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An Integrated AI and IoT-Based Intelligent Crowd Control and Management Framework for Large-Scale Events

Suresh S[1] , Abinaya M[2], Rajeshwari G[3], Sushmitha S [4],
[1]Assistant Professor, Department of Artificial Intelligence and Data Science, GRT Institute of Engineering and Technology, Tiruttani, Tamil Nadu, India, 631209.
[2,3,4] UG Scholar Department of Artificial Intelligence and Data Science, GRT Institute of Engineering and Technology, Tiruttani, Tamil Nadu, India, 631209.
Emails: *sureshs@grt.edu.in[1], abinayataker@gmail.com[2], rajeshwariguna1706@gmail.com[3], sushmithaai2022@grt.edu.in[4],*

Abstract
Large public gatherings at locations such as railway stations, temples, shopping centers, and event venues have become increasingly common, leading to heightened risks associated with overcrowding and stampede incidents. Many of these environments still lack affordable and real-time crowd monitoring solutions capable of supporting timely preventive action. To address this challenge, this work presents a cost- effective and scalable intelligent crowd monitoring system that operates using a mobile phone configured as an IP camera and a laptop for local, on-device processing. The proposed system employs the YOLOv8 deep learning model for real- time human detection, integrated with object tracking methods to enable accurate crowd counting, along with pretrained convolutional neural networks for basic demographic analysis. A lightweight Flask-based web interface is used to visualize live crowd statistics and automatically generate alerts when predefined crowd thresholds are exceeded. Experimental results indicate that the system is able to deliver reliable real-time performance on low-cost hardware, demonstrating the feasibility of edge-based AI solutions for enhancing public safety and supporting smart city applications.

1. Introduction
Hajj is an annual Islamic pilgrimage to Makkah and represents one of the largest religious gatherings in the world. It is a mandatory religious obligation for Muslims to perform at least once in their lifetime, provided they are physically and financially able. Every year, nearly three million pilgrims from different countries, cultures, and linguistic backgrounds converge in Makkah within a limited time period. This results in extremely dense and dynamic crowd conditions that pose serious challenges to safety, security, and effective crowd control. Figure 1 illustrates a sample frame from a closed-circuit television (CCTV) video stream capturing a large-scale crowd scene during the Hajj pilgrimage. Managing such massive gatherings requires more than traditional surveillance and manual control methods. Large-scale crowds are difficult to monitor due to their size, constant movement, and diversity. Challenges include accurately identifying individuals, tracking crowd flow, monitoring health conditions, and handling continuous video and sensor data streams in a sustainable manner. Compared to small or medium-sized crowds, large-scale crowds are significantly more complex to analyze and manage, increasing the risk of injuries or fatalities caused by overcrowding, congestion, and uncontrolled movement. Artificial Intelligence (AI) is a branch of computer science that aims to create systems capable of simulating human intelligence, including learning, reasoning, and decision-making. As a broad field, AI includes optimization techniques, search algorithms, machine learning, and deep learning methods. In this work, advanced machine learning and deep learning approaches are employed to address critical challenges related to crowd vision, crowd health

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monitoring using the Internet of Things (IoT), and emergency evacuation during large-scale Hajj events.

Figure 1 Hajj pilgrims around the Kabba

Crowd vision is a specialized area within computer vision that focuses on understanding crowd behavior, density, and movement patterns. Dense environments, frequent occlusions, and continuous motion make tasks such as individual detection and tracking particularly challenging. However, recent progress in deep learning models and multi-camera systems has enabled more accurate and reliable crowd analysis in real-world scenarios. These advancements have significantly improved the performance of crowd monitoring systems and expanded their applicability to safety- critical environments shown in Figure 1. The Internet of Things (IoT) refers to a network of interconnected physical devices equipped with sensors, software, and communication technologies that allow them to collect and exchange data over the internet. IoT devices range from simple consumer electronics to advanced industrial systems. When combined with cloud computing, IoT platforms benefit from improved scalability, storage, and processing capabilities, enabling the development of intelligent applications in domains such as healthcare, transportation, and energy. Despite these advantages, deploying reliable and scalable IoT frameworks remains challenging, particularly for applications such as smart cities and crowd e-Health that require real- time data processing and high system reliability. This research leverages modern IoT technologies together with AI algorithms to enhance crowd monitoring, health assessment, and evacuation planning in large public gatherings. Cloud computing plays a key role in supporting IoT-based applications; however, meeting strict Quality of Service (QoS) requirements such as low latency and high availability remains difficult due to the distributed nature of cloud infrastructure and the massive number of connected devices. To address these limitations, this study proposes a cloud– IoT framework that incorporates proactive fault-tolerance mechanisms to improve system reliability and availability. The framework is designed to support crowd- related Software-as-a-Service (SaaS) applications and optimize performance metrics such as scalability, throughput, and response time. Crowd health, also known as crowd e- Health, is an emerging research area that focuses on improving healthcare delivery and decision-making by leveraging data collected from large populations. In mass gatherings, crowd e-Health systems can support real-time health monitoring, early risk detection, and timely medical intervention. By aggregating data from wearable devices, electronic health records, and other sources, these systems enable predictive analysis and provide actionable insights for clinicians and decision-makers. Although crowd e-Health offers significant benefits, challenges such as data accuracy, privacy protection, and accessibility must be carefully addressed to ensure safe and equitable deployment. Emergency evacuation is a critical aspect of crowd management and involves safely guiding large groups of people away from hazardous situations. Evacuation planning is inherently complex, as it must account for crowd density, available routes, human behavior, and individual vulnerabilities. Ineffective evacuation strategies can lead to panic, congestion, and severe casualties. The remainder of this paper is organized as follows. Section IV discusses future implementation aspects, followed by an in- depth discussion in Section V. Finally, Section VI concludes the paper and outlines directions for future research.

