,800
Micro SD Card (64GB)	1x	P600
WiFi Dongle	1x	P250
Total		**P21,140**

Appendix J

Certificates

PNC:PRE-FO-93 rev.0 05102023

Republic of the Philippines
Pamantasan ng Cabuyao
(UNIVERSITY OF CABUYAO)
Office of the Executive Vice President
Research Ethics Review Office
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna

RESEARCH ETHICS CLEARANCE

This is to certify that the research **REAL-TIME CROWD BEHAVIOR CONTROL AND MONITORING SYSTEM USING 3D-CONVOLUTIONAL NEURAL NETWORK BY JED ERIONE L. DE LUNA, JOHANN-ERL S. LAPUZ, NETHOUIE LJOY ANGELO R. ORBIDA, JOHN LEXTER D. PULIDO, AND JOSEPH S. SARDOMA** has undergone a thorough ethical review and has been granted clearance to proceed with the study.

The research study has been evaluated based on the guidelines set by the University's Research Ethics Review Committee and is found to be in compliance with the ethical principles of research involving human subjects, including informed consent, confidentiality, and data privacy.

This clearance is valid for the duration of the study as specified in the research proposal and subject to periodic review by the Research Ethics Review Committee.

MS. JANINE M. LIBOSADA
Chair
Research Ethics Review Committee

DR. MARIA EMMALYN ASUNCION D. CAPUNO
Head
Research Ethics Review Office

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Planning, Research, and Extension Division
Research and Development Department
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

CERTIFICATION

This is to certify that **ENGR. ALDRIN J. SORIANO** a teaching personnel of the College of **ENGINEERING** served as a **PANELIST** during the Thesis Oral Defense of the **BACHELOR OF SCIENCE IN COMPUTER ENGINEERING** students with research title: **REAL-TIME CROWD BEHAVIOR CONTROL AND MONITORING SYSTEM USING 3D-CONVOLUTIONAL NEURAL NETWORK**.

Given this **7TH** day of **APRIL, 2025** at Pamantasan ng Cabuyao, Katapatan Homes Subdivision, Brgy. Banay-banay, Cabuyao City, Laguna.

DR. JOANNA MARIE A. DE BORJA
Director
Research and Development Department

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Research and Development Department
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

CERTIFICATION

This is to certify that DR. MARIA EMMALYN ASUNCION D. CAPUNO a teaching personnel of the College of ENGINEERING served as an ADVISER during the Thesis Oral Defense of the BACHELOR OF SCIENCE IN COMPUTER ENGINEERING students with research title: REAL-TIME CROWD BEHAVIOR CONTROL AND MONITORING SYSTEM USING 3D-CONVOLUTIONAL NEURAL NETWORK.

Given this 7TH day of APRIL, 2025 at Pamantasan ng Cabuyao, Katapatan Homes Subdivision, Brgy. Banay-banay, Cabuyao City, Laguna.

DR. JOANNA MARIE A. DE BORJA
Director
Research and Development Department

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Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

CERTIFICATION

This is to certify that **ENGR. CARLO B. CIMACIO** a teaching personnel of the College of **ENGINEERING** served as a **PANELIST** during the Thesis Oral Defense of the **BACHELOR OF SCIENCE IN COMPUTER ENGINEERING** students with research title: **REAL-TIME CROWD BEHAVIOR CONTROL AND MONITORING SYSTEM USING 3D-CONVOLUTIONAL NEURAL NETWORK**.

Given this **7TH** day of **APRIL, 2025** at Pamantasan ng Cabuyao, Katapatan Homes Subdivision, Brgy. Banay-banay, Cabuyao City, Laguna.

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CERTIFICATION

This is to certify that **ENGR. JOMER C. SANTOS** a teaching personnel of the College of **ENGINEERING** served as a **PANELIST** during the Thesis Oral Defense of the **BACHELOR OF SCIENCE IN COMPUTER ENGINEERING** students with research title: **REAL-TIME CROWD BEHAVIOR CONTROL AND MONITORING SYSTEM USING 3D-CONVOLUTIONAL NEURAL NETWORK**.

Given this **7TH** day of **APRIL, 2025** at Pamantasan ng Cabuyao, Katapatan Homes Subdivision, Brgy. Banay-banay, Cabuyao City, Laguna.

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Appendix K

Plagiarism Check Report

Chapter 1-5 Plagiarism Check Report

turnitin Page 2 of 135 - Integrity Overview

Submission ID trn:oid:::3618:96085836

8% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text
- Cited Text
- Submitted works

Match Groups

192 Not Cited or Quoted 8%
Matches with neither in-text citation nor quotation marks

0 Missing Quotations 0%
Matches that are still very similar to source material

0 Missing Citation 0%
Matches that have quotation marks, but no in-text citation

0 Cited and Quoted 0%
Matches with in-text citation present, but no quotation marks

Top Sources

4% Internet sources
6% Publications
0% Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

No suspicious text manipulations found.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

Chapter 1 Grammarly Checked

Report: Chapter1-5-Revision9

Chapter1-5-Revision9

by z

General metrics

23,032	3,379	187	13 min 30 sec	25 min 59 sec
characters	words	sentences	reading time	speaking time

Writing Issues

✓ No issues found

Plagiarism

This text hasn't been checked for plagiarism

Chapter 2 Grammarly Checked

Report: Chapter1-5-Revision9

Chapter1-5-Revision9

by z

General metrics

31,713	4,380	233	17 min 31 sec	33 min 41 sec
characters	words	sentences	reading time	speaking time

Writing Issues

✓ No issues found

Plagiarism

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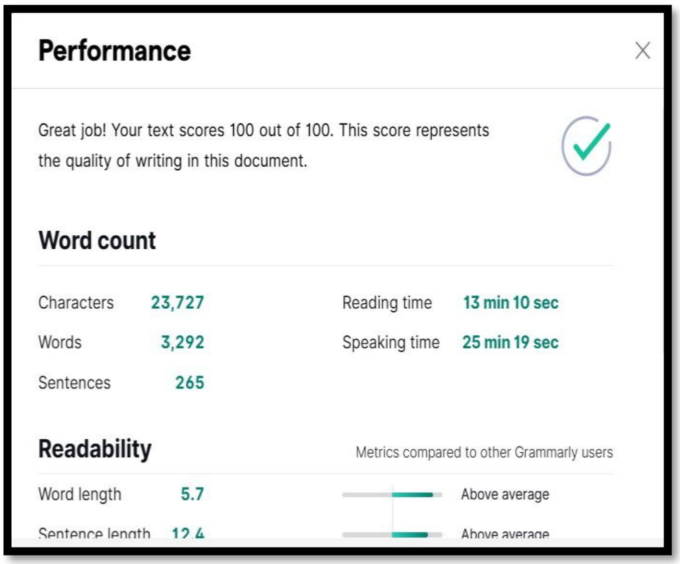
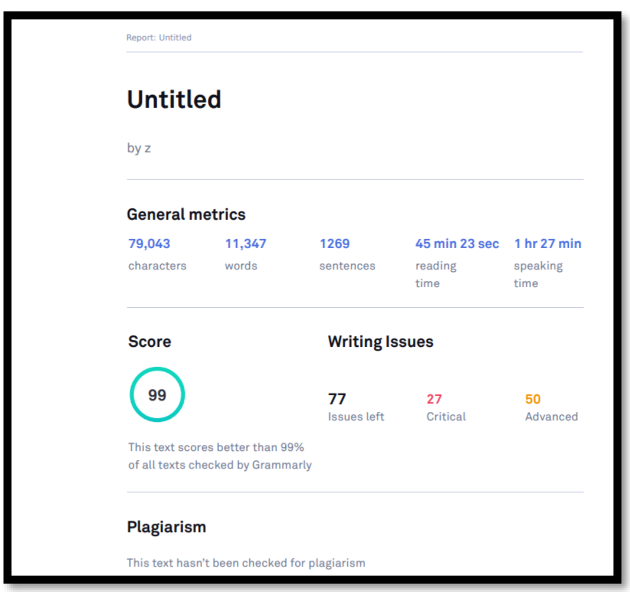
Chapter 3 Grammarly Checked



Chapter 4 Grammarly Checked



Chapter 5 Grammarly Checked

Report: Chapter1-5-Revision9

Chapter1-5-Revision9

by z

General metrics

6,330	864	46	3 min 27 sec	6 min 38 sec
characters	words	sentences	reading time	speaking time

