Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Yolo-Panic: A Real-Time Ai-Based Gesture Recognition System for Smart Panic Alarm System

Mohammed Ikramullah khan[1], B. Vivekanandam[2]
[1]*Ph.D. Scholar, Department of Computer Science, Lincoln university college, Malaysia.*
[2]*Deputy Dean in Faculty of AI Computing and Multimedia, Lincoln university college, Malaysia.*

ARTICLE INFO

Received: 25 Dec 2024

Revised: 17 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Rapid and effective responses during emergencies are critical in today's fast-paced environments, including industrial facilities, commercial hubs, public institutions, and transportation networks. Traditional panic alarm systems largely depend on physical hardware—such as buttons or switches—which may be inaccessible or ineffective in high-stress or hazardous situations. To address these challenges, we introduce **YOLO-Panic**, a real-time AI-based gesture recognition system designed to activate smart panic alarms using intuitive hand gestures. Built upon a customized YOLO (You Only Look Once) deep learning architecture, the system is trained to detect a specific panic gesture—four fingers extended with the thumb folded inward—with exceptional accuracy.

The YOLO-Panic model achieves outstanding performance metrics, including a **precision of 98.56%**, **mAP@50 of 99.30%**, and **recall of 97.99%**, ensuring high reliability with minimal false positives. To enhance spatial gesture interpretation, a keypoint-based module is also integrated, achieving **94.06% mAP@50** and **83.27% mAP@50–95**, enabling robust, fine-grained analysis of hand poses. The system operates with a high degree of efficacy in real-time, rendering it exceptionally suitable for application in dynamic and bustling environments.

As cities evolve into smarter and more connected ecosystems, YOLO-Panic offers a vital layer of safety and situational awareness. Its contactless, AI-driven approach aligns seamlessly with the goals of smart city infrastructure, where intelligent surveillance and rapid emergency response are paramount. By enabling intuitive human-machine interaction for crisis communication, YOLO-Panic represents a scalable, adaptive solution that enhances public safety, reduces emergency response times, and supports the development of resilient, technology-enabled urban environments.

Keywords: YOLO, Panic alarm systems, gesture recognition, Smart cities. AI surveillance.

INTRODUCTION

In recent years, the rapid advancement of technology has ushered in the era of *smart cities*—urban environments that leverage artificial intelligence (AI), the Internet of Things (IoT), and real-time data analytics to improve infrastructure, services, and overall quality of life [1]From clever traffic solutions and automated waste handling to eco-friendly buildings and AI-powered security, smart cities are changing the way we live, work, and tackle everyday challenges with a smile!. The core philosophy behind smart cities is not just automation, but intelligent responsiveness—particularly in the context of safety, security, and emergency management [2]. However, while innovations such as smart surveillance, AI-driven traffic management, and automated public services are now commonplace, one critical domain remains largely underexplored **panic alarm systems**.

Conventional panic alarms are typically physical devices such as wall-mounted buttons, foot pedals, or hidden switches that individuals can use to signal distress. While these tools have been the standard in many settings—such as **bank counters**, **hospital receptions**, **hotel front desks**, and **industrial control rooms**—they come with serious limitations. In an actual emergency, especially under stress or threat, a person might be unable to physically reach the alarm, or may be too afraid to make a move that could alert the aggressor [3]. This limitation makes it

Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

essential to rethink how distress is communicated—preferably through **natural, non-verbal, and contactless means**.

This paper introduces **YOLO-Panic**, an AI-powered, real-time hand gesture recognition system designed to serve as an intelligent panic alarm interface. The system focuses on detecting a specific and intuitive panic gesture—**four fingers extended, thumb folded in**—that can be performed subtly and recognized reliably across various contexts. By leveraging the expressive nature of human hands and the advancements in real-time object detection, YOLO-Panic reimagines how emergency alerts can be triggered in **smart city environments**.

Hand gestures represent a significant modality of non-verbal communication, historically employed to convey intent, affect, or directives [4]. In contemporary contexts, gesture recognition technology has been integrated into various domains, including gaming, virtual and augmented reality environments, sign language interpretation, robotic control systems, and assistive technologies designed for individuals with disabilities[5]. However, its potential in **emergency response systems** remains underutilized. By recognizing specific hand configurations, gesture-based systems can provide a **natural and silent** way for individuals to interact with machines or alert authorities without speaking or touching a device.

