MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 3352-3356

Safe-Walk AI:A Proactive Multi-Model Intelligent Framework For Real-Time Last-Mile Personal Safety Using Vision, Audio, And Community Intelligence

INDHUMATHI S, ASSISTANT PROFESSOR,
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING,
KGISL INSTITUTE OF TECHNOLOGY,
COIMBATORE,TAMIL NADU,INDIA
indhumathisme@gmail.com

PRIYADHARSHAN K, UG STUDENT,
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING,
KGISL INSTITUTE OF TECHNOLOGY,
COIMBATORE,TAMIL NADU,INDIA
dharshank751@gmail.com

SABITHA P, UG STUDENT,
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING,
KGISL INSTITUTE OF TECHNOLOGY,
COIMBATORE,TAMIL NADU,INDIA
sabitha2672005@gmail.com

SIMI PATRISIA P, UG STUDENT,
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING,
KGISL INSTITUTE OF TECHNOLOGY,
COIMBATORE,TAMIL NADU,INDIA
simipatrisia@gmail.com

VENMATHI J, UG STUDENT,
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING,
KGISL INSTITUTE OF TECHNOLOGY,
COIMBATORE,TAMIL NADU,INDIA
venmathi0706@gmail.com

***Abstract*—**Even now, staying safe on short trips remains tough, particularly for women and those working late shifts once buses or trains stop. Most apps people rely on today only respond after something already went wrong - requiring a conscious tap for help once danger shows up. These setups fall short when someone cannot act fast enough because fear takes over, arms get locked, or surprise strikes happen. A fresh approach to staying safe rolls out through Safe Walk AI - one that acts ahead of trouble. Instead of reacting, it watches for warning signs before they grow. Instant responses come not from guesswork but from processed data in real time. Risk levels shift based on where someone goes, who they are, what they carry. Routes change automatically when conditions turn uncertain. Sounds around you can reveal hidden risks if patterns get analyzed on the fly. Cameras spot odd behavior earlier because software learns what normal looks like. Neighbors near and far contribute knowledge that shapes how warnings spread. Live video feeds get analyzed using a YOLO-style model to spot odd actions - like people hanging around too long, bunching up, or sticking behind others. Meanwhile, strange sounds possibly linked to stress or hostility are caught through an audio flag system. Context shapes how risky each moment feels: clock settings, darkness levels, user history, even local warning notices all influence the alert level assigned to every scene. When warning signs rise, Safe Walk AI kicks off safety steps - like turning on companion tracking, adjusting paths, or sending urgent alerts - by pushing live position updates. Unlike older systems using single panic buttons, tests in fake urban routes found better insight into threats, faster help arrival, and sharper reaction times. You might see this setup woven into urban networks, tech clusters, or school grounds - it bends without breaking, grows as needed.

Personal Safety, Last-Mile Security, Proactive Risk Detection, YOLO, Audio Anomaly Detection, Multi-Sensor Fusion, Dynamic Route Intelligence, Community Safety Mesh, Smart Cities, Artificial Intelligence

I. Introduction

Starting off, city transportation methods have changed a lot since ride-sharing became normal. Companies also provide group rides, while buses and subways exist too. Still, once you leave one of those vehicles near your destination, problems show up. Short walks afterward can feel unsafe. Many people, especially women and those working late hours, worry about getting home alone. That last bit of ground? Hard to protect. Panic buttons, manual SOS triggers, and emergency calling features are often seen in basic safety apps. Instead of preventing issues, these tools react once trouble begins. What happens before - the root cause - stays unaddressed. During critical moments, someone could be restrained, disoriented, or too far away to access such features. Protection stops short when safety relies on quick button presses after danger already arrived. So, when things slow down, risk goes up too. New shifts - like smarter AI, edge tech, and how we handle multiple sensors - are nudging defenses from just reacting to staying ahead. With live vision tools, odd actions can now be caught instantly. That leap changes what we watch and when. Odd shifts in nature's rhythms show up when you analyze sound. Paths less traveled might be mapped out by shifting the way we see Earth's surface. Safety webs built by people nearby could grow stronger with shared knowledge. Even so, today's systems often manage these tools one by one. A missing piece remains - a unified, live, forecasting safety structure able to predict what happens next in the space, Personalized risk assessment with context awareness, Multimodal detection of anomalies, Mechanisms for automatic preventive response, Alerts spread differently within communities.This paper suggests Safe-Walk AI, a multi-modal intelligent safety framework created especially for last-mile protection, as a solution to these drawbacks. Safe-Walk AI focuses on predicting risks instead of only reporting after something happens, unlike standard systems. By combining live route scoring, community mesh networking, audio anomaly recognition, and vision-based detection, the system aims to boost awareness and shorten reaction time before dangers grow worse.This piece adds several key points. Each one plays a role in shaping the overall result. A safety rating system that actively considers surroundings and real-time conditions. Using sound and image processing together allows systems to spot unusual patterns while things happen. Real-time detection becomes possible through this blend of technologies. Shifting safety needs reshape routes on the fly. A system pings rescue teams when someone signals distress, logging locations plus proof on the fly. Built on flexible designs, this setup fits well within smart city environments along with public institutions. What follows dives into linked studies, system layout, algorithm structure, how things will be built, testing methods, results from trials, plus paths ahead.