Writing Issues

No issues found

Plagiarism

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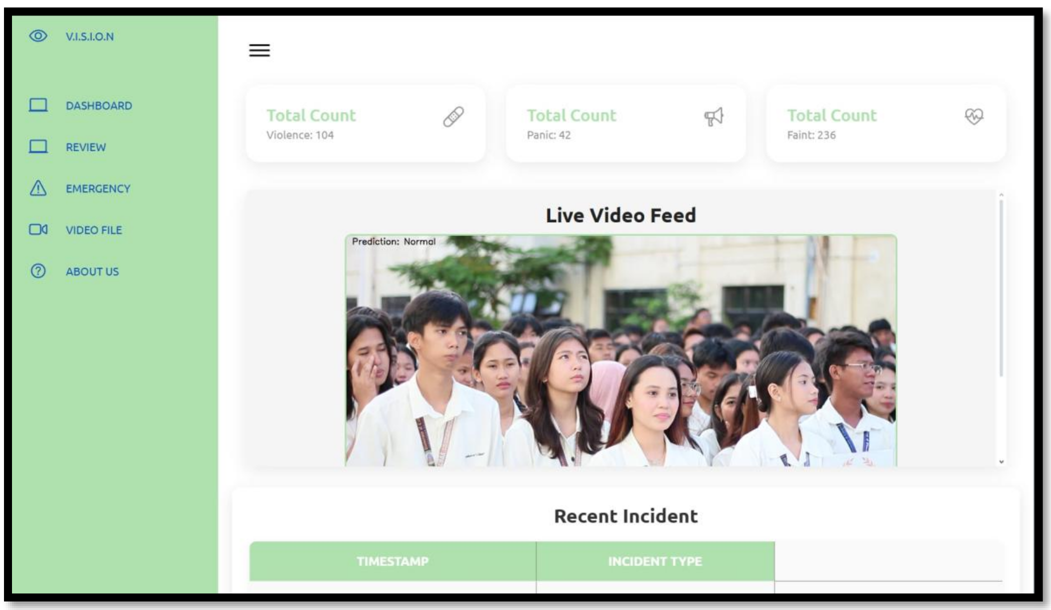
Appendix L

Project User Manual

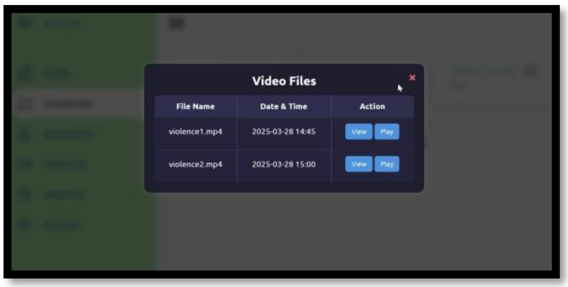
Project User Manual

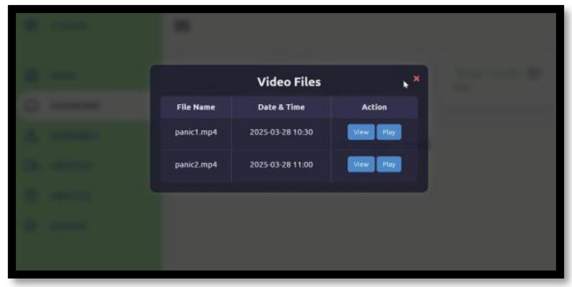
For User:

1) When you open the website, you will see the DASHBOARD the live video feed

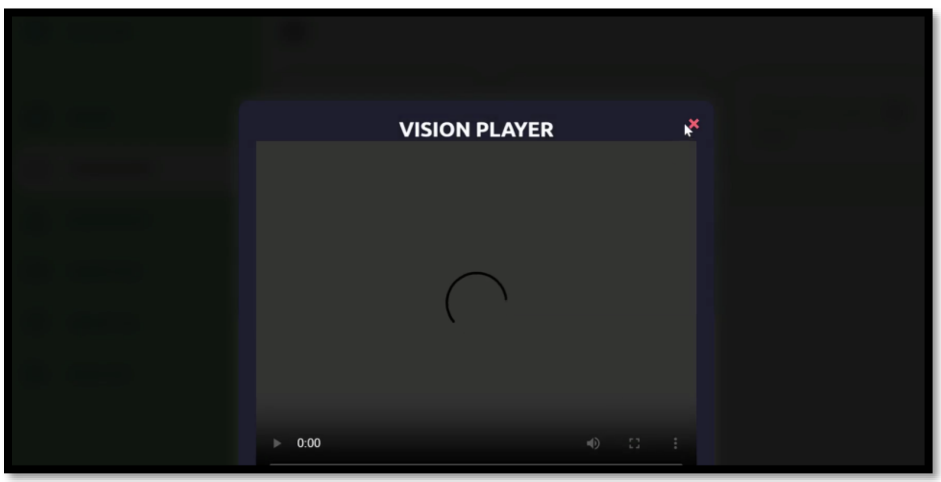


2) Clicking the Total Count shows the videos that were recorded showing Violence/Brawl, Panic or Fainting

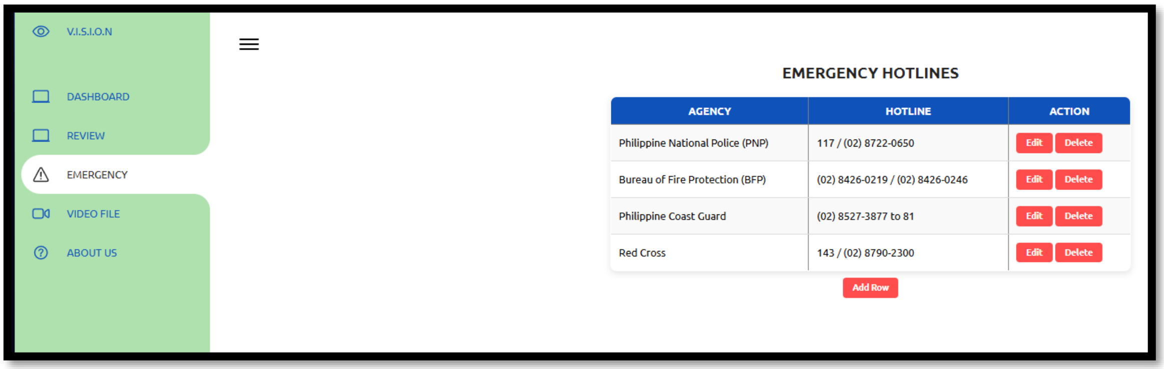




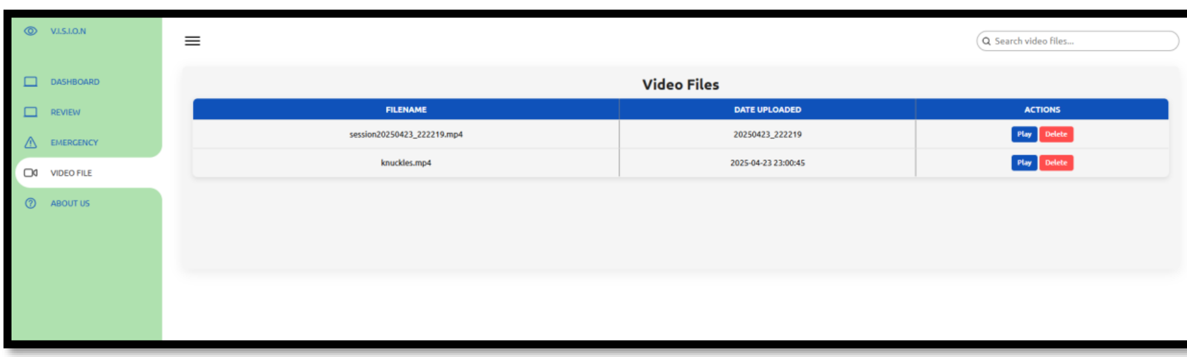
3) Clicking View or Play will show them



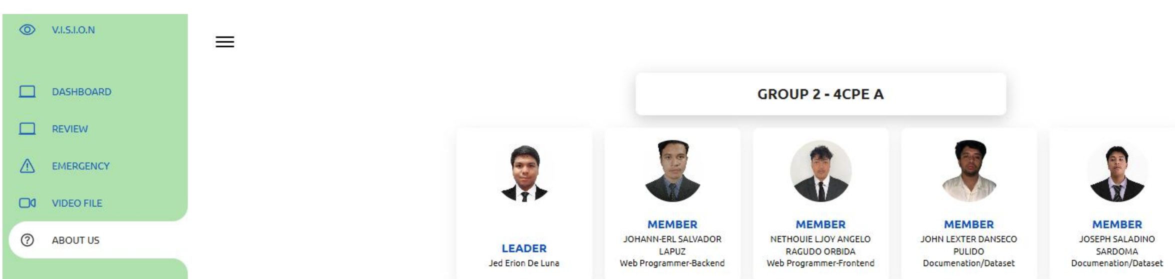
4) Clicking Emergency takes you to the hotlines in case of emergency



5) Clicking VIDEO FILE shows the whole recording of the session and also shows the date it was taken. You can play or delete the file.



