

Smart Home Surveillance and Monitoring System: A Comprehensive Survey

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ABSTRACT

Smart residential environments increasingly rely on intelligent surveillance and monitoring systems to ensure safety, reliability, and occupant well-being. Residential buildings face various risks, including structural damage, gas leaks, electrical faults, and poor indoor air quality. Traditional safety systems work separately and are usually reactive, responding only after dangerous conditions go beyond set limits. This limits early detection of problems and proactive maintenance.

Recent advances in the Internet of Things (IoT), deep learning, and edge computing allow for continuous and integrated monitoring with low-cost sensors and vision-based systems. These technologies support real-time data collection, smart analysis, and automatic alert generation. Vision-based systems increase the accuracy of structural inspections, while smart sensors enable the early detection of unusual gas levels and electrical issues. This survey looks at smart home surveillance frameworks that combine vision-based crack detection, gas leak monitoring, electrical fault detection, and indoor air quality evaluation. The paper highlights learning-based methods, system designs, deployment challenges, and future research possibilities found in recent studies.

General Terms

Smart Systems, Home Automation, Artificial Intelligence

Keywords

Smart Home Surveillance, IoT, Structural Health Monitoring, Gas Leakage Detection, Electrical Fault Detection, Indoor Air Quality, Deep Learning

1. INTRODUCTION

Smart home technologies have evolved from basic automation solutions to smart monitoring platforms that can continuously sense, analyze, and make decisions. Today's homes use sensors, communication networks, and computing power to manage safety and comfort actively. However, traditional