II. LITERATURE SURVEY

With the rise of mobile computing, artificial intelligence, and smart city infrastructures, personal safety technologies have come a long way. A lot of the safety apps that are already out there are mostly about reactive response mechanisms like emergency buttons, live location sharing, and instant alert messaging. While these features provide essential post- incident assistance, their effectiveness is often limited in real- world emergency situations where users may be unable to manually activate alerts due to panic, physical restraint, or sudden escalation of threats. Studies analyzing mobile-based SOS systems highlight improvements in alert transmission speed and GPS precision; however, they consistently depend on user initiation rather than predictive intelligence. Research on computer vision has advanced significantly in the areas of activity recognition and automated surveillance at the same time. Real-

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 3352-3356

time object identification models like YOLO and convolutional neural networks, two types of deep learning architectures, have proven to be highly effective in spotting suspicious clusters in video streams, aggressive motions, and aberrant human behaviors. Several surveillance systems installed in public areas use these models to track crowd behavior and identify violent incidents. Nevertheless, these systems are primarily centralized and function within CCTV infrastructures for post-event research purposes instead of providing real-time, personal security.

Another crucial area in environmental safety monitoring is audio-based anomaly detection. Machine learning classifiers in conjunction with spectral feature extraction techniques, such as Mel-Frequency Cepstral Coefficients (MFCC), have demonstrated encouraging outcomes in detecting distress signals like gunshots, screams, or unusual noise spikes. It is feasible to differentiate between normal ambient noise and potentially hazardous acoustic events, according to research in urban sound categorization. Despite these developments, the majority of implementations are not incorporated into mobile personal safety frameworks, but rather are made for stationary smart city sensors. By recognizing high-risk areas and suggesting safer routes based on past crime data and lighting conditions, geospatial analytics and crime mapping technologies have significantly advanced safety studies. Al- though these systems provide useful macro-level information, they frequently lack personalized risk assessment and real-time adaptation. Individual user profiles, dynamic environmental changes, and behavioral anomalies that occur at a particular time are not taken into consideration by static safety maps.Even though mobile SOS apps, computer vision surveil- lance, audio anomaly detection, and safety-aware routing all show significant advancements on their own, there is still a clear lack of cohesive, multi-modal frameworks that combine these elements into an ecosystem for proactive personal safety. Detection, alerting, and routing are the main functions of cur- rent systems, which rarely integrate into a coherent predictive design. By combining dynamic safety scoring, acoustic risk analysis, vision-based anomaly detection, and automated emergency response into a single mobile-accessible framework, Safe-Walk AI aims to close this gap. The proposed system shifts the paradigm from response-based safety to predictive personal protection by emphasizing continuous environmental assessment and preventive intervention, in contrast to traditional reactive applications.

II. PROBLEM STATEMENT

Despite the fast-paced evolution of transportation networks and digital safety solutions, the last mile of a journey still poses a substantial personal security risk to users. People, especially women and employees who work late hours, often feel insecure during short walking routes following the drop- off by public or private transport services. Such settings are characterized by poorly lit roads, a lack of crowd presence, and easily accessible help, which may be expected at any time.