6) Clicking ABOUT US displays the information about the researchers.



Appendix M

Forms

Research Ethics Application Form Page 1

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Planning, Research, and Extension Division
Research and Development Department
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

RESEARCH ETHICS APPLICATION FORM

Research Project Title	Real-time Crowd Behavior Monitoring and Control System Using 3D-CNN			
Category	☐ Full-blown research ☑ Action research			
Duration of the research project	2 semesters			
Proponents	**Name**	**Email Address**	**Contact Number**	**Department**
Research Lead	Jed Erlone L. De Luna	delunajederlon82@gmail.com	09815380976	College of Engineering
Member/s	Johann-Erl S. Lapuz	lapuzjohannerl32@gmail.com	09458026715	College of Engineering
	Nethouie Ljoy Angelo R. Orbida	orbidanethouie80@gmail.com	09661491007	College of Engineering
	John Lexter D. Pulido	pulidojohnlexter78@gmail.com	09282982810	College of Engineering
	Joseph S. Sardoma	sardomajoseph976@gmail.com	09663355346	College of Engineering
Thesis Adviser (for student research)	Dr. Maria Emmalyn De Vigal Capuno	meadcapuno@pnc.edu.ph	—	College of Engineering

DECLARATION OF CONFLICT OF INTEREST

☑ I do not have a conflict of interest in any form (personal, financial, proprietary, or professional) with the sponsor/grant-giving organization, the study, the researchers/personnel, or the site.

☐ I do have a conflict of interest, specifically:

☐ I have a personal/family or professional interest in the results of the study (family members who are co-proponents or personnel in the study, membership in relevant professional associations/organizations). Please describe the personal/family or professional interest: ______

☐ I have propriety interest vested in this proposal (with the intent to apply for a patent, trademark, copyright, or license) Please describe propriety interest: ______

☐ I have significant financial interest vested in this proposal (remuneration that exceeds P250,000.00 each year or equity interest in the form of stock, stock options or other ownership interests). Please describe financial interest: ______

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Research Ethics Application Form Page 2

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Research and Development Department
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

CERTIFICATION FROM THESIS ADVISER (FOR UNDERGRADUATE AND GRADUATE THESIS ONLY)

I confirm that the student(s) is/are capable of undertaking this research in a safe and ethical manner.

Dr. Maria Emmalyn Asuncion De Vigal Capuno
Name and signature of the Thesis Adviser
Date: **October 30, 2024**

PART 1. GENERAL CHECKLIST
In accordance with our commitment to promoting ethical research practices, we require researchers to complete a detailed checklist for any category that they answered "YES" to. It is important to note that a "YES" answer does not necessarily mean that the research proposal will be disapproved. Rather, this serves as an indicator that potential ethical concerns have been identified, and that further attention and adherence to the University Research Ethics is required.

The University shall ensure that all potential ethical concerns are identified and addressed, and that research activities are conducted in a responsible and ethical manner. This checklists help to ensure that our University upholds the highest ethical standards in research involving human participants/subjects, and that research activities are conducted in a manner that respects the rights, welfare, and dignity of research participants.

Question	YES	NO	Action Point
Does your research involve human participants (this includes new data gathered or using pre-existing data)?			If yes, answer Part 2 of this checklist
Will you be conducting Action Research in an existing business, company, or school?	✓		If yes, answer Part 2 of this checklist
Does your research involve online communities (this includes culling data from social media platforms, online forums and blogs)?			If yes, answer Part 3 of this checklist
Does your research involve human participants who are situated in a community and may necessitate permission to acquire access to them?			If yes, answer Part 4 of this checklist
Will your research make use of documents which are not in the public domain and, thus, require permission for use from the custodian of such documents?			If yes, please attach a certification that permission from the custodian of the data was sought and granted
Will your research make use of secondary data (e.g., surveys, inventories, plans, official documents, etc.) from an institution, organization, or agency, which are not in the public domain and, thus, require permission for use from the custodian of such documents?			
Does your research involve animals (non-human subjects)?			If yes, answer Part 5 of this checklist
Does your research involve toxic/chemicals/ substances/materials?			If yes, answer Part 6 of this checklist

PART 2. RESEARCH ETHICS CHECKLIST FOR RESEARCHES INVOLVING HUMAN PARTICIPANTS
Attachments:
☐ A copy of the informed consent form to be used in the study.
☐ A copy of the instrument/tool that will be administered to the participants.
☐ If applicable, a copy of the letter seeking permission to collect data from participants who are under the supervision of an agency, institution, department, or office.
☐ If applicable, a copy of the parental consent form for participants below 18 years old

Research Ethics Application Form Page 3

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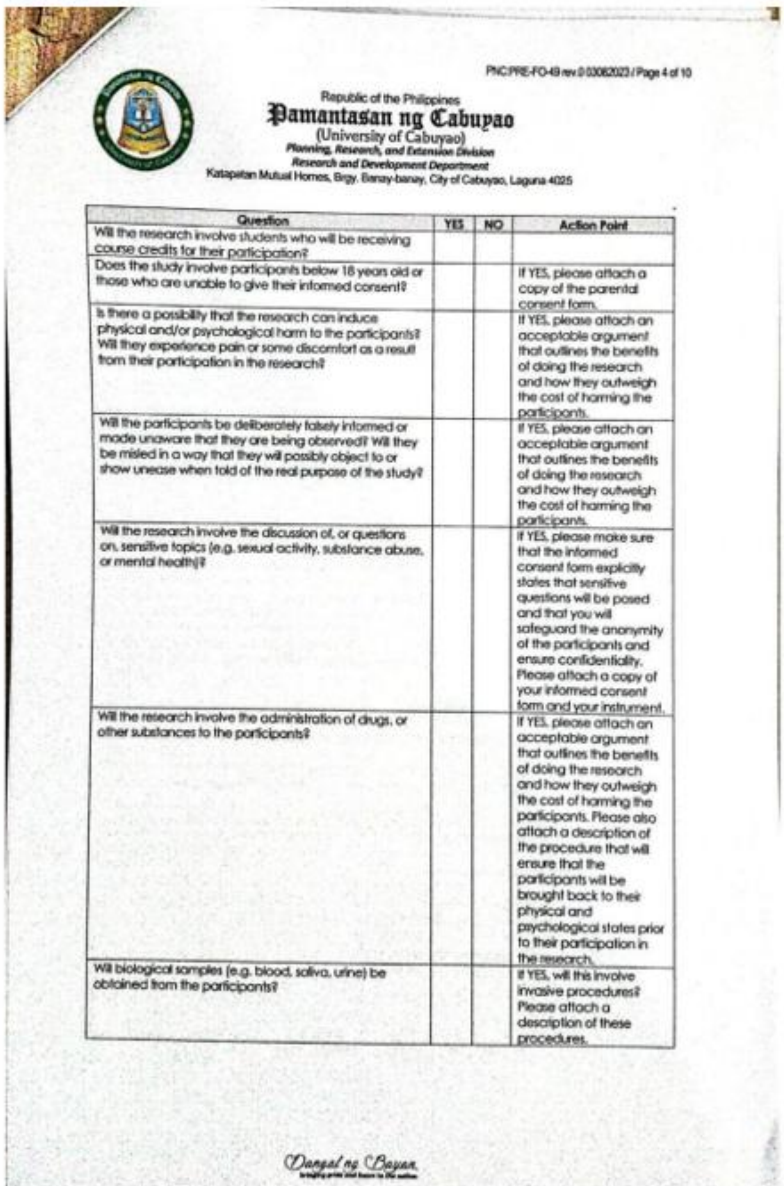
Research and Development Department
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

Questions			
Source of Data. ☐ New data will be collected from human participants	How will the new data be gathered? Please check all that apply ☐ Experimental procedures ☐ Focus Group Discussions ☐ Personal interviews ☐ Self-administered questionnaires ☐ Survey ☐ Observations ☐ Others. ______________		
	Number of Participants/Subjects		
	Location where the participants will be recruited/ where subjects will be obtained?		
	How long will the data collection take place?		
	Who will perform the data collection?		
	Location(s) where data collection will take place		
	What procedures will be employed to ensure voluntary consent from participants?	☐ Written consent ☐ Audio-recorded consent ☐ Online/Email recorded consent	
	How long will data with participant identifiers be kept after the publication of the first paper from the project?		
	How long will anonymized data be kept after the publication of the first paper from the project?		
☐ Use of Pre-existing data collected from human participants	Question	YES	NO
	Does the original dataset have personal identifiers?		
	Is the data publicly available, i.e., the access to which does not necessitate an approval process?		
	Was the original dataset originally collected for the present study's purpose?		