YOLO-Panic is built on a customized version of the YOLO (You Only Look Once) object detection architecture, tailored for real-time performance and optimized to recognize the defined panic gesture—four fingers extended with the thumb folded inward. The system leverages advanced computer vision techniques to detect this gesture quickly and accurately, enabling rapid alert activation. To further improve recognition accuracy and spatial understanding, a keypoint-based hand pose estimation module is integrated. This dual-approach architecture allows the system to effectively distinguish panic gestures from regular hand movements, ensuring robust functionality even in dynamic, crowded, or low-light environments.

Unlike traditional panic systems that require direct interaction, YOLO-Panic offers a contactless and discreet alternative, making it especially suitable for high-risk environments where subtle communication is critical. In a bank, for instance, a teller could raise the gesture while appearing calm; in a hospital, a nurse facing a threatening situation could alert security without leaving a patient's side. The system can also be integrated with existing CCTV infrastructure, turning passive cameras into active safety tools.

As cities strive for increased automation and resilience, safety remains a cornerstone of urban innovation. Smart cities aim not only to improve convenience and efficiency but also to ensure that emergency services can respond rapidly and effectively [6]. By embedding gesture-based panic alarms into the broader surveillance and AI ecosystem, YOLO-Panic supports the development of cities that are not only intelligent but also responsive and human-centric.

In the post-pandemic world, contactless interaction has become more desirable than ever. Gesture recognition offers an intuitive and hygienic method of communication that aligns well with modern public health standards [7]. Furthermore, because hand gestures are language-independent and culturally widespread, such a system can be deployed across diverse populations without the need for extensive training or localization[8].

Despite advancements in computer vision and AI, most current emergency systems are still reactive—they depend on events being reported verbally or manually. YOLO-Panic introduces a proactive model that enables individuals to initiate alerts instantly and silently, thereby reducing response time and potentially saving lives.

To our knowledge, YOLO-Panic is among the first implementations to focus specifically on gesture-based panic signalling using deep learning in real-time environments. It represents a new direction for human-AI interaction in critical scenarios, demonstrating how a simple hand motion can interface with complex machine systems to deliver timely assistance.

This research lays the groundwork for integrating gesture-driven safety mechanisms into the next generation of smart surveillance and emergency systems. By empowering citizens to communicate distress through natural gestures, YOLO-Panic enhances both the safety fabric of urban life and the intelligence of city-wide infrastructure.

LITERATURE REVIEW

Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The convergence of artificial intelligence (AI), computer vision, and smart infrastructure has led to the emergence of intelligent systems capable of supporting safer, more responsive urban environments[9]. Among these exciting advancements, gesture recognition has become a delightful and intuitive way for humans to interact with computers (HCI), particularly in wonderful areas like augmented reality, robotics, automotive interfaces, and assistive technologies [10]. However, its application in critical emergency alert systems—particularly in the context of panic alarms—remains relatively unexplored.

GESTURE RECOGNITION SYSTEMS

Gesture recognition involves interpreting human motions, primarily hand or body gestures, using sensors or computer vision techniques[11]. Conventional methodologies have depended on wearable apparatuses, including data gloves or motion sensors, which have posed difficulties regarding financial expenditure, user comfort, and ease of use[12]. The shift to vision-focused recognition systems has greatly improved user experience and effectiveness, especially with the progress in deep learning models like Convolutional Neural Networks (CNNs) and object detection systems such as YOLO, SSD, and Faster R-CNN[13]. These models have demonstrated excellent results in object detection and classification tasks, making them suitable for dynamic and real-time environments.

Recent works have explored hand gesture recognition using CNNs for applications like sign language interpretation, gaming, and home automation. For instance,[14] presented an impressive CNN-based model that is effective in identifying both static and dynamic hand gestures, demonstrating how deep features can effectively capture complex patterns. Similarly,[15] utilized Recurrent Neural Networks (RNNs) for the ongoing recognition of gestures in 3D video sequences, emphasizing the significance of temporal modelling. However, many of these systems mainly concentrate on general tasks and are not specifically designed for critical, time-sensitive emergency signalling scenarios.

PANIC ALARM SYSTEMS

Conventional panic alarm systems typically rely on physical triggers—such as buttons, foot pedals, or wearable devices—that send distress signals when manually activated [16]. These systems are prevalent in banks, schools, hospitals, and public transport systems. While reliable, they have inherent limitations. In situations involving direct threats, individuals may not have the freedom or time to reach or activate these devices. This shortcoming has prompted researchers to consider contactless, AI-enabled alternatives.