Current safety solutions are based on a reactive strategy, where users have to press the SOS button or call emergency services manually after feeling threatened. In practical scenarios where panic, physical force, or surprise attacks occur, the capability to press such buttons may be affected. Furthermore, most safety solutions provide static safety information that does not consider dynamic environmental changes such as human behavior, sound patterns, or situational risks. More- over, the existing solutions are prone to handling the safety components separately, such as location tracking, emergency notification, or surveillance, without combining them into a single predictive model. The lack of continuous environmental monitoring, risk assessment, and preventive actions hinders the efficiency of the existing solutions in dealing with the threats before they are escalated.Thus, there is a great need for an intelligent safety system that can continuously monitor the environmental factors, identify abnormal behaviors using multi-modal sensing, dynamically compute the risk levels, and take preventive measures without depending on the user input. This need is addressed by the Safe-Walk AI system proposed in this research.

TABLE I

COMPREHENSIVE LITERATURE SURVEY ON PROACTIVE PERSONAL SAFETY

S.No	Title	Author(s)	Year	Methodology	Identified Gap
1	Real-Time Video Anomaly Detection (YOLOv8 + DeepSORT)	Hua, Li, Zhang	2024	YOLOv8 + DeepSORT for multi- object tracking; detects loitering & crowd formation	Visual-only; no audio fusion; lacks context-aware risk prediction
2	Audio Anomaly Recognition (VGGish + AVACA)	Wilkinghoff & Müller	2023	VGGish embeddings with AV cross-attention	False positives in noisy environments; lacks video fusion
3	Mobile Crowdsensing for Smart City Safety	Cicek et al.	2023	Federated mobile crowdsensing for safety data collection	Dependent on user participation; lacks AI validation
4	YOLO-ABD Pedestrian Anomaly Detection	Hua et al.	2024	Multi-scale lightweight YOLO for abnormal behavior detection	Limited dataset; no multimodal fusion
5	MAVAD Audio-Visual Traffic Anomaly Dataset	Leporowski et al.	2023	AV dataset + temporal-spatial fusion for traffic anomalies	Limited to traffic domain; not urban pedestrian safety
6	Weakly Supervised Video Anomaly Detection (Transformer)	Wan et al.	2024	Sparse-label transformer-based anomaly detection	No audio integration; weak supervision limitation
7	Audio-Visual Collaboration for Anomaly Detection	Gao et al.	2024	Cross-attention fusion of audio and video features	Limited real-time evaluation; no edge deployment
8	Edge YOLO for Real-Time Detection	Anonymous	2021	Edge-cloud cooperative YOLO deployment	Hardware-dependent; lacks multimodal optimization
9	Survey on Video Anomaly Detection	Mahareek et al.	2024	Comparative review of anomaly detection techniques	Lacks real-time urban implementation insights
10	Interpretable Anomalous Sound Detection	Jian et al.	2025	Attention-based ASD models for safety-critical events	Limited deployment; no video integration
11	Pretrained Embeddings for ASD	Wilkinghoff et al.	2023	VGGish-based abnormal sound detection	Noise sensitivity; lacks contextual filtering
12	VGGish-Based Biological Sound Detection	Wang et al.	2023	Audio feature extraction using pretrained embeddings	Not applied to human safety environments
13	LPCF-YOLO Pedestrian Detection	Anonymous	2025	Lightweight YOLO for small/occluded pedestrians	Dataset limitation; no audio fusion
14	Crowdsourced Mobile App Safety Labels	Levasseur et al.	2025	Community-based safety labeling system	User engagement variability; lacks AI validation
15	Mobile Crowdsensing for Disaster Management	Cicek et al.	2023	Crowdsensing for environmental safety data	Participant dependency; limited AI analytics
16	AVACA Audio-Visual Cross-Attention	Anonymous	2023	Cross-modal attention for AV anomaly detection	Limited dataset diversity; no real-time edge testing