Dangal ng Bayan

Research Ethics Application Form Page 4



PNC:PRE-FO-49 rev.0 03082023 / Page 4 of 10

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Question	YES	NO	Action Point
Will the research involve students who will be receiving course credits for their participation?			
Does the study involve participants below 18 years old or those who are unable to give their informed consent?			If YES, please attach a copy of the parental consent form.
Is there a possibility that the research can induce physical and/or psychological harm to the participants? Will they experience pain or some discomfort as a result from their participation in the research?			If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants.
Will the participants be deliberately falsely informed or made unaware that they are being observed? Will they be misled in a way that they will possibly object to or show unease when told of the real purpose of the study?			If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants.
Will the research involve the discussion of, or questions on, sensitive topics (e.g. sexual activity, substance abuse, or mental health)?			If YES, please make sure that the informed consent form explicitly states that sensitive questions will be posed and that you will safeguard the anonymity of the participants and ensure confidentiality. Please attach a copy of your informed consent form and your instrument.
Will the research involve the administration of drugs, or other substances to the participants?			If YES, please attach an acceptable argument that outlines the benefits of doing the research and how they outweigh the cost of harming the participants. Please also attach a description of the procedure that will ensure that the participants will be brought back to their physical and psychological states prior to their participation in the research.
Will biological samples (e.g. blood, saliva, urine) be obtained from the participants?			If YES, will this involve invasive procedures? Please attach a description of these procedures.

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Research Ethics Application Form Page 5

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Question	YES	NO	Action Point
Will financial inducements (other than reasonable expenses, like transportation or meal allowances) be offered to the participants for their participation in their research?			If YES, the researcher(s) should be mindful of how the inducements can influence the participants' responses or behaviors during the research. Indicate the financial inducements offered to the participants:
Is there a possibility for groups or communities to be harmed by the dissemination of the research findings?			If YES, please attach a description of procedures to ensure the anonymity and confidentiality of the research findings.
Will the results of this study have a commercial value?			If yes, do you intend to apply for a patent for the output of this research? ☐ Yes ☐ No
Will your research involve the participation of vulnerable stakeholders? Vulnerable stakeholders are persons whose situation or characteristics may make them unable to provide free and informed consent to participate in the research. This group includes children, institutionalized, persons, students, those who have cognitive impairments, customers, employees in subordinate positions, suppliers, students, etc.			If yes, attach Informed Consent Form
Is there a probability that a participant will drop out from the study?			If yes, present a course of action in the methodology section of your research proposal.

PART 3. RESEARCH ETHICS CHECKLIST FOR RESEARCHES CONDUCTING INTERNET RESEARCH

Attachments:

☐ A copy of the informed consent form to be used in the study.
☐ If applicable, a copy of the parental consent form for participants below 18 years

Questions	
Which of the following online data will you be using in your research? Check all that apply:	☐ Social Media Platform (e.g. Twitter, Facebook, Tiktok) ☐ Blogs & Forum including Comments ☐ E-mails & Chats ☐ Video Blogs (e.g. YouTube) ☐ Collaborative (e.g. Wikipedia) ☐ Websites ☐ Online Recruitment Platform ☐ Others, ______________

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Questions	
What type of data will be collected?	☐ Text ☐ Audio ☐ Video/Film ☐ Photo ☐ Metadata (e.g. Profile, Geographic Location, Tags) ☐ Presentations (e.g. downloaded PowerPoint or Keynote presentations) ☐ Contents of an application such as input, output, log files for analysis software, simulation software, schemas ☐ Correspondence, including electronic mail
What is the period coverage of data collection? (indicate in years and months)	
How many participants will you collect data from?	
What are all the websites you will source your data from? Please list all URLs:	
What procedures will be employed to ensure voluntary consent from participants?	☐ Written consent ☐ Audio-recorded consent ☐ Online/Email recorded consent
How will the participants obtain a copy of the informed consent form? Please check.	☐ Hard copy ☐ Online copy
How long will data with participant identifiers be kept after the publication of the first paper from the project?	
How long will anonymized data be kept after the publication of the first paper from the project?	

Question	YES	NO	Action Point
Is the data you are planning to gather publicly available?			If NO...attach a letter of support from the website or server owner/moderator indicating approval to use this for data gathering
Will the participants be compensated for participating?			If YES, indicate the type of compensation to be provided and provide information on how appropriate and just compensation
Will you have minors as participants in your study? Minors are individuals under the age of 18 years old			Attach Parent Consent Form
Will data collection involve students?			Attach Informed Consent Form

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Question	YES	NO	Action Point
Will data collection involve persons who belong to a vulnerable group (PWDs, minorities, abuse victims, students, etc.)			Attach Informed Consent Form
Will the results of this study have a commercial value?			If yes, do you intend to apply for a patent for the output of this research? ☐ Yes ☐ No

PART 4. RESEARCH ETHICS CHECKLIST FOR RESEARCHES CONDUCTING COMMUNITY RESEARCH

Attachments:

☐ A copy of the informed consent form to be used in the study.

☐ If applicable, a copy of the parental consent form for participants below 18 years

Question	YES	NO	Action Point
Will you be conducting research in an indigenous community that has or is found inside an ancestral domain?			If YES, provide a Certification Precondition issued by the National Commission on Indigenous Peoples (NCIP) allowing collection of data with the members of the indigenous community
Have the research activities been explained to and approved by the community in which the research will be undertaken?			Attach the letter of approval
Will your presence as a researcher and the research team pose major disruptions to the community's daily activities?			

PART 5. RESEARCH ETHICS CHECKLIST FOR RESEARCHES INVOLVING ANIMALS

Question	Details	
Animal information	Common Name of the Laboratory animal:	
	Scientific name:	
	Strain:	
	Number of animals to be used in the study:	
	Source (e. g. local supplier, pet owner, impounding facility):	
	(If imported: please state the country and laboratory/company.)	
Please provide a brief description of the data collection procedure to be undertaken in the research:		

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Question	YES	NO	Action Point	Response
Will the animals be transported from the source place to the research site/laboratory?			If yes, please describe the conditions that the animals will be subjected to during the transport	
Will the animals be housed inside the University during the conduct of the experiment?			If yes, please describe the preparations/arrangements that have been made with the Laboratory for the housing of the animals	
Does your study involve manipulation of the animal's environment using a procedure that is not normally being performed in husbandry or habitat management?			If yes, please describe why the manipulation is needed and how it will be done	
Does your study involve the introduction of an infectious agent on the animal?			If yes, please identify this infectious agent and describe how this is going to be introduced to the animal.	
Is there a risk that these animals will transmit this infectious agent to other animals or humans?			If yes, what measure will be done to avoid this?	
Is there a risk of causing pain, suffering, or psychological stress/change in the animal as a consequence of this research?			If yes, what measures are in place to lessen this physical/psychological outcome?	
Will the animals be disposed of after they are killed?			If yes, please describe the procedure for the disposal and where these animals will be disposed.	

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PART 6. RESEARCH ETHICS CHECKLIST FOR RESEARCHES INVOLVING USE OF TOXIC SUBSTANCES
If a special permit is required, please secure permit from the Department of Environment and Natural Resources-Environmental Management Bureau (DENR-EMB) indicating that permission was granted. Please attach the documents to the research proposal

Questions	
How would you classify the toxic chemicals that will be used in your study (see last page for list of chemicals that require special permits): Check all that apply:	☐ Corrosive (can injure body tissue or corrode metals) ☐ Flammable (have the potential to catch fire readily and burn in air) ☐ Oxidizer and reactive (chemicals that can explode or react violently with water or atmospheric oxygen) ☐ Toxin (substances that even in small amounts can injure body tissues) ☐ Mutagen/Carcinogen (can cause mutation or cancer) ☐ Allergen (can cause adverse reaction to the immune system) ☐ Irritant (can cause inflammatory effects on living tissues) ☐ Neurotoxin (can induce adverse effect on the central or peripheral nervous system)
Please provide a brief description of the data collection procedure to be undertaken in the research:	

Question	YES	NO	Action Point	Response
Will the experiment require your exposure to the toxic chemical for a long period of time?			If yes, please indicate the duration of exposure:	
Will you need to treat, store and dispose toxic/hazardous waste generated by your research?			If yes, please describe the preparations/arrangements that have been made with the Laboratory	

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INFORMED CONSENT FORM

Research Project Title	Implementation of IoT-Based Temperature Monitoring for Pig Health Management Systems			
Proponents	**Name**	**Email Address**	**Contact Number**	**Department**
Research Lead	Jed Erione L. De Luna	delunajederione82@gmail.com	09815380976	College of Engineering
Member/s	Johann-Eri S. Lapuz	lapuzjohanneri32@gmail.com	09458026715	College of Engineering
	Nethoule Ljoy Angelo R. Orbida	orbidanethoule80@gmail.com	09661491007	College of Engineering
	John Lexter D. Pulido	pulidojohnlexter78@gmail.com	09282982810	College of Engineering
	Joseph S. Sardoma	sardomajoseph976@gmail.com	09663355346	College of Engineering
Thesis Adviser (for student research)	Dr. Maria Emmalyn De Vigal Capuno	meadcapuno@pnc.edu.ph	-	College of Engineering

You are being invited to participate in a research study. Before you decide whether to participate, it is important that you understand why the research is being done and what your participation would involve. Please read the following information carefully and take time to ask any questions that you may have. You are free to choose whether or not to participate in this study. If you do not want to participate, you do not have to give a reason, and your decision will not affect any relationship you may have with the researchers or the institution.