Some recent studies have explored audio-based distress detection using natural language processing or abnormal activity recognition through surveillance feeds[17]. For instance, audio analysis of screaming or specific keywords has been used to initiate emergency responses [18]. However, audio-based systems struggle in noisy environments and may raise privacy concerns. Similarly, activity recognition systems while promising often lack precision in identifying subtle, intentional gestures like a panic signal.

COMPUTER VISION IN SMART CITIES

With the global push toward smart cities, the role of AI-powered computer vision has expanded beyond surveillance to include crowd analysis, anomaly detection, public behaviour monitoring, and emergency response [19]. Smart CCTV systems have been enhanced with facial recognition, weapon detection, and fall detection capabilities[20]. While these systems provide a foundation for public safety, most are reactive rather than proactive, requiring a situation to escalate before action is triggered.

Gesture recognition in surveillance has recently gained attention for touchless access control, traffic regulation, and smart signage interaction [21]. However, very few implementations directly connect hand gestures to panic or emergency alert systems. A study by [22] attempted to recognize distress signals in sign language to alert guardians or medical professionals, but such systems often lack real-time responsiveness and generalizability to diverse environments.

GAP IN LITERATURE

Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Despite advancements in gesture recognition and smart surveillance, there is a noticeable gap in systems that are specifically designed for real-time panic alerting using intuitive hand gestures[23]. Most existing gesture-based systems focus on controlled environments or entertainment applications, with limited emphasis on emergency use cases. Moreover, traditional panic systems lack adaptability, scalability, and the intelligent decision-making capacity needed in smart city infrastructures.

YOLO-Panic addresses this critical gap by combining the speed and precision of the YOLO object detection framework with hand pose keypoint estimation to develop a gesture-based panic alarm system suitable for public institutions, corporate environments, and high-risk zones. It provides a contactless, real-time, and user-friendly alternative to manual panic alarms, aligning with the vision of responsive, human-centric smart cities.

YOLO OBJECT DETECTION AND POSE ESTIMATION

YOLO (You Only Look Once) is a family of real-time object detection algorithms that revolutionized computer vision by formulating detection as a single regression problem. Instead of performing classification and localization as separate tasks, YOLO directly predicts bounding boxes and class probabilities from the entire image in one evaluation, making it extremely efficient.

Pose Estimation with YOLO: Modern versions of YOLO (e.g., YOLOv8) have expanded beyond object detection to include pose estimation using keypoint detection. This involves identifying specific points on the human body (like wrist, elbow, shoulder, etc.), enabling the system to interpret body posture and hand gestures accurately—deal for recognizing panic gestures in real time.

YOLO Series Evolution (Summary Table)

YOLO Version	Year	Key Highlights
YOLOv1	2016	First unified detector; grid-based detection.
YOLOv2	2016	Introduced anchor boxes and fine-grained features.
YOLOv3	2018	Multi-scale detection; deeper feature extractor.
YOLOv4	2020	Bag-of-freebies/specials; enhanced real-time performance.
YOLOv5	2020	PyTorch-based; improved training/deployment ease.
YOLOv6	2022	Designed for industrial applications; refined architecture.
YOLOv7	2022	Introduced E-ELAN; faster and more accurate.
YOLOv8	2023	Supports object detection, segmentation, pose estimation.
YOLOv9	2024	Introduced GELAN and PGI for efficient learning.
YOLOv10	2024	Reduced reliance on NMS; boosted efficiency.
YOLOv11	2024	Advanced architecture; state-of-the-art speed and accuracy.

METHODOLOGY

The proposed YOLO-Panic system employs a deep learning pipeline for real-time gesture-based panic detection using a unified approach that combines hand detection and pose keypoint estimation. The methodology comprises four key

Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

components: dataset preparation, model architecture, post-inference logic for gesture classification, and performance evaluation.

1.1. Dataset Preparation

A custom dataset was constructed to train the YOLOv11 model for both hand detection and keypoint estimation. The dataset consists of:

- **Training set**: 18,776 images
- **Validation set**: 7,992 images
- **Annotations**: Each sample includes hand bounding boxes and 21 annotated key points per hand, representing anatomical landmarks such as fingertips, knuckles, and wrist joints.