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 3352-3356

17	First/Last-Mile Urban Safety Survey	Kåresdotter et al.	2022	Survey of last-mile mobility & safety challenges	No actionable detection system
18	Acoustic-Based Condition Monitoring Review	Jombo et al.	2023	Review of ASD techniques transferable to safety	Limited pedestrian safety adaptation
19	Smartphone-Based Urban Crowd Sensing	Anonymous	2022–24	Edge-cloud mobile sensing for safety data	Data reliability & privacy concerns
20	Mobile Crowdsourcing Platforms for Road Safety	Anonymous	2022–25	Evaluation of crowdsourcing safety platforms	No real-time anomaly detection
21	Audio-Visual Representation Learning	Gao et al.	2024	Cross-modal AV feature learning for anomaly events	Limited deployment environments
22	Edge-Based Real-Time Anomaly Detection	Anonymous	2022–24	Edge AI balancing latency and accuracy	Hardware dependency; lacks multimodal fusion
23	First-Shot Unsupervised ASD	Anonymous	2024	Few-shot unsupervised anomalous sound detection	Audio-only; no video integration
24	Survey on Pedestrian Anomaly Detection	Anonymous	2023–24	Comparative review of pedestrian anomaly methods	Lacks real-time multimodal prototype
25	Lightweight Edge Pedestrian Anomaly Detection	Anonymous	2022–25	Edge-deployable DL for real-time anomaly detection	Edge constraints; limited multimodal integration
26	Acoustic-Visual Human Aggression Detection	Anonymous	2022–24	Combined AV detection of shouting & aggression	Limited dataset diversity
27	YOLOv5 with Light Perception Fusion	Anonymous	2023–24	Low-light pedestrian detection using YOLOv5	Limited lighting evaluation; no audio cues
28	First/Last-Mile Pedestrian Safety Study	Anonymous	2021–24	Empirical analysis of pedestrian safety factors	Observational; no proactive detection system
29	RNN-Based Multimodal AV Anomaly Detection	Tariq et al.	2024	RNN for spatio-temporal audio-visual anomaly detection	Limited dataset; not tested in urban real-time
30	Edge-Server Pedestrian Abnormal Detection	Song	2024	Edge-server CCTV abnormal behavior detection	Limited testing; no integrated multimodal analytics

III. METHODOLOGY

The proposed Safe-Walk AI framework is designed to be a proactive, multi-modal safety solution capable of continuously monitoring environmental factors, interpreting safety context, and initiating preventive measures when necessary. The methodology follows a comprehensive approach that integrates visual analysis, auditory anomaly detection, geospatial intelligence, and contextual awareness along with automated response generation within a unified architectural framework. Unlike traditional safety systems that rely on isolated safety features, this framework operates through multiple interconnected modules that collaboratively evaluate risk conditions in real time. By enabling synchronized multimodal processing and adaptive decision-making, the system ensures dynamic safety assessment and timely intervention, as elaborated in the following subsections.

A. *Environmental Data Acquisition*

The functionality of Safe-Walk AI is predicated on the acquisition of environmental information, which is conducted via the user's mobile device. Once a safety session is initiated, the application conducts controlled background acquisition of visual, auditory, and spatial information via the device's camera, microphone, and Global Positioning System module, respectively. The purpose of this phase is to acquire information from the environment in a controlled manner, with minimal resource requirements.

Visual information is acquired at specified time intervals to ensure that detection is conducted in a timely manner, with battery life taken into consideration. Instead of acquiring video feeds, visual information is sampled to ensure that resource requirements are minimized, with awareness of the environment maintained at all times. Simultaneously, auditory information is acquired within specified time windows to ensure that spatial information is acquired in a timely manner.

B. *Vision-Based Behavioral Analysis*

To analyze human activity in the environment, Safe-Walk's framework relies on a deep learning-based object detection approach. The basis of this approach is a real-time object detection framework based on YOLO. The choice of this approach is due to the model's ability to perform object detection with high speed without compromising detection accuracy on mobile platforms.

Each frame of the video is processed to identify human presence, positioning, and motion characteristics. In addition to object detection, the framework analyzes behavioral patterns in subsequent frames. The temporal consistency evaluation helps the framework to identify potential anomalies in human behavior. These anomalies may include consistent directional orientation towards the user, abnormal proximity to the user, acceleration patterns, or clustering behaviors that may indicate potential threats.

The focus on motion continuity rather than frame-based object detection helps to eliminate false alarms due to random pedestrian movements. The behavioral inference engine provides confidence scores to anomalies detected by the framework. These confidence scores are then used in the risk assessment process.

C. *Acoustic Pattern Recognition*

In addition to visual intelligence, Safe-Walk AI also im- proves overall awareness of the situation using acoustic pattern anomalies. Audio samples from the environment are converted into frequency-domain representations using feature extrac- tion algorithms such as Mel-Frequency Cepstral Coefficients (MFCCs) or other similar techniques that identify unique patterns that can distinguish between normal environmental sounds and abnormal acoustic anomalies

The trained model classifies the extracted features of the environment to determine whether the identified acoustic patterns are indicative of normal activity or abnormal distress signals. Rather than focusing on sudden spikes in sounds, the overall acoustic pattern is analyzed over a series of time windows to identify abnormal acoustic anomalies.