Purpose of the Study	
Risks, Benefits, or Discomforts of the Study	The following are the potential risks, benefits, or discomforts of participating in this study: Risks. There may be risks associated with participating in this study. We will take all necessary precautions to minimize these risks. ☐ Physical risks include physical discomfort, pain, injury, illness or disease brought about by the methods and procedures of the research. A physical risk may result from the involvement of physical stimuli such as noise, electric shock, heat, cold, electric magnetic or gravitational fields, etc. Engaging a subject in a social situation which could involve violence may also create a physical risk. ☐ Psychological risks include the production of negative affective states such as anxiety, depression, guilt, shock and loss of self-esteem and altered behavior. Sensory deprivation, sleep deprivation, use of hypnosis, deception or mental stresses are examples of psychological risks. ☐ Social/Economic risks include alterations in relationships with others that are to the disadvantage of the subject, including embarrassment, loss of

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respect of others, labeling a subject in a way that will have negative consequences, or in some way diminishing those opportunities and powers a person has by virtue of relationships with others. Economic risks include payment by subjects for procedures not otherwise required, loss of wages or other income and any other financial costs, such as damage to a subject's employability, as a consequence of participation in the research.

☑ Loss of confidentiality

☐ Legal risks exist when the research methods are such that the subject or others will be liable for a violation of the law, either by revealing that the subject or others have or will engage in conduct for which the subject or others may be criminally or civilly liable, or by requiring activities for which the subject or others may be criminally or civilly liable.

Benefits. You may benefit from this research. However, we cannot guarantee that you will receive any benefits from participating in this study.

☑ Contribute to the advancement of scientific knowledge
☐ Develop participants' new skills or learn more about themselves.
☐ Receive access to resources, such as support groups or educational materials, that may be beneficial to their health or well-being.
☐ Receive access to interventions or treatments that could improve their health outcomes.
☐ Receive compensation.

Discomforts There may be discomfort associated with participating in this study. We will take all necessary precautions to minimize these discomforts.

☐ Time Commitment: Participating in this study may require a significant amount of time and effort on your part, including attending appointments and completing questionnaires or other assessments.

☐ Emotional Distress: Some participants may find that discussing sensitive topics or answering personal questions can cause emotional distress or discomfort.
☐ Physical Discomfort: Depending on the nature of the study, there may be physical discomfort associated with participating, such as experiencing side effects from medication or undergoing a medical procedure.

☑ Confidentiality Concerns: While we will take all reasonable steps to protect your confidentiality, there is always a risk that your information could be inadvertently disclosed.

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	☐ Unforeseen Risks: Despite our efforts to minimize risks and discomforts, there may be unforeseen risks or discomforts associated with participating in this study that we cannot anticipate
Duration of Participation:	Your participation in this study will take approximately **N/A** to complete.
Confidentiality:	We will take all reasonable steps to ensure that your information is kept confidential. However, there are certain circumstances where we may be required to disclose your information, such as if we suspect that you or someone else may be at risk of harm. In addition, your de-identified data may be used in future research.
Voluntary Nature of Participation:	Participation in this study is entirely voluntary, and you have the right to withdraw from the study at any time without penalty or loss of benefits to which you are otherwise entitled. If you choose to withdraw from the study, any data that you have provided up to that point will still be used in the study, unless you specifically request that it be deleted.
Contact Information:	If you have any questions or concerns about the study, you can contact the researchers at delunajederione82@gmail.com. If you have any concerns about your rights as a participant, you can contact the Research Ethics Review Committee (RERC) at rdd@pnc.edu.ph
Consent:	By signing below, you indicate that you have read and understood the information provided above and that you voluntarily agree to participate in this study.

Name of the Research-Participant	Signature	Date
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	N/A
N/A	N/A	N/A

Research Adviser Application Form

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RESEARCH ADVISER APPLICATION FORM

Name:	ENGR.	Dr. Ma. Emmalyn A. D. [illegible]
Educational Background:	Bachelor	BACHELOR OF Science in Computer Engg.
	Masterate	Master in Management
	Doctorate	PhD in IT Mgt.
Employment Status	☐ Full-time Permanent ☒ Full-time COS ☐ Full-time Temporary ☐ Part-Time	
Department:		
	Research Track (Use APA)	
Thesis Title (Bachelor)		
Thesis Title (Masterate)	Record available in HR	
Dissertation Title (Doctorate)		
Other Research Outputs		

QUALIFICATIONS OF ADVISER

- ✔ Preferably full-time teaching personnel of the University. Part-time teaching personnel may be given advisorship, as needed.
- ✔ The VPAA, RDD Director, Deans, and Department Chairs (directly under their jurisdiction) are not allowed to accept advisorship.
- ✔ With Master's degree of Thesis track or with research experience (evidenced by research outcomes or publications) in lieu of a thesis
- ✔ With at least "Satisfactory" evaluation rating (PNC:PRE-FO-75) based on previous advisees' evaluation. If the adviser got a mean average rating of unsatisfactory, s/he will be suspended for a year in advising student research. After the cleansing period of one year, s/he will be included again in the roster of Research Adviser.
- ✔ Possess and maintain knowledge of the research area to provide adequate supervision of the research project.
- ✔ Possess and continue to develop the appropriate skills to facilitate the production of high quality research work by the student/s.

RESPONSIBILITIES OF ADVISER

- ✔ Determine the research topic's feasibility and ethical soundness.
- ✔ Oversee and ensure satisfactory progress and completion of the research project as agreed upon.
- ✔ Develop and provide an appropriate schedule for each stage of the research project to meet the deadline.
- ✔ Promote high research ethics standards for students, emphasizing the avoidance of misconduct such as plagiarism or data fabrication.
- ✔ Notify the student/s of unsatisfactory progress or work quality and take any necessary action to support them.
- ✔ Be available for regular contact with the student/s, providing adequate time to meet their individual research needs.
- ✔ Review the student's written work and provide constructive feedback.
- ✔ Maintain clear, accurate, detailed, and accessible records of the student's work.
- ✔ Arrange consultation hours for students to seek advice and guidance.
- ✔ Introduce advisees and address concerns before and after the defense.
- ✔ Attend the student's defense as an observer and take notes but not participate in the presentation.
- ✔ Communicate regularly with Research Teachers regarding the students' progress and status.
- ✔ Inform the student/s about the rules and regulations governing the collaborating organization's premises, working practices, health, safety, and confidentiality.
- ✔ Ensure that the research paper undergoes a language and plagiarism check using appropriate software.

FOR COLLEGE USE ONLY

(✓) APPROVED ( ) DISAPPROVED

SEP 12 2024

Dr. Rizal M. Mosquera

SIGNATURE OVER PRINTED NAME OF COLLEGE DEAN

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Thesis Advising and Commitment Form

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THESIS ADVISING AND COMMITMENT FORM
First semester, AY 2024-2025

Group No.	2	Program:	BACHELOR OF SCIENCE IN COMPUTER ENGINEERING
Name of Researchers	DE LUNA, JED ERIONE		
	LABUZ, JOHANN-ERL		
	PURIDO, JOHN LEXTER		
	OBBIDA, NETHOUIE LJOY ANGELO		
	SARDOMA, JOSEPH		

I, Dr. Maria Emmalyn Asuncion De Vigal Capuno, agree to serve as the thesis adviser for the above-mentioned students. I hereby commit to the following:

1. To provide guidance and advice throughout the entire thesis process, from conceptualization to completion.
2. To ensure that the thesis is researchable and ethically sound, and that it meets the academic standards and requirements of the program.
3. To provide appropriate planning schedule for successive stages of the thesis project so that it may be completed and submitted within the appropriate timescale.
4. To encourage and instill a high standard of research ethics on the part of the student, in particular, avoiding conduct which may lead to fabrication of research results or plagiarism.
5. To maintain and ensure availability for regular contact with the student/s, making sufficient time available to fulfill the needs of the individual research student.
6. To review written work produced by the student/s and provide appropriate and constructive criticism.
7. To ensure that the students have a clear, accurate, detailed and accessible records of work undertaken.
8. To schedule consultation hours and make appropriate arrangements for meetings and feedback sessions.
9. To attend the defense of the thesis and provide feedback, but not allowed to participate in the presentation.
10. To constantly communicate with the student/s regarding the progress or status of the thesis project.