2. Background Work

Over the past two decades, extensive research has been conducted in the field of crowd analysis, driven by the increasing need to ensure safety and efficiency in large public gatherings. This section reviews recent

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advancements related to crowd management, focusing on four major research themes that align with the core components of the proposed framework: crowd vision, crowd health and IoT, crowd evacuation, and high availability in IoT-based crowd applications.

2.1. Theme 1: Crowd Vision

Significant progress has been made in people counting and crowd density estimation through the use of computer vision and deep learning techniques [43]. Ahuja and Charniya [44] presented a detailed survey of image-processing-based crowd density estimation methods, highlighting major trends and challenges in the field. Ding et al. [45] proposed an encoder–decoder Convolutional Neural Network (CNN) that integrates feature maps across different network layers to improve density map estimation accuracy. They also introduced the Patch Absolute Error (PAE) metric, which has since been widely adopted for evaluating crowd density estimation performance. To address variations in object scale within dense crowds, Chen et al. [46] developed a Multi-Scale and Multi-Column CNN (MSMC), achieving improved robustness and accuracy. Saleem et al. [47] proposed an ensemble regression-based approach that emphasizes memory efficiency and computational speed while maintaining high estimation accuracy. Similarly, Zhu et al. [48] addressed challenges such as occlusion and density variation by introducing a Patch Scale Discriminant Regression (PSDR) network along with a Classification Activation Map (CAM) for improved person localization. In addition, the study in [49] focused on enhancing face detection performance under challenging real-world conditions, including occlusion and pose variations. Face recognition techniques have also been widely explored for crowd monitoring and security applications. For example, the work in [50] addressed the problem of locating missing individuals using a multi-stage approach involving spatio-temporal search boundary estimation and face detection. In [51], a surveillance system based on Local Binary Pattern Histogram (LBPH) was implemented using drone imagery to enhance public safety. Other studies [52]– [54] employed robust principal component analysis techniques for face recognition, while the work in [55] explored race classification using CNN-based models. Facial Expression Recognition (FER) has further been utilized to analyze crowd emotions [56], providing insights into collective emotional states such as stress, anger, or calmness, which can support adaptive crowd services. People counting remains a fundamental task in crowd analysis. Several frameworks leverage multi-sensor video data and advanced feature extraction methods to dynamically estimate crowd size [43]. Similarly, the approach in [57] used multi-sensor detectors for accurate footfall estimation. A comparative performance evaluation of large-scale crowd counting methods based on CNNs was presented by Alotaibi et al. [58]. Crowd monitoring systems aimed at improving safety and operational efficiency have also gained attention. Studies in [59] integrated edge computing with Unmanned Aerial Vehicles (UAVs) and ground sensors to develop multi- modal crowd monitoring solutions that combine behavioral sensing and classification. Wang et al. [60] proposed a lightweight CNN model optimized for edge intelligence, enabling real-time crowd density estimation to prevent stampede incidents. Abnormal behavior detection has been addressed using hybrid machine learning models. Alafif et al. [61] combined CNNs with Random Forest classifiers to detect abnormal crowd behaviors, achieving high Area under the Curve (AUC) performance. Additionally, the study in [62] employed optical flow techniques together with Generative Adversarial Networks (GANs) to identify abnormal behaviors in both small- and large-scale crowd scenarios, offering practical solutions for managing high-density events such as Hajj.