D. *Context Aware Risk Scoring Mechanism*

Another important part of the Safe-Walk AI methodology is its dynamic risk assessment system, which continuously calculates a customized safety score by taking into account a range of contextual and behavioral factors. These factors include time, lighting, crowd density by analyzing visual inputs, anomaly confidence levels derived from vision and audio inputs, and contextual risk factors derived from location.

E. *Safety-Aware Route Adaptation*

In cases where the contextual risk index exceeds a certain threshold, a re-evaluation of the route is performed. Unlike conventional shortest-path algorithms that focus on the shortest distance, Safe-Walk's AI system also considers safety factors in the routes chosen. Factors such as

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 3352-3356

the presence of lighting, population density, safe zones, and anomalies detected in real time are considered during geospatial analysis.
In cases where a different route provides a safer environment, even if it means going a little out of the way, the system will suggest a different route, thus changing the focus from convenience to safety

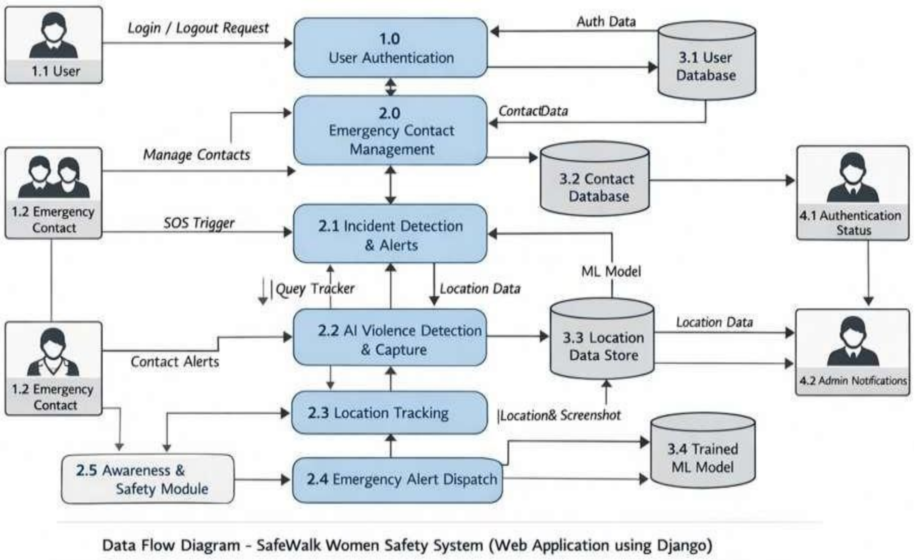
F. Automated Preventive Response Framework

An important feature of the Safe-Walk framework is the automation of preventive responses based on dynamic risk assessment. Once the risk level changes to a high-risk state, the system automatically triggers emergency responses. The user's location information is sent to pre-registered contacts in case of an emergency. The user's location information is sent in real-time to provide situational awareness. At the same time, live tracking functionality is enabled to provide continuous tracking of user movements until the risk level normalizes.

G. Privacy-Preserving Processing Strategy

In consideration of the issues that are involved in the continuous monitoring of the environment, the Safe-Walk AI approach has integrated the privacy-preserving principles that are relevant to the design of the methodological framework. This means that the visual and audio processing of the data is carried out locally on the device, thus preventing the cloud from transmitting the data. This approach ensures that the proactive safety intelligence maintains its protective features without compromising the privacy of the user.

This design ensures that proactive safety intelligence does not compromise user privacy, maintaining a responsible balance between protection and confidentiality.



`Fig. 1. Complete system flow diagram of the Safe-Walk Women Safety Application

H. Multi-Modal Feature Fusion Strategy

Safe-Walk AI fuses visual and audio signals within a unified framework instead of processing them separately. Normalized anomaly scores from both modules are combined using weighted fusion with temporal alignment, giving higher confidence to events detected across modalities simultaneously. Synchronized video and audio timestamps reduce misclassification from sensor mismatch. This multimodal integration strengthens predictive accuracy by ensuring decisions are supported by multiple sources of evidence.