Figure1: Hand detection with Keypoints

Model Architecture

The core architecture is based on **YOLOv11**, a high-performance object detector augmented for **pose estimation**. Unlike traditional two-stage pipelines, our model simultaneously detects hand regions and estimates keypoints in a **single forward pass**, optimizing speed and accuracy.

- **Detection Module**: Predicts bounding boxes for the "Hand" class with class confidence.
- **Keypoint Estimation Module**: Predicts 21 keypoints per detected hand using the kpt_shape: [21, 3] format, where each keypoint includes (x, y) coordinates and a visibility score.
- **Enhancements**:
  - Custom anchor sizes for hand-scale optimization
  - Data augmentation techniques (mosaic, mixup, cutmix) for robust generalization
  - Focal loss to handle class imbalance during detection training

These innovations collectively contribute to a model that not only achieves superior performance in real-time applications but also adapts effectively to diverse hand poses and orientations, making it suitable for various interactive systems.

Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Gesture Logic and Panic Detection

The hand gesture used in YOLO-Panic—four fingers extended with the thumb folded across the palm—was deliberately selected due to its global recognition as a non-verbal sign for help or distress. Popularized through social media and advocacy campaigns, this gesture has emerged as a discreet yet powerful signal for individuals to silently communicate danger or request assistance, especially in situations involving abuse, abduction, or personal threat. Its simplicity and cultural neutrality make it easily interpretable across diverse populations and contexts. By incorporating this widely recognized "help" gesture into the YOLO-Panic system, the model ensures both intuitive usability and emotional resonance, enhancing its effectiveness in real-world emergency scenarios.

Post-inference, the system analyzes keypoint geometry to classify gestures. A panic gesture is defined as **four fingers extended upward and the thumb folded inward toward the palm**.

- **Keypoint Logic**:
    - Fingers: A fingertip (e.g., index at point 8) is considered “up” if it is vertically above its corresponding lower joint (e.g., point 6).
    - Thumb: Considered “folded” if point 4 (thumb tip) lies horizontally inward of point 3 (thumb base).
- **Classification Rule**:
    - If all four fingertips (index, middle, ring, pinky) are up and thumb is folded, the frame is flagged as **PANIC**.
    - Else, it is labeled as **NORMAL**.

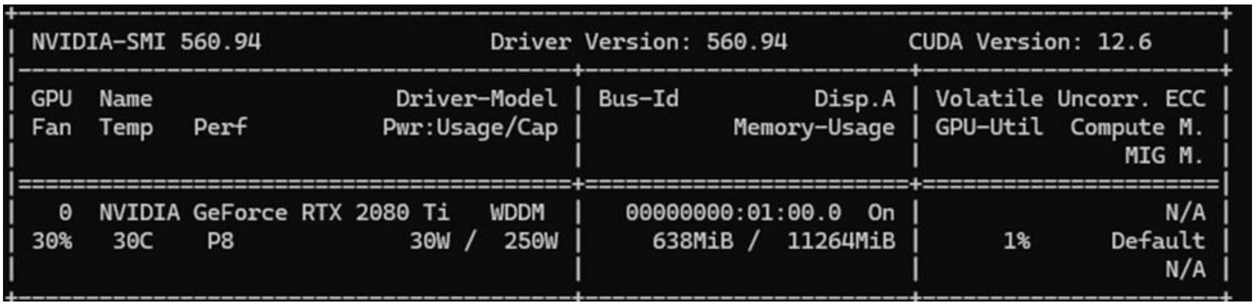
This logic is evaluated for every frame to enable real-time panic detection.

RESULTS

Environmental Settings

Our experimental procedures were conducted on workstation with below specs. Workstation Specs Processor: Intel Core i7-8700 CPU @3.20 GHz RAM: 32 GB OS: Windows 11 Pro

Graphic card



```
+-----------------------------------------------------------------------------------------+
| NVIDIA-SMI 560.94                 Driver Version: 560.94         CUDA Version: 12.6     |
|-----------------------------------------+------------------------+----------------------+
| GPU  Name                  Driver-Model | Bus-Id          Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |           Memory-Usage | GPU-Util  Compute M. |
|                                         |                        |               MIG M. |
|=========================================+========================+======================|
|   0  NVIDIA GeForce RTX 2080 Ti   WDDM  |   00000000:01:00.0  On |                  N/A |
| 30%   30C    P8             30W /  250W |     638MiB /  11264MiB |      1%      Default |
|                                         |                        |                  N/A |
+-----------------------------------------+------------------------+----------------------+
```

Figure 2: Graphic card details.