I understand that serving as a thesis adviser is a significant responsibility, and I am committed to fulfilling this role to the best of my abilities.

DR. MARIA EMMALYN ASUNCION DE VIGAL CAPUNO
Signature Over Printed Name
Date: 2024-9-10

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Student Research Grouping Form

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STUDENT RESEARCH GROUPING FORM

Group No	GROUP 2	
Research Title:	"Web-based Crowd Detecting and Monitoring System Using Wireless Sensor Network"	
Program:	BACHELOR OF SCIENCE IN COMPUTER ENGINEERING	
Lead Researcher:	DE LUNA, JED ERIONE	
Members	LAPUZ, JOHANN-ERL	ORBIDA, NETHOUIE LJOY ANGELO
	PULIDO, JOHN LEXTER	SARDOMA, JOSEPH

ENDORSED BY:		APPROVED BY:
ENGR. ANNA LIZA F. SIGUE	ENGR. ALDRIN J. SORIANO	DR. REAL M. MOSQUERA
Research Teacher	Department Chair	Dean
Date:	Date: 9-12-24	Date: SEP 12 2024

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STUDENT RESEARCH GROUPING FORM

Group No	GROUP 2	
Research Title:	"Web-based Crowd Detecting and Monitoring System Using Wireless Sensor Network"	
Program:	BACHELOR OF SCIENCE IN COMPUTER ENGINEERING	
Lead Researcher:	DE LUNA, JED ERIONE	
Members	LAPUZ, JOHANN-ERL	ORBIDA, NETHOUIE LJOY ANGELO
	PULIDO, JOHN LEXTER	SARDOMA, JOSEPH

ENDORSED BY:		APPROVED BY:
ENGR. ANNA LIZA F. SIGUE	ENGR. ALDRIN J. SORIANO	DR. REAL MOSQUERA
Research Teacher	Department Chair	Dean
Date:	Date: 9-12-24	Date: SEP 12 2024

Confidentiality and Non-Disclosure Agreement (NDA) On Student Research

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CONFIDENTIALITY AND NON-DISCLOSURE AGREEMENT (NDA)
ON STUDENT RESEARCH
(PNC is a research data site)

This Confidentiality and Non-Disclosure Agreement is made and entered into on **November 19, 2024** between **JED ERIONE L. DE LUNA, JOHANN-ERL S. LAPUZ, NETHOUIE LJOY ANGELO R. ORBIDA, JOHN LEXTER D. PULIDO, JOSEPH S. SARDOMA** and **Pamantasan ng Cabuyao (University of Cabuyao)** in connection with the proposed student research project titled **Real-Time Crowd Behavior Control and Monitoring System Using 3D-CNN.**

Confidential Information. For purposes of this Agreement, "Confidential Information" means any and all information disclosed by the Disclosing Party to the Recipient, including without limitation, any and all data, research findings, results, and reports related to the proposed student research project.

Obligations of Recipient. Recipient agrees to hold all Confidential Information in strict confidence and to take all reasonable steps to prevent unauthorized access or disclosure of such Confidential Information. Recipient agrees not to use any Confidential Information for any purpose other than to complete the proposed student research project.

Non-Disclosure. Recipient agrees not to disclose any Confidential Information to any third party without the prior written consent of the Disclosing Party. Recipient further agrees not to disclose any Confidential Information to any employee, agent, or contractor of the Recipient, except on a need-to-know basis and only to the extent necessary to complete the proposed student research project.

Ownership. The Disclosing Party retains ownership of all Confidential Information disclosed to the Recipient, including all data, research findings, results, and reports related to the proposed student research project.

Term. This Agreement shall remain in effect for a period of Nov 19, 2024 – Nov 19, 2025 from the date of execution. Recipient's obligations under this Agreement shall survive the termination or expiration of this Agreement.

Remedies. The Recipient acknowledges that any breach of this Agreement may cause irreparable harm to the Disclosing Party. In addition to any other remedies available at law or in equity, the Disclosing Party may seek injunctive relief to prevent any breach or threatened breach of this Agreement.

Governing Law. This Agreement shall be governed by and construed in accordance with the laws of Laguna, Philippines without giving effect to any principles of conflicts of law.

Entire Agreement. This Agreement constitutes the entire agreement between the parties concerning the subject matter hereof and supersedes all prior negotiations, discussions, or agreements between the parties.

Confidentiality and Non-Disclosure Agreement (NDA) On Student Research

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IN WITNESS WHEREOF, the parties have executed this Agreement as of the date first above written.

Pamantasan ng Cabuyao (University of Cabuyao)

Dr. Zandro N. Maningas
Vice President for Planning, Research, and Extension

Student Researchers:

Jed Erione L. De Luna
Joseph [illegible]
Johann-[illegible] S. Lapuz
John Lexter D. Pulido
Nethoule Ljoy Angelo R. Orbida

WITNESSES

NOV 19 2024
Dr. [illegible] M. Mosquera
Dean, College of Engineering

Dr. Joanna Marie A. de Borja
Director, Research and Development

ACKNOWLEDGMENT

REPUBLIC OF THE PHILIPPINES)
CITY OF CITY OF CABUYAO

BEFORE ME, a Notary Public for and in City of Cabuyao, on NOV 21 2024, personally appeared the following, to wit:

Name	Valid ID / Passport Number	Date and Place Issued
Jed Erione L. De Luna	Student ID (2101382)	September 30, 2024
Nethoule Ljoy Angelo R. Orbida	Student ID (2101180)	May 14, 2024

KNOWN TO ME to be the same persons who executed the foregoing Grant Agreement consisting of __ pages including this page and acknowledged to me that the same is their own free act and deed.

WITNESS MY HAND AND SEAL on this __ day of __________, 202_.

Doc No. 1892
Page No. 367
Book No. 02
Series of 2024

RANDY G. HEMEDEZ
Commission No. 10-C-2023-NC
Notary Public City of Cabuyao, Laguna
Until December 31, 2025
Unit A Don Onofre Bldg. III FB Bailon St.,
Sala, City of Cabuyao Laguna 4025
Roll No. 53840
IBP No. 42833; 1/23/2024; Quezon City
PTR No. [illegible]; 1/22/2024; City of Cabuyao Laguna