III. Algorithms And Models

Safe-Walk AI operates using a real-time deep learning–based object detection framework designed to identify violent activities from continuous video streams and initiate automated emergency responses. The system models incoming video as sequential frames that are preprocessed through resizing and normalization before being passed into a YOLO-based convolutional neural network.
The detection architecture divides each frame into a structured grid and performs simultaneous bounding box regression, objectness estimation, and class probability prediction within a single forward pass, enabling efficient real-time inference. To improve reliability, the system aggregates detection confidence at the frame level and applies temporal smoothing across consecutive frames to reduce false positives caused by brief or ambiguous motion patterns.A threshold-based decision mechanism evaluates the smoothed confidence score, and when it exceeds a predefined limit, the system automatically activates alert protocols, including SMS and email notifications along with backend event logging. The integration of single-stage deep learning detection, temporal validation, and deterministic alert logic ensures computational efficiency, scalability, and suitability for proactive surveillance-based safety monitoring.

IV. Conclusion

This paper introduced Safe-Walk AI, a real-time, vision- oriented system for detecting violence and automating emergency responses, aiming to go beyond traditional safety applications that react only after incidents occur. Unlike standard mobile safety solutions that require users to manually trig- ger SOS alerts, the proposed system continuously observes visual input streams and autonomously activates alert mechanisms when it identifies high-confidence violent behavior. This forward-thinking method decreases reliance on user action during critical or incapacitated moments.The system combines a YOLO-based deep learning detection model with a Django-supported backend framework to create a smooth process from perception to action. Predictions at the frame level are refined through confidence aggregation and threshold-based decision logic to ensure reliable detection while reducing false positives. Once alert conditions are met, the system automatically sends SMS and email notifications to registered emergency contacts. The system combines a YOLO-based deep learning detection model with a Django backend framework to create a smooth pipeline from perception to action. Predictions at the frame level are processed through confidence aggregation and decision logic based on thresholds to guarantee reliable detection while reducing false positives. When alert criteria are met, the system automatically sends SMS and email notifications to designated emergency contacts and records the incident in a centralized database. This organized integration of computer vision, temporal validation, and automated escalation creates a unified real-time safety monitoring framework. From a computational standpoint, the single-stage detection framework facilitates efficient inference, making it suitable for near real- time deployment situations. Additionally, the modular backend design offers scalability, user management, and potential for integrating future sensors or contextual intelligence modules. Safe-Walk AI plays a vital role in creating smart public safety systems by shifting from passive surveillance to active intervention. Future upgrades may incorporate multi-faceted threat evaluation, learning from adaptive thresholds, optimizing edge devices, and enhancing integration with geolocation services to improve response accuracy and flexibility in deployments.

In conclusion, Safe-Walk AI provides a practical and scalable approach for early violence detection and automated emergency alerts, representing a significant step toward intelligent, AI-driven safety systems that are apt for real-world situations.