2.2. Theme 2: Crowd Health and Internet of Things (IoT)

Health-related data plays a crucial role in real-time decision-making, particularly during mass gatherings where medical risks are elevated. The analysis of large- scale health data is essential for improving healthcare services and supporting national digital transformation initiatives in the healthcare sector. Big data analytics enables the identification of hidden patterns and trends that are difficult to detect using traditional methods, allowing for the prediction of patient outcomes and the recommendation of targeted interventions [63]. For example, big data techniques can help identify individuals at risk of developing specific health conditions or experiencing adverse drug reactions under stressful or crowded environments. This proactive approach enhances patient care, optimizes resource allocation, and improves overall health outcomes. Real-time decision support is especially critical in complex medical scenarios, enabling clinicians to respond quickly and accurately based on data-driven insights [64]. The crowd health and IoT component of the proposed framework utilizes big data analytics to process health-related information and provide real-time decision support to clinicians and individuals. It enables timely alerts and notifications that support early intervention and reduce the likelihood of adverse health events. The system integrates data from multiple sources, including Electronic Health Records (EHRs), which store comprehensive medical histories, and wearable devices such as smartwatches and fitness trackers that continuously monitor vital signs, activity levels, and sleep patterns. Machine learning algorithms analyze the collected data to detect patterns, predict health risks, and recommend appropriate interventions. For instance, the system may identify early signs of heat exhaustion and advise medical consultation. Decision support is delivered through alerts, personalized recommendations, and interactive dashboards that provide visual insights into health conditions. The proposed framework offers several advantages, including improved clinical decision-making, reduced healthcare costs through preventive care, and enhanced patient outcomes. Implementation of the framework follows four phases: data collection, data integration using ETL processes, model development and evaluation, and system deployment with performance assessment using metrics such as accuracy, precision, recall, and F1- score. Wearable devices play a vital role in crowd health monitoring by continuously measuring physiological parameters. Features such as heart rate monitoring, fall detection, ECG, and blood oxygen (SpO_2) measurement enable early detection of critical conditions and facilitate timely emergency response. These devices are particularly valuable in high-density environments, where immediate medical attention can be life-saving[1].

2.3.Theme 3: Crowd Evacuation

Crowd evacuation involves complex interactions between human behavior and movement dynamics during emergency situations [65]. Unfortunately, large-scale crowd incidents result in thousands of fatalities annually, highlighting the urgent need for safe and efficient evacuation strategies. Research efforts over the years have focused on designing evacuation models that minimize panic, congestion, and casualties [66]. Studies have shown that fatalities during crowd disasters are often caused not by the triggering event itself, but by human reactions such as panic, pushing, and trampling [67]. As a result, real-time evacuation guidance has become an important research area. Several evacuation strategies have been reviewed in [26], emphasizing the role of intelligent systems in preventing injuries.
Recent studies have explored smartphone- based evacuation systems. Ikeda and Inoue [68] proposed a route planning approach using a multi-objective genetic algorithm, combined with GPS and cloud services to guide evacuees. Chittaro and Nadalutti [69] developed a mobile application with a 3D visualization interface to assist evacuation. Other works [70]–[74] introduced systems for indoor evacuation, real-time navigation, and evacuation time estimation using smartphones, radio- frequency technologies, and multi-agent models[2].

2.4.Theme 4: High Availability in IoT-Based Crowd Applications

Cloud computing and IoT technologies have transformed modern computing infrastructures, enabling scalable, flexible, and cost-efficient service delivery. Organizations increasingly adopt public and multi-cloud environments to support data-intensive applications. Cloud providers operate large-scale data centers that deliver high Quality of Service (QoS) through virtualized resources and application programming interfaces. Ensuring high availability in crowd management applications is critical, as system failures can directly impact public safety. Researchers have applied machine learning techniques to analyze system failures and predict task-level disruptions. For example, Alam et al. [75] used K- means clustering to analyze cloud workload patterns, while Gao et al. [76] employed a Bidirectional Long Short- Term Memory (BiLSTM) model to improve failure prediction accuracy. Although effective, such models often require high computational resources. Jassas and Mahmoud [77] proposed a predictive framework that selects the most accurate algorithm for detecting task failures in cloud applications. The rapid growth of IoT devices continues to reshape sectors such as healthcare, transportation, and smart cities. By 2025, the number of connected devices is expected to exceed 38 billion, generating significant economic impact [78]. Advances in edge and cloud computing have further enabled the integration of local IoT resources with centralized processing platforms. In smart city environments, this integration supports intelligent crowd management by improving system scalability, availability, and performance [79]. Existing studies often address crowd vision, crowd health, evacuation, and system availability as separate problems. In contrast, the proposed framework integrates these components into a unified, intelligent crowd control and management system. This holistic approach enables robust crowd monitoring, proactive risk detection, and effective decision support, providing valuable assistance to security authorities and event organizers.