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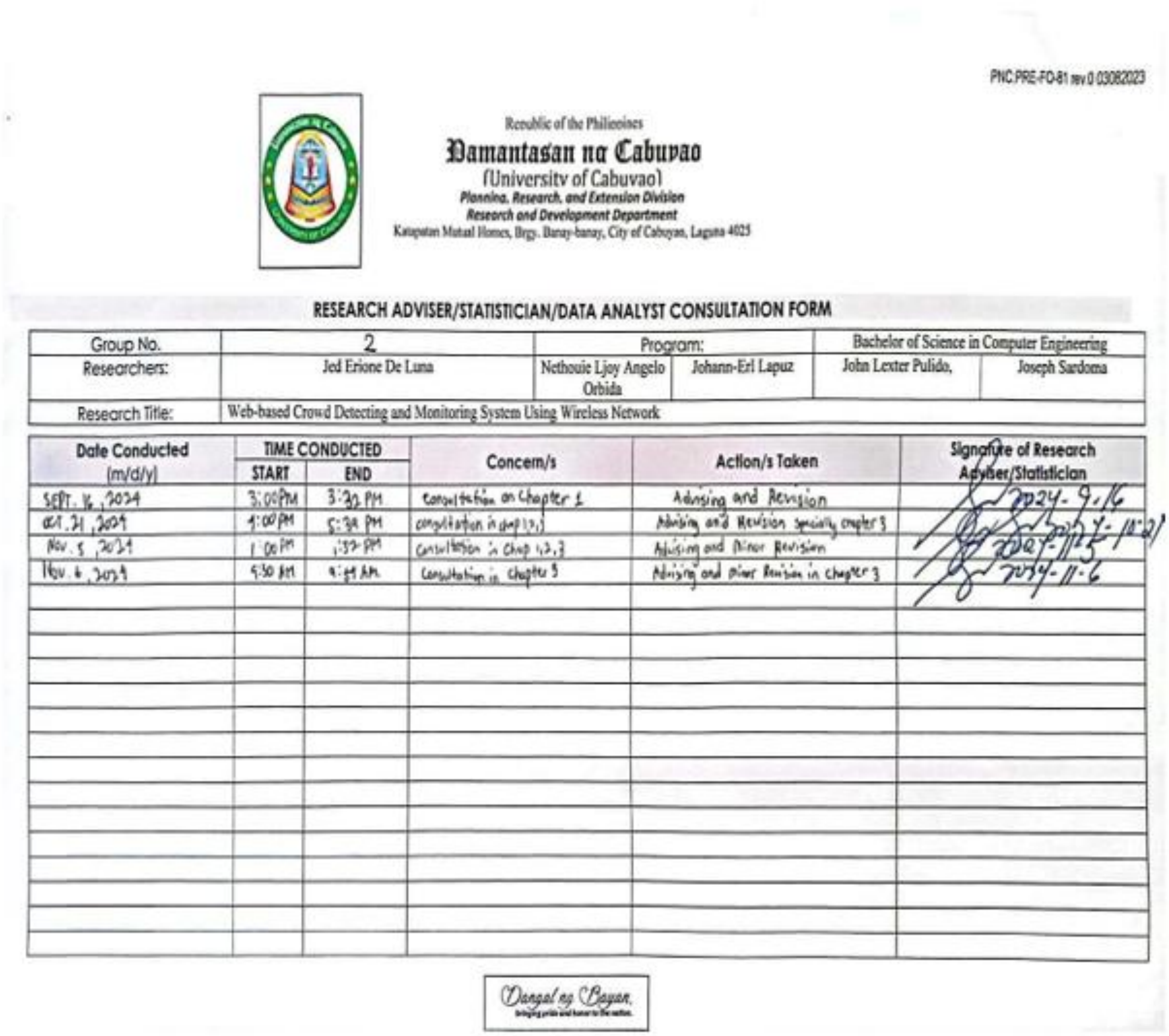
Research Adviser/Statistician/Data Analyst Consultation Form



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Planning, Research, and Extension Division

Research and Development Department

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RESEARCH ADVISER/STATISTICIAN/DATA ANALYST CONSULTATION FORM

Group No.	2	Program:		Bachelor of Science in Computer Engineering	
Researchers:	Jed Erione De Luna	Nethouie Ljoy Angelo Orbida	Johann-Erl Lapuz	John Lexter Pulido,	Joseph Sardoma
Research Title:	Web-based Crowd Detecting and Monitoring System Using Wireless Network				

Date Conducted (m/d/y)	TIME CONDUCTED		Concern/s	Action/s Taken	Signature of Research Adviser/Statistician
	START	END			
SEPT. 16, 2024	3:00PM	3:30 PM	Consultation on Chapter 1	Advising and Revision	2024-9.16
OCT. 21, 2024	4:00PM	5:30 PM	consultation in chap 1,2,3	Advising and Revision specially chapter 3	2024-10-21
NOV. 5, 2024	1:00PM	1:30 PM	Consultation in Chap 1,2,3	Advising and Minor Revision	2024-11-5
NOV. 6, 2024	9:30 AM	9:49 AM	Consultation in Chapter 3	Advising and Minor Revision in Chapter 3	2024-11-6

Dangal ng Bayan.

Student Research Recommendation Form

PNC:PRE-FO-71 rev.0 03082023

Republic of the Philippines
Pamantasan ng Cabuyao
(University of Cabuyao)
Planning, Research, and Extension Division
Research and Development Department
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

STUDENT RESEARCH RECOMMENDATION FORM

Group No.	2	Date Filed:	November 6, 2024
Researchers:	De Luna, Jed Erione L.	Johann-Erl S. Lapuz	Nethoule Ljoy Angelo R. Orbida
	John Lexter D. Pulido	Joseph S. Sardoma	
Research Title:	Real-Time Crowd Behavior Control and Monitoring System Using 3D-CNN		

This research has been thoroughly examined and is now recommended for Proposal Defense.

Dr. Maria Emmalyn Asuncion De Vigal Capuno
(Signature Over Printed Name) 2024 - 11 - 6
Adviser

Declaration of Generative AI and AI-Assisted Technologies in the Writing Progress Page 1

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Republic of the Philippines
Pamantasan ng Cabuyao
(UNIVERSITY OF CABUYAO)
Planning, Research, and Extension Division
Research and Development Department
Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

Group No.	2	Program	BSCPE
Department	COLLEGE OF ENGINEERING		
Researchers		*Signature*	
	DE LUNA, JED		
	LAPUZ, JOHANN-ERL		
	ORBIDA, NETHOUIE LJOY ANGELO R.		
	PULIDO, JOHN LEXTER D.		
	SARDOMA, JOSEPH S		
Research Adviser	DR. Maria Emmalyn Asuncion De Vigal Capuno	*Signature*	
Research Title	REALTIME-BASED CROWD BEHAVIOR AND MONITORING SYSTEM USING 3D-CNN		

We hereby declare that the work submitted for *Realtime-Based Crowd Behavior and Monitoring System Using 3d-Cnn* includes the use of Generative AI and/or AI-assisted technologies. In accordance with the guidelines set forth by the University of Cabuyao, I confirm the following:

Description of AI Tools Used:	
AI Tool(s) Employed:	☐ GPT-4 (or similar models) ☐ BERT (Bidirectional Encoder Representations from Transformers) ☑ ChatGPT ☐ DALL-E ☐ Jasper AI ☑ Zotero / EndNote / Mendeley ☐ Grammarly / Hemingway Editor / or any language editor ☐ IBM Watson Discovery / SPSS / Tableau / Power BI ☑ Ref-N-Write / QuillBot ☐ Plagiarism detector ☐ Others, please specify: ______
Attachments	☐ Screenshots of Prompts and responses ☐ Others, please specify: ______
Extent of AI Assistance:	
Percentage of Work Assisted by AI:	
Nature of Assistance Provided by AI:	☑ Text generation, summarization, translation, and content creation ☐ Natural language understanding and contextual analysis ☐ Assists in drafting sections of research papers, generating hypotheses, or providing feedback on research ideas ☑ Image generation from textual descriptions ☐ Peer review simulator ☑ Reference management and citation generation. ☐ Writing enhancement and grammar checking. ☐ Data analysis and insights extraction from large volumes of text. ☑ Paraphrasing and text rewriting ☐ Others, please specify: ______

Ethical Considerations:	
1. Have you ensured that the AI tools used are in compliance with academic integrity standards?	☑ Yes ☐ No
2. Are there any sections of the work that were entirely or predominantly generated by AI?	☐ Yes ☑ No
3. If yes, please specify which sections:	
4. **Human Contribution:** Please check if the statements best describe your role as human researchers in the final content and decision-making process.	☑ **Conceptualization and Research Design:** We are responsible for the initial conceptualization of the research topic, formulating the research questions or hypotheses, and designing the methodology. I determine the scope and objectives of the study, ensuring alignment with academic and research standards.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Progress Page 2

Republic of the Philippines

Pamantasan ng Cabuyao

(UNIVERSITY OF CABUYAO)

Planning, Research, and Extension Division

Research and Development Department

Katapatan Mutual Homes, Brgy. Banay-banay, City of Cabuyao, Laguna 4025

	☑ **Data Collection and Analysis:** We oversee the data collection process, whether it involves conducting experiments, surveys, interviews, or other methods. We are involved in analyzing the data, applying appropriate statistical or qualitative analysis techniques to draw meaningful conclusions. ☑ **Interpretation of Results:** We interpreted the results of the analysis in the context of the research questions. I critically assess the findings, identify patterns or trends, and consider the implications of the results. ☑ **Writing and Drafting:** We are primarily responsible for writing the research paper or report. This includes drafting sections such as the introduction, literature review, methodology, results, discussion, and conclusion. We ensure that the content is coherent, logically structured, and effectively communicates the research findings. ☑ **Decision-Making:** Throughout the research process, we make critical decisions regarding the direction of the study, adjustments to the methodology, and interpretation of data. We also decide on the inclusion and exclusion of content based on relevance and significance to the research objectives. ☑ **Review and Revision:** We are actively involved in the review and revision process. We incorporate feedback from peer reviewers, collaborators, or supervisors, making necessary revisions to improve the quality and clarity of the final document. ☑ **Ethical Considerations:** We ensure that the research adheres to ethical guidelines, including obtaining necessary approvals, maintaining participant confidentiality, and accurately reporting data without fabrication or falsification. ☐ **Others, please specify:**

Acknowledgment:

The researchers acknowledge that the use of Generative AI and AI-assisted technologies is disclosed in accordance with the University of Cabuyao's guidelines and that we have cited any external tools or resources used as part of this process. After using this tool/service, the researchers(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the research.