CCTV Camera: Mobotix (Model: Mx-VB1A-8-IR-VA)

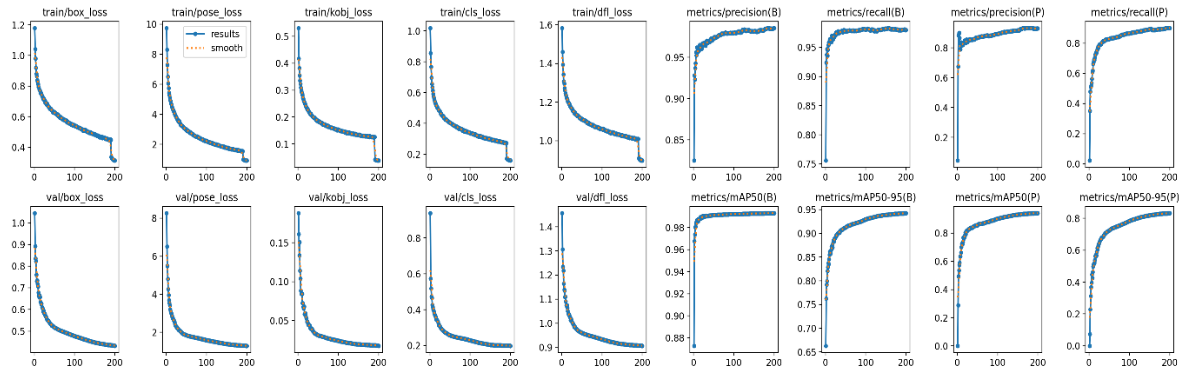
Training Performance

Model	Epoch	mAP50 (B)	mAP50-95 (B)	mAP50 (P)	mAP50-95 (P)
	1	87.28%	66.30%	0.17%	0.02%

Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

YOLO-PANIC	25	98.97%	89.17%	81.72%	64.50%
	50	99.13%	91.25%	85.49%	72.50%
	75	99.18%	92.16%	87.83%	75.56%
	100	99.22%	92.93%	90.16%	78.38%
	125	99.25%	93.54%	91.90%	80.55%
	150	99.28%	93.90%	93.06%	81.93%
	175	99.29%	94.12%	93.74%	82.80%
	200	99.30%	94.26%	94.06%	83.28%

Table1: Training Model Performance



Graph 1: Training Result Graph

The graph1 and table1 illustrate the consistent and progressive performance improvements of the YOLOv11 model across 200 training epochs, evaluated using mean Average Precision (mAP) at different Intersection over Union (IoU) thresholds for both **Bounding Box (B)** detection and **Pose (P)** estimation:

Bounding Box Detection (B):

1. **mAP@50 (B)** improved markedly from **87.28% at epoch 1** to **99.30% by epoch 200**, indicating highly accurate object localization and confident predictions.
2. **mAP@50-95 (B)**, a more stringent and comprehensive metric that accounts for a range of IoU thresholds, increased from **66.30% to 94.26%**, reflecting the model's robustness and generalization capability across varying object sizes and positions.

Pose Estimation (P):

1. The model demonstrated substantial improvements in **mAP@50 (P)**, growing from a negligible **0.17%** at epoch 1 to a highly reliable **94.06%** by epoch 200. This underscores the model's ability to learn spatial configurations and keypoint relationships over time.
2. Similarly, **mAP@50-95 (P)** rose from **0.02%** to **83.28%**, confirming that the model not only detects poses effectively but also maintains precision under diverse spatial constraints.

These results collectively indicate:

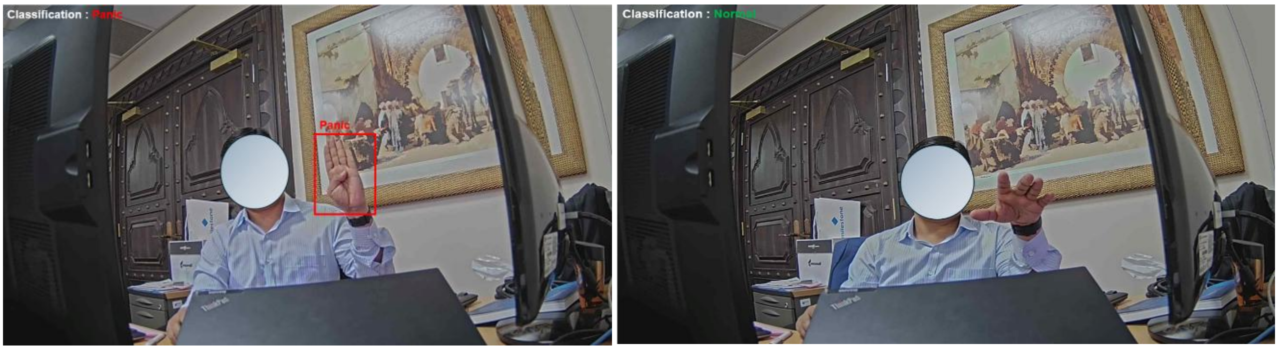
- **Efficient convergence and optimization**, especially visible in the early training phases.
- **Stable generalization without signs of overfitting**, as shown by the alignment between training and validation loss trends.

Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

- **Strong dual-task capability**, where the model performs well in both detection and keypoint estimation under complex conditions.

OUTPUT



CONCLUSION

YOLO-Panic presents a transformative step forward in emergency response systems by replacing traditional, contact-based alarms with an intelligent, gesture-driven solution. Leveraging the speed and accuracy of a customized YOLO architecture, combined with key point-based gesture interpretation, the system achieves real-time performance with exceptional precision and reliability. Its ability to operate in complex, real-world environments make it a practical fit for modern smart city infrastructures, where rapid communication and non-intrusive technologies are crucial. By enabling natural, contactless interaction in high-stress scenarios, YOLO-Panic not only enhances public safety but also aligns with the broader vision of resilient, AI-powered urban ecosystems. Future work may focus on expanding gesture vocabularies and integrating multimodal sensors to further improve robustness and user inclusivity.

REFRENCES

[1] Abdullahi, M., Oyelade, O. N., Kana, A. F. D., Bagiwa, M. A., Abdullahi, F. B., Junaidu, S. B., Iliyasu, I., Ore-ofe, A., & Chiroma, H. (2024). A systematic literature review of visual feature learning: Deep learning techniques, applications, challenges and future directions. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-024-19823-3

[2] Ahmad, K., Maabreh, M., Ghaly, M., Khan, K., Qadir, J., & Al-Fuqaha, A. (2022). Developing future human-centered smart cities: Critical analysis of smart city security, Data management, and Ethical challenges. *Computer Science Review*, *43*, 100452. https://doi.org/10.1016/j.cosrev.2021.100452

[3] Alahi, M. E. E., Sukkuea, A., Tina, F. W., Nag, A., Kurdthongmee, W., Suwannarat, K., & Mukhopadhyay, S. C. (2023). Integration of IoT-Enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends. *Sensors*, *23*(11), 5206. https://doi.org/10.3390/s23115206

[4] Amingad, S. C., Rahul, M., Sathvik Reddy, P. S., & Gupta, N. S. (2023). Enhancing Public Safety with AI-Powered Intelligent Surveillance: An Examination of Immediate Incident Detection and Rapid Response in Urban Settings. *2023 International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT)*, 205–210. https://doi.org/10.1109/ICAICCIT60255.2023.10465690

[5] Cristina, S., Despotovic, V., Pérez-Rodríguez, R., & Aleksic, S. (2024). Audio- and Video-Based Human Activity Recognition Systems in Healthcare. *IEEE Access*, *12*, 8230–8245. https://doi.org/10.1109/ACCESS.2024.3353138

[6] Herath, H. M. K. K. M. B., & Mittal, M. (2022). Adoption of artificial intelligence in smart cities: A comprehensive review. *International Journal of Information Management Data Insights*, *2*(1), 100076. https://doi.org/10.1016/j.jjimei.2022.100076

[7] Iqbal, M. Z., & Campbell, A. G. (2021). From luxury to necessity: Progress of touchless interaction technology. *Technology in Society*, *67*, 101796. https://doi.org/10.1016/j.techsoc.2021.101796

Journal of Information Systems Engineering and Management
2025, 10(48s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[8] Janis, I. L., & Mann, L. (1977). Emergency Decision Making: A Theoretical Analysis of Responses to Disaster Warnings. *Journal of Human Stress*, *3*(2), 35–48. https://doi.org/10.1080/0097840X.1977.9936085