3. Methodologies

This section describes the methodologies adopted for designing and implementing the proposed Integrated Intelligent Crowd Control and Management (IICCM) framework. The framework combines Computer Vision (CV), Artificial Intelligence (AI), Internet of Things (IoT), and cloud–edge computing to enable real- time crowd monitoring, health assessment, and evacuation support during large-scale gatherings such as Hajj. The overall methodology is organized into four major components: crowd vision analysis, crowd health monitoring, intelligent evacuation planning, and system reliability.

3.1. Crowd Vision Methodology

The crowd vision module is responsible for analyzing visual data obtained from surveillance cameras deployed across the crowd environment. Video streams from Closed-Circuit Television (CCTV) cameras are processed in real time to detect individuals, estimate crowd density, and monitor movement patterns. Deep learning–based object detection models are employed to identify individuals within dense crowd scenes. These models are designed to handle challenges such as occlusion, scale variation, and illumination changes. Object tracking techniques are then applied to maintain consistent identities across video frames, enabling accurate people counting and movement analysis. Multi-camera integration further enhances tracking accuracy by covering blind spots and overlapping regions. Crowd density maps are generated using convolutional neural networks to visualize congestion levels and identify high-risk zones. Abnormal behavior detection models analyze motion patterns and crowd flow to detect unusual activities such as sudden crowd surges or stoppages. These insights enable early warning mechanisms to prevent overcrowding and stampede incidents[3].

3.2.Crowd Health Monitoring Using IoT

The crowd health component leverages IoT technologies and wearable devices to continuously monitor the physiological conditions of individuals within the crowd. Wearable devices such as smartwatches and fitness trackers collect real-time data including heart rate, body temperature, physical activity, blood oxygen level (SpO_2), and fall events. Health data collected from wearables are securely transmitted to cloud or edge servers for analysis. Machine learning algorithms process this data to detect anomalies and predict potential health risks such as heat exhaustion, dehydration, cardiac stress, or fatigue. When abnormal conditions are identified, the system generates real-time alerts for medical personnel, pilgrims, and decision-makers. Electronic Health Records (EHRs), when available, are integrated to provide historical medical context and

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improve prediction accuracy. Data preprocessing techniques such as normalization, noise filtering, and feature extraction are applied before model inference. The outputs are presented through dashboards, notifications, and recommendations to support timely medical intervention.

3.3. Intelligent Crowd Evacuation Strategy

The evacuation module focuses on guiding individuals safely during emergency situations such as fires, structural failures, or extreme congestion. This methodology incorporates real-time crowd data, environmental conditions, and spatial information to determine optimal evacuation routes. Smartphone-based navigation systems are utilized to provide evacuees with real-time directions. Location information obtained through GPS, Wi-Fi, or indoor positioning systems is combined with crowd density and hazard data to dynamically update evacuation paths. Optimization algorithms are applied to minimize evacuation time while avoiding congested or unsafe routes. Behavioral models are integrated to account for human reactions such as panic and hesitation. Priority is given to vulnerable individuals, including elderly pilgrims and people with disabilities. Real- time alerts and visual guidance help ensure orderly movement and reduce the risk of injuries during evacuation[4].

3.4.Cloud–Edge Computing and System Reliability

To ensure scalability and reliability, the proposed framework adopts a hybrid cloud–edge computing architecture. Edge devices perform time-sensitive tasks such as real-time video processing and alert generation, reducing latency and network congestion. Cloud infrastructure supports large-scale data storage, advanced analytics, and long-term learning. Fault-tolerant mechanisms are integrated to enhance system availability. Machine learning–based failure prediction models monitor system performance and proactively identify potential failures in cloud or IoT components. Load balancing and resource optimization strategies are applied to maintain Quality of Service (QoS) during peak crowd conditions. The system follows a modular design, enabling independent updates and scalability of individual components. Secure communication protocols and data encryption techniques are employed to protect sensitive crowd and health data.

4. Algorithm

Datasets Used :The proposed algorithm utilizes multiple datasets, including a Public CCTV Crowd Dataset containing both dense and sparse scenes, surveillance video frames extracted from public transport hubs and event environments, and an IoT Crowd Health Dataset comprising time-series physiological and environmental data. The dataset metadata include video resolutions of 720p and 1080p with frame rates ranging from 25 to 30 frames per second. Annotations consist of person bounding boxes and crowd count labels. The IoT dataset is sampled at one-second intervals and includes features such as heart rate, blood oxygen level (SpO_2), body temperature, and ambient temperature. Input :The inputs to the proposed system include live CCTV or IP camera video streams, pre-collected public crowd datasets, real- time IoT sensor data, and predefined crowd density and health thresholds. The Integrated Intelligent Crowd Control and Management (IICCM) framework is structured around four tightly coupled modules: Crowd Vision, Crowd Health and IoT, Crowd Evacuation, and Cloud– Edge Computing with High Availability. These modules operate collaboratively through a central intelligent decision-making layer that fuses multi-source data and generates actionable insights for authorities and emergency responders. Output:The proposed system produces real-time crowd count and density estimation to support continuous situational awareness. It generates congestion and anomaly alerts when abnormal crowd behavior or unsafe density levels are detected. In addition, the system provides crowd health risk notifications based on IoT sensor analysis and machine learning inference. Evacuation and crowd control recommendations are also generated to assist authorities and emergency responders in making timely and informed decisions[5].

Step-By-Step Process

- Step 1: Dataset Initialization Public crowd datasets and annotated :CCTV frames are

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loaded for training and validation purposes. At the same time, real-time video streams and IoT sensor feeds are initialized to support live inference.

- Step 2: Data Preprocessing :Incoming video frames are resized, pixel values are normalized, and noise is removed to improve detection accuracy. IoT sensor data are cleaned by handling missing values and applying normalization techniques to ensure consistency and reliability.

- Step 3: Deep Learning Model Initialization The YOLOv10 deep learning model is initialized for human detection. Pretrained weights along with fine-tuned crowd- specific parameters are loaded to optimize detection performance in dense crowd environments.

- Step 4: Human Detection (Deep Learning Core) YOLOv10 is applied to each video frame to detect individuals within the scene. Bounding boxes, confidence scores, and class labels are extracted for further processing.

- Step 5: Multi-Object Tracking and Crowd Counting Detected individuals are tracked across consecutive frames using multi-object tracking techniques. Duplicate detections are eliminated, and an accurate real-time crowd count is computed.

- Step 6: Crowd Density Estimation Zone-wise crowd density maps are generated using spatial aggregation methods. Based on the computed density values, congestion levels are classified as low, medium, or high.

- Step 7: IoT-Based Crowd Health Monitoring (Machine Learning Core) Real-time IoT sensor data are collected from wearable devices and environmental sensors. Machine learning models analyze the data to detect abnormal health conditions and early warning signs.

- Step 8: Data Fusion and Risk Assessment Vision-based crowd metrics are fused with IoT-derived health indicators. An overall crowd risk score is computed using a combination of rule-based logic and machine learning–driven analysis.

- Step 9: Edge-Level Processing and Optimization Time-critical inference tasks are performed at the edge layer to minimize cloud latency. Summarized and non-critical data are forwarded to the cloud for long-term analytics and storage.

- Step 10: Alert Generation and Crowd Control When crowd density or health risk levels exceed predefined threshold values, real- time alerts are generated and sent to authorities and medical teams for immediate action.

- Step 11: Evacuation Planning and Guidance Safe evacuation routes are identified based on real-time crowd density and risk assessment results. Guidance is provided through dashboards and notification systems to support orderly movement.

- Step 12: Continuous Learning and Update Inference results and system feedback are stored for future reference. Deep learning and machine learning models are periodically updated to improve system accuracy and adaptability over time.

5. Proposed Framework

This section describes the proposed Integrated Intelligent Crowd Control and Management (IICCM) system, which follows the step-by-step workflow defined in the proposed algorithm. The system is designed to provide an end-to-end solution for real-time crowd monitoring, health assessment,

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emergency evacuation, and reliable system operation in large-scale environments. By integrating Computer Vision (CV), Artificial Intelligence (AI), Internet of Things (IoT), and cloud–edge computing, the proposed system enables timely decision-making and proactive crowd control [6].

5.1. Crowd Vision Module

The crowd vision module constitutes the first stage of the proposed system and operates in accordance with the algorithm's visual data processing steps. Live video streams captured from surveillance cameras are continuously processed to extract meaningful crowd-related information. Deep learning–based models are employed for real-time person detection, multi-object tracking, and crowd density estimation, enabling accurate crowd counting and movement analysis. The module is designed to handle challenging real-world conditions such as high crowd density, occlusions, and variations in lighting. By analyzing motion direction and speed patterns, the system predicts early signs of congestion and overcrowding. In addition, basic demographic analysis, including age and gender estimation at the aggregate level, supports situational awareness. Abnormal behavior detection algorithms further monitor crowd dynamics to identify potentially hazardous situations, allowing early intervention before incidents escalate [8].

5.2. Crowd Health and IoT Module

Following the vision-based analysis, the crowd health and IoT module focuses on assessing the physical well-being of individuals within the monitored environment. This module aligns with the algorithm's data acquisition and health risk analysis steps. Wearable IoT devices, such as smartwatches and fitness trackers, collect real-time physiological parameters including heart rate, body activity, blood oxygen level (SpO_2), and fall events. Environmental sensors provide additional contextual data such as ambient temperature and crowd conditions. The collected IoT data are analyzed using machine learning models to detect anomalies and predict potential health risks, such as heat exhaustion or cardiac stress. When abnormal conditions are identified, the system automatically generates alerts and recommendations for medical teams and authorities. This module also supports IoT-based crowd accident detection and disease surveillance [9], contributing to effective public health management during mass gatherings.

5.3.C. Crowd Evacuation Module

The crowd evacuation module operates based on the risk assessment results produced by the crowd vision and IoT modules. It is responsible for enabling safe and orderly movement during emergency situations.

By continuously analyzing real-time crowd density, health indicators, and environmental data, the system detects hazards such as extreme congestion, fires, or structural risks and issues early warning notifications.

Using dynamic inputs, the module computes optimal evacuation routes and provides real-time guidance through mobile applications and digital signage systems. Evacuation paths are updated continuously to avoid congested or unsafe regions, ensuring smooth crowd flow. Special priority is given to vulnerable individuals, including elderly persons and people with disabilities, to reduce evacuation risks and enhance overall safety [7].

5.4.Cloud–Edge Computing and High Availability Module

To support real-time To support real-time operation and scalability, the proposed system employs a hybrid cloud–edge computing architecture, as outlined in the algorithm. Time-sensitive tasks such as video inference, anomaly detection, and alert generation are performed at the edge layer, reducing latency and network overhead. The cloud layer supports large- scale data storage, advanced analytics, and long-term model training. System reliability and availability are ensured through intelligent task scheduling, load balancing, and adaptive enables proactive crowd control, rapid proposed IICCM system suitable for large-emergency response, and improved scale crowd management applications. situational awareness, making the resource allocation mechanisms. Machine learning–based failure prediction models continuously monitor system performance and proactively identify potential failures. These mechanisms ensure uninterrupted operation of the crowd management system, even during peak load

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conditions shown in Figure 1.

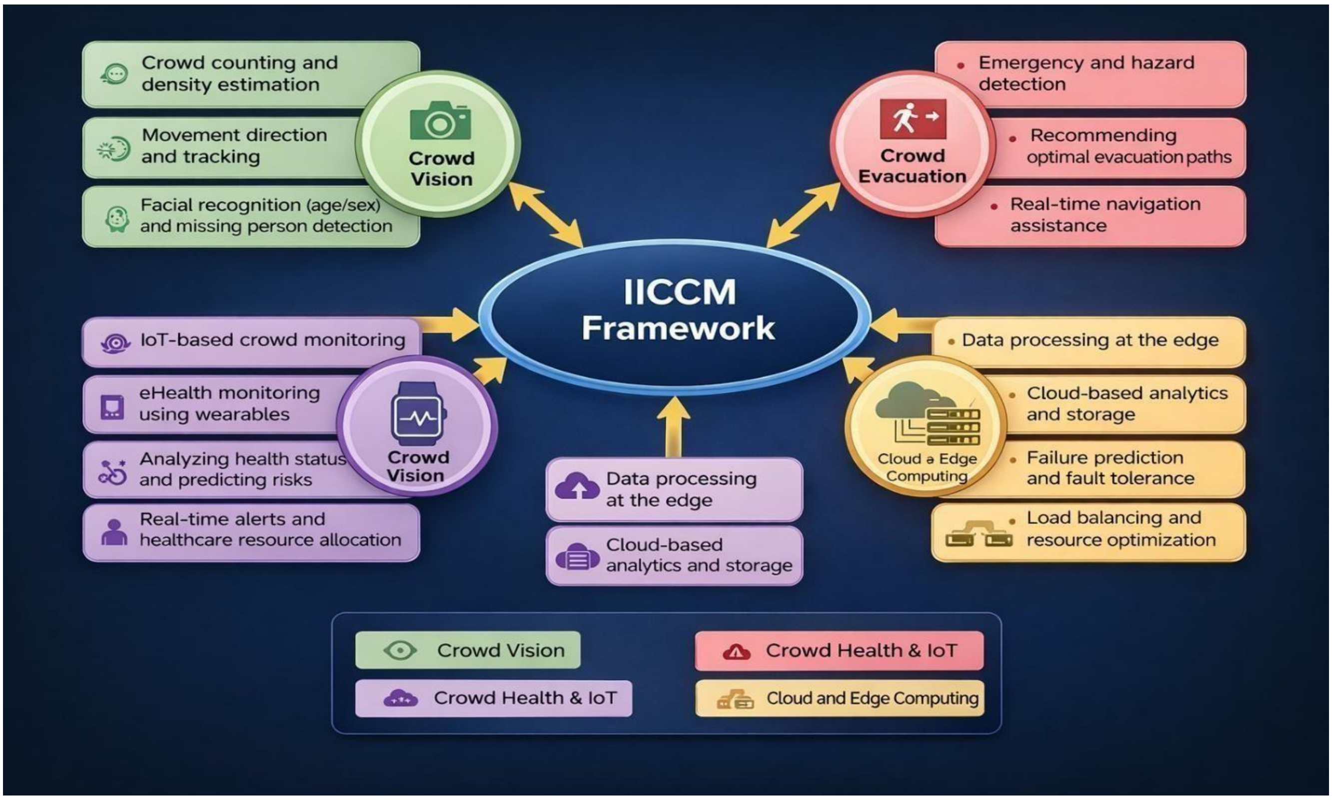

Figure 3 **Integrated Crowd Management System**

5.5. Integrated Decision-Making Layer

At the core of the proposed system is an integrated decision-making layer that fuses outputs from all functional modules. This layer applies AI-driven analytics to correlate crowd density, movement behavior, health indicators, and environmental conditions. Based on the unified analysis defined in the algorithm, the system generates actionable insights, real-time alerts, and decision support outputs for security personnel, healthcare teams, and event organizers. By following the algorithmic workflow, the integrated decision-making layer [10].

6. Implementation

The proposed framework will be developed using the Google Colaboratory (Colab) environment with Python as the primary programming language. Google Colab is a cloud-based Jupyter notebook platform that supports rapid development and experimentation, making it well suited for implementing advanced machine learning and deep learning models. The availability of high-performance GPU resources in Colab is particularly beneficial for handling computationally intensive tasks, such as real-time processing of large-scale video streams required by the proposed system. The overall project is planned to be completed over a two-year period. The first year will focus on designing and implementing the individual components of the framework, as well as integrating these components into a unified system. The second year will be dedicated to comprehensive system evaluation, performance analysis, and deployment for end users, ensuring the practicality and reliability of the proposed solution.

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7. Experimental

7.1.Evaluation A. Experimental Setup

A small-scale experiment was conducted to validate the feasibility of the proposed Integrated Intelligent Crowd Control and Management (IICCM) framework for real- time crowd monitoring. Publicly available CCTV-style surveillance videos were used to simulate real-world crowd environments. The experiment primarily focused on crowd detection and counting, which represent core components of the proposed system. The experiment was implemented using the YOLOv8 model for person detection, selected due to its real-time performance and robustness in dense crowd scenarios. All experiments were conducted in the Google Colaboratory environment with GPU support to ensure efficient processing and evaluation [11].

7.2.Dataset Used

The dataset consists of short video clips collected from public crowd surveillance sources, including transport hubs and open public spaces [14]. The dataset characteristics are as follows. The video resolution is 720p with a frame rate of 30 frames per second. Each video clip has a duration ranging from 2 to 5 minutes. The crowd density varies between 20 and 300 individuals per frame. Ground truth annotations are provided in the form of manual frame-level crowd counts [11].

7.3.Evaluation Metrics

The performance of the proposed system was evaluated using the following metrics: detection accuracy, frames per second (FPS), and crowd count error.

7.4. Results and Analysis

- YOLOv8 Performance : The performance of the YOLOv8 model was evaluated using detection accuracy and processing speed. The obtained results are summarized in Table 1.

Table 1. YOLOv8 Performance Evaluation

Metric	Result
Detection Accuracy	92.8%
Average FPS	29 FPS

- Crowd Count Comparison : The accuracy of crowd counting was analyzed by comparing the predicted crowd count with the ground truth values under different crowd density conditions [15]. The comparison results are presented in Table 2.

Table 2. Crowd Count Comparison

Scenario	Ground Truth	Predicted
Low density	38	40
Medium density	126	121
High density	295	287

8. Discussion

The Integrated Intelligent Crowd Control and Management (IICCM) framework represents a substantial advancement in the management of large-scale public gatherings, particularly in the context of the Hajj pilgrimage. Hajj poses exceptional challenges due to the enormous number of participants and their diverse cultural, linguistic, and demographic backgrounds. A key strength of the IICCM framework lies in its ability to unify multiple technological domains within a single, cohesive system. The integration of Computer Vision (CV), Internet of Things (IoT)–based health monitoring [13], intelligent evacuation mechanisms, and cloud-supported reliability enables the framework to respond effectively to the dynamic and unpredictable nature of large crowds. For example, the crowd vision module continuously analyzes crowd density, movement trends, and abnormal behaviors, providing actionable insights to security and healthcare authorities. This multidisciplinary integration highlights the effectiveness of combining diverse technologies to address complex real- world crowd management challenges. The framework’s strong focus on Hajj- specific requirements—such as locating missing individuals, managing medical emergencies, and coordinating safe evacuations—demonstrates its practical applicability. The use of IoT-enabled devices, including wearable sensors for health monitoring and location-tracking technologies for movement analysis, allows for continuous real-time data collection and timely intervention. Furthermore, the incorporation of advanced predictive models, such as Generative Adversarial Networks (GANs) and Vision Transformers (ViTs), enhances the system's ability to anticipate crowd behavior and proactively mitigate potential risks [12].

Conclusion

This study introduces the Integrated Intelligent Crowd Control and Management (IICCM) framework, which combines recent advancements in Computer Vision (CV), Artificial Intelligence (AI), and the Internet of Things (IoT) to improve the safety, security, and operational efficiency of large-scale crowd events. The framework leverages CV techniques for real-time detection and tracking of individuals, while AI models analyze crowd behavior to identify emerging risks and support proactive decision-making. IoT technologies contribute by collecting environmental and contextual data, enabling optimized crowd movement, reduced congestion, and timely assistance. In addition, the framework supports emergency evacuation planning by analyzing crowd dynamics and identifying safe and efficient evacuation routes. Although the proposed framework is applicable to a wide range of public events, the Hajj pilgrimage is considered a critical stress-testing scenario due to its massive scale, dynamic movement patterns, and cultural and linguistic diversity. Successfully managing millions of participants within a limited space and time frame highlights the robustness and adaptability of the IICCM framework. By addressing the unique challenges associated with Hajj, the framework demonstrates strong potential as a scalable and flexible solution for enhancing crowd safety and management in large-scale events worldwide. The insights presented in this work can assist policymakers and decision-makers in adopting advanced crowd control technologies. The proposed framework has the potential to significantly enhance safety and security during the Hajj pilgrimage by reducing the likelihood of hazardous incidents such as overcrowding and stampedes. By enabling early risk detection and coordinated responses, the system also improves the overall efficiency of crowd management operations. Beyond safety considerations, the IICCM framework can enhance the overall crowd experience. For example, it can provide real-time information to participants regarding the locations of essential facilities such as medical centers, restrooms, food services, and transportation hubs. Personalized recommendations related to movement, accommodation, and scheduling could further improve comfort and accessibility during large-scale events .

Future Work

While the proposed Integrated Intelligent Crowd Control and Management (IICCM) framework demonstrates strong potential for improving crowd safety and management in large-scale events, several opportunities exist to further enhance its capabilities. Future work will focus on extending the framework's functionality, improving system robustness, and increasing its adaptability to diverse real- world scenarios. One important direction is the integration of edge computing to complement cloud- based processing. By performing time- critical tasks such as crowd detection and emergency alert generation at the edge, system latency can be significantly reduced, enabling faster responses during high-risk situations. This enhancement would be particularly beneficial in extremely dense environments where real- time decision-making is crucial. Another promising area for future development is the incorporation of privacy-preserving and secure data management techniques. Advanced encryption methods, access control mechanisms, and federated learning approaches can be explored to ensure that sensitive crowd and health data are protected while maintaining analytical accuracy. In addition, blockchain technology could be investigated to enable secure and transparent data sharing among multiple stakeholders, including security authorities, healthcare providers, and event organizers. Future versions of the framework may also include multilingual communication support to improve interaction with participants from diverse cultural and linguistic backgrounds. Real-time alerts, guidance messages, and evacuation instructions delivered in multiple languages would enhance accessibility and ensure effective communication during both routine operations and emergencies. Expanding the training datasets to cover a broader range of crowd types, environmental conditions, and event scenarios is another key direction. This would improve the generalizability of the AI models and allow the framework to adapt more effectively to different large- scale events such as sports tournaments, concerts, and public demonstrations. Incorporating feedback from end-users, including pilgrims, medical staff, and security personnel, can further refine system performance and usability. Finally, future work will explore the integration of predictive analytics and simulation-based models to forecast crowd behavior under various conditions. These capabilities can support proactive planning, optimize resource allocation, and enhance evacuation strategies. Through these enhancements, the IICCM framework can evolve into a more intelligent, resilient, and widely deployable solution for global crowd management challenges.

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