Bionote

PNC:AA-FO-27 rev.0 02012023

JOHANN-ERL S. LAPUZ

I'm a Computer Engineering student capable of handling programming and also computer literate. Additionally, I also excel in interpersonal communication, conveys ideas and collaborating with others to accomplish given tasks and projects. I am willing to learn and adapt to different environments. Always eager to broaden my horizons and grab opportunities for learning more things.

CONTACT

lapuzjohannerl32@gmail.com
09458026715 (Globe)
Blk8 Lot 19 Ph1 Celina Plains Subd. Brgy. Labas, Santa Rosa, Laguna 4026

EXPERTISE

- Arduino IDE Handling
- AutoCAD/Autodesk Handling
- Computer Programming using Python
- HTML
- Proteus 8 Handling
- Adaptable to Various Tasks
- Communications
- Quick Thinking Skills

REFERENCES

Oliver A. Medina
OJT Instructor | Pamantasan ng Cabuyao
bienmedina@gmail.com
0910 973 6986

EDUCATION

Bachelor of Science in Computer Engineering
Pamantasan ng Cabuyao — **2021-Current**
- Dean's Lister 2nd Year 2nd Sem

Secondary (SHS) — **2019-2021**
Labas Senior Highschool
- Graduated with High Honors

Secondary (JHS)
- None

Elementary
SRES Central III — **2012-2015**
- Graduated with honors

SRES Central I — **2009-2012**
- None

CERTIFICATES

CISCO
- Network Academy Course Completion in Networking Basics Certificate

EF SET
- English Certification: C2 Proficient

WORK EXPERIENCE

PESO (Public Employment Service Office) - OJT
- June 25, 2024 – August

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NETHOUIE LJOY ANGELO R. ORBIDA

I'm a dedicated Computer Engineering student known for my problem-solving abilities and proactive mindset. I'm passionate about developing efficient and innovative tech solutions. Committed to continuous learning, I excel in both individual and team projects.

CONTACT

Orbidanethouie80@gmail.com
+639661491007
Blk 3 Lot 27 Phase Cluster, Mabuhay City Subd. Mamatid, City of Cabuyao, Laguna 4025

EXPERTISE

- Computer Literate
- Organization Skills
- Communication Skills
- Critical Thinking
- EFSET C1 Advanced
- Cisco Certified

REFERENCES

Oliver A. Medina
OJT Instructor| Pamantasan ng Cabuyao
bienmedina9@gmail.com
09109736986

EDUCATION

Bachelor of Science Major in Computer Engineering — **2021 - Current**
Pamantasan ng Cabuyao
- Dean's Lister 3rd Year 1st Sem

Secondary (SHS) — **2019 - 2021**
Saint Vincent College of Cabuyao
- Gr. 11 to Grade 12 – With honor
- Graduated with Honor

Secondary (JHS) — **2015 - 2019**
Gulod National Highschool
- Gr. 9 – Top 9 Achiever

Elementary — **2013 - 2015**
Mamatid Elementary School
- None

LATEST SEMINAR ATTENDED

ACOES PNC
Innotech: Igniting Passion in Computer Engineering
- March 9, 2024

OJT SEMINAR
Ojt pre-orientation for COE and ECE

WORK EXPERIENCE

PESO (PUBLIC EMPLOYMENT OFFICE) - OJT
- June 25, 2024 – August 5, 2024

PNC:AA-FO-27 rev. 0 02012023

JOSEPH S. SARDOMA

As a third-year Computer Engineering student, I am seeking a position where I can apply my technical skills and knowledge to contribute to the growth and success of the company. I am eager to bring my passion for computer engineering and my dedication to the field to a dynamic and innovative company.

CONTACT

sardomajoseph976@gmail.com

09663355346

Saint Joseph Village 7
Marinig, Cabuyao Laguna

EXPERTISE

- Ability to work independently or as part of a team
- Flexible
- Adaptive and Fast Learner
- Time Management

REFERENCES

MR. MARK ANTHONY J. ESMERALDA
MBA Director, Placement,
Alumni and Linkages
Department
University of Cabuyao(PnC)
0995 893 5277
pald@pnc.edu.ph

EDUCATION

Bachelor of Science in Computer Engineering (On-going) — Present
Pamantasan ng Cabuyao

Secondary
CITI GLOBAL COLLEGE — 2021
- With Honor

Elementary
South Marinig Elementary School — 2015
- With Honor

WORK EXPERIENCE

Sorter — 2023
Lazada Philippines
- Learn various techniques for sorting and develop skills in inspecting products for damage or defects, and reporting any issues to the appropriate departments to prevent the shipment of substandard items to customers.

Packager — 2022
Flash Express Philippines
- Develop the ability to adapt to changing circumstances and priorities, as well as the flexibility to work in a fast-paced and dynamic environment.

LATEST SEMINAR ATTENDED

On Job Training Seminar
2024

JOHN LEXTER D. PULIDO

IM A DEDICATED COMPUTER ENGINEERING STUDENT KNOWN FOR MY PROBLEM SOLVING SKILLS AND PASSIONATE TO DEVELOP A SOLUTION TO A PROBLEM. AND WILLING TO LEARN MORE KNOWLEDGE.

CONTACT

Pulidojohnlexter78@gmail.com
+639282982810 or 09282982810
708 PUROK 5 BRGY GULOD CITY OF CABUYAO LAGUNA

EXPERTISE

- Computer Literate
- Communication Skills
- Problem Solver
- Cisco Certified
- Math
- Python (Basic)

REFERENCES

OLIVER A MEDINA
OJT INSTRUCTOR |PAMANTASAN NG CABUYAO |
bienmedina9@gmailcom | 09109736986

MR. MARK ANTHONY J. ESMERALDA, MBA
Director, Placement, Alumni and Linkages Department
University of Cabuyao(PnC)
0995 893 5277
pald@pnc.edu.ph

EDUCATION

Bachelor of Science Major in Computer 2021 -
Current
Pamantasan ng Cabuyao
- NONE

Secondary (SHS) 2019 - 2021
Saint Vincent College of Cabuyao
- Gr. 11 to Grade 12 – With honor
- Graduated with Honor

Secondary (JHS) 2015 - 2019
Gulod National Highschool
- G8 – TOP 3 ACHIEVER

Elementary 2013 - 2015
GULOD ELEMENTARY SCHOOL
- None

LATEST SEMINAR ATTENDED

ACOES PNC
Innotech: Igniting Passion in Computer Engineering
- March 9, 2024

OJT SEMINAR
Ojt pre-orientation for COE AND ECE
- MAY 28,2024

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JED ERIONE L. DE LUNA

I'm a dedicated Computer Engineering student known for my problem-solving Abilities, proactive mindset and a strong foundation in terms of Software Programming, I am eager to apply my knowledge in practical settings. Seeking internship to leverage skills in in real matter, programming, problem-solving and teamwork.

CONTACT

delunajederion82@gmail.com
+639815380976
Blk 3 Lot 26 Ph2 Centennial Homes, Pulo, City of Cabuyao, Laguna 4025

EXPERTISE

- Computer Literate
- Organization Skills
- Communication Skills
- Critical Thinking
- Programming Language
  - Python
  - C++
  - Java
- Software Platform
  - AutoCAD Inventor
  - LOGO!Soft
  - FluidSim
  - Arduino IDE
  - MULTISIM
  - CISCO
- Database Management (MySQL)
- Cisco Certified
  - Network Basics
  - Networking Basics
- EFSET C2 Proficient

REFERENCES

Oliver A. Medina
OJT Instructor| Pamantasan ng Cabuyao
bienmedina9@gmail.com
09109736986

EDUCATION

Bachelor of Science Major in Computer Engineering — 2021 - Current
Pamantasan ng Cabuyao

- Dean's Lister 3rd Year 1st Sem

Secondary (SHS) — 2019 - 2021
St. Ignatius Technical Institute of Business and Arts – Cabuyao Campus

Secondary (JHS) — 2015 - 2019
Cabuyao Integrated National High School

Elementary — 2009 - 2015
San Isidro Elementary School

- Grade 1 – Grade 6 Top Achiever

LATEST SEMINAR ATTENDED

ACOES PNC
Innotech: Igniting Passion in Computer Engineering

- March 9, 2024

OJT SEMINAR
Ojt pre-orientation for COE and ECE

- May 28, 2024