REFERENCES

[1] N. A. Patel, "An Integrated Robotic System for MRI-Guided Neu- roablation: Preclinical Evaluation," IEEE Transactions on Biomedical Engineering, vol. 67, no. 10, pp. 2990–3003, 2020.
[2] S. Liang, "Edge YOLO: Real-Time Intelligent Object Detection System Based on Edge-Cloud Cooperation in Autonomous Vehicles," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 12, pp. 25345–25360, 2022.
[3] R. Machlev, Y. Levron, and Y. Beck, "Modified Cross-Entropy Method for Classification of Events in NILM Systems," IEEE Transactions on Smart Grid, vol. 10, no. 5, pp. 4962–4973, 2019.
[4] H. J. van Waarde, M. K. Camlibel, and H. L. Trentelman, "A Distance-Based Approach to Strong Target Control of Dynamical Net- works," IEEE Transactions on Automatic Control, vol. 62, no. 12, pp. 6266–6280, 2017.
[5] J. Xu, Q. Li, and J. Wang, "Multiple Norms and Boundary Constraint Enforced Image Deblurring via Efficient MCMC Algorithm," IEEE Signal Processing Letters, vol. 27, pp. 41–45, 2020.
[6] W. Sultani, C. Chen, and M. Shah, "Real-World Anomaly Detection in Surveillance Videos," Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 6479–6488, 2018.
[7] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779–788, 2016.
[8] R. S. Tozetto, Z. C. Pravia, A. Toazza, and F. D. Rosa, "Development of a Vibration Measurement System for Bridges," Proceedings of the IEEE International Instrumentation and Measurement Technology Conference (I2MTC), pp. 1–6, 2017.
[9] E. Arıbas¸ and E. Dag˘larlı, "Realtime Object Detection in IoT (Internet of Things) Devices," Proceedings of the IEEE International Conference on Artificial Intelligence and Data Processing (IDAP), pp. 1–6, 2019.
[10] J. Reena K. et al., "Real-Time Object Detection on Edge Devices Using Mobile Neural Networks," Proceedings of the International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), pp. 1–6, 2024.
[11] T.-H. Tsai and C.-H. Yao, "A Real-Time Tracking Algorithm for Human Following Mobile Robot," Proceedings of the International SoC Design Conference (ISOCC), pp. 1–4, 2018.
[12] N. A. Smith et al., "A Safety Index for Smart Mobility Using Real-Time Crowdsourced Data," Proceedings of the IEEE International Smart Cities Conference (ISC2), pp. 1–6, 2020.
[13] S. M. Fahim Faisal and A. H. Joarder, "A Real-Time Blinking Reminder Supportive System for Eye Care of Computer Gamers," Proceedings of the International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2), pp. 1–6, 2021.
[14] M. U. Ahmed, R. Begg, and P. McCullagh, "Modeling Cognitive Load for Predicting Human Error in Healthcare Using Machine Learning," Journal of Biomedical Informatics, vol. 62, pp. 234–245, 2016.
[15] R. Akila and K. Duraiswamy, "An Efficient Object Detection System Using YOLOv3 Algorithm for Security Applications," International Journal of Advanced Research in Computer Science, vol. 11, no. 3, pp. 15–19, 2020.
[16] A. Ali, F. Jamil, and D. Al-Kababji, "Fake Medicine Detection Using Deep Learning," Proceedings of the IEEE International Conference on Computing, Networking and Communications (ICNC), pp. 132–138, 2019
[17] S. Basu and S. Saha, "Real-Time Violence Detection in Video Surveil- lance Systems Using Deep Learning," International Journal of Computer Vision and Image Processing, vol. 11, no. 2, pp. 45–61, 2021.
[18] A. Bhardwaj and N. Jain, "A Survey on Emergency Alert Systems for Personal Safety Using Mobile and Web Platforms," Journal of Ambient Intelligence and Humanized Computing, vol. 12, no. 9, pp. 8787–8803, 2021.
[19] J. Brownlee, Machine Learning Mastery With Python, Machine Learning Mastery Press, 2019.
[20] Django Software Foundation, "Django Documentation: The Web Framework for Perfectionists with Deadlines," (https://docs.djangoproject.com/),2023.
[21] P. Ekta and P. Raj, "Automated Violence Detection in Videos Using Deep Convolutional Neural Networks," Journal of Intelligent Fuzzy Systems, vol. 43, no. 1, pp. 1105–1115, 2022.
[22] R. Ghadeer and A. Aziz, "Emergency Management Models and Technologies for Safety and Security," IEEE Access, vol. 8, pp. 187652–187667, 2020.
[23] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 580–587, 2014.
[24] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016.
[25] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, "A Survey of the Recent Architectures of Deep Convolutional Neural Networks," Artificial Intelligence Review, vol. 53, pp. 5455–5516, 2020.
[26] Ultralytics,"YOLOv8 Documentation," [https://docs.ultralytics.com, 2022.
[27] S. Patel, A. Rege, and K. Muthal, "Emergency Alerting Systems Using SMS and Email Integration in Web Applications," International Journal of Engineering Research Technology, vol. 10, no. 8, pp. 1012–1017, 2021.
[28] X. Zhang, D. Liu, W. Wang, and H. Shen, "Real-Time Human Action Recognition Using Deep Learning: A Review," IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 12, pp. 6873–6890, 2022.
[29] M. Won, A. Shrestha, K.-J. Park, and Y. Eun, "Safer Cross: Enhancing Pedestrian Safety Using Embedded Sensors of Smartphone," IEEE Access, vol. 8, pp. 49657–49670, 2020.
[30] Z. Wang and J. Yang, "Acoustic-Based Object Detection for Pedestrians Using Smartphone," Proceedings of the IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), pp. 1–6, 2021.