[9] Javed, A. R., Shahzad, F., Rehman, S. U., Zikria, Y. B., Razzak, I., Jalil, Z., & Xu, G. (2022). Future smart cities: Requirements, emerging technologies, applications, challenges, and future aspects. *Cities*, *129*, 103794. https://doi.org/10.1016/j.cities.2022.103794

[10] Management Association, I. R. (Ed.). (2018). *Virtual and Augmented Reality: Concepts, Methodologies, Tools, and Applications*. IGI Global. https://doi.org/10.4018/978-1-5225-5469-1

[11] Mohamed, A. S., Hassan, N. F., & Jamil, A. S. (2024). Real-Time Hand Gesture Recognition: A Comprehensive Review of Techniques, Applications, and Challenges. *Cybernetics and Information Technologies*, *24*(3), 163–181. https://doi.org/10.2478/cait-2024-0031

[12] Molchanov, P., Yang, X., Gupta, S., Kim, K., Tyree, S., & Kautz, J. (2016). Online Detection and Classification of Dynamic Hand Gestures with Recurrent 3D Convolutional Neural Networks. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 4207–4215. https://doi.org/10.1109/CVPR.2016.456

[13] Moryossef, A. (2024). *Real-Time Multilingual Sign Language Processing* (Version 1). arXiv. https://doi.org/10.48550/ARXIV.2412.01991

[14] Myagmar-Ochir, Y., & Kim, W. (2023). A Survey of Video Surveillance Systems in Smart City. *Electronics*, *12*(17), 3567. https://doi.org/10.3390/electronics12173567

[15] Oudah, M., Al-Naji, A., & Chahl, J. (2020). Hand Gesture Recognition Based on Computer Vision: A Review of Techniques. *Journal of Imaging*, *6*(8), 73. https://doi.org/10.3390/jimaging6080073

[16] Pooneh Sahebi. (2024). Enhancing User Experience for Real-Time Panic Attack Detection with Wearable Technology: A Human-Computer Interaction Approach with Machine Learning Integration. *International Journal of Advanced Human Computer Interaction*, *2*(2), 55–66.

[17] Principi, E., Squartini, S., Bonfigli, R., Ferroni, G., & Piazza, F. (2015). An integrated system for voice command recognition and emergency detection based on audio signals. *Expert Systems with Applications*, *42*(13), 5668–5683. https://doi.org/10.1016/j.eswa.2015.02.036

[18] Roman, G., Demian, C., Love, T., & Yousefi-Nooraie, R. (2024). Occupational Safety, Health, and Well-Being Concerns and Solutions for Management Reported by Sign Language Interpreters: A Qualitative Study. *International Journal of Environmental Research and Public Health*, *21*(11), 1400. https://doi.org/10.3390/ijerph21111400

[19] Sarma, D., & Bhuyan, M. K. (2021). Methods, Databases and Recent Advancement of Vision-Based Hand Gesture Recognition for HCI Systems: A Review. *SN Computer Science*, *2*(6), 436. https://doi.org/10.1007/s42979-021-00827-x

[20] Seneviratne, S., Hu, Y., Nguyen, T., Lan, G., Khalifa, S., Thilakarathna, K., Hassan, M., & Seneviratne, A. (2017). A Survey of Wearable Devices and Challenges. *IEEE Communications Surveys & Tutorials*, *19*(4), 2573–2620. https://doi.org/10.1109/COMST.2017.2731979

[21] Wang, J., Lin, W., Chen, Z., Nikolaeva, V. O., Alimi, L. O., & Khashab, N. M. (2024). Smart touchless human–machine interaction based on crystalline porous cages. *Nature Communications*, *15*(1), 1575. https://doi.org/10.1038/s41467-024-46071-8

[22] Zhang, Z., Tian, Z., & Zhou, M. (2024). HandSense: Smart multimodal hand gesture recognition based on deep neural networks. *Journal of Ambient Intelligence and Humanized Computing*, *15*(2), 1557–1572. https://doi.org/10.1007/s12652-018-0989-7

[23] Zoric, G., Smid, K., & Pandžić, I. S. (2007). Facial Gestures: Taxonomy and Application of Nonverbal, Nonemotional Facial Displays for Embodied Conversational Agents. In T. Nishida (Ed.), *Conversational Informatics* (1st ed., pp. 161–182). Wiley. https://doi.org/10.1002/9780470512470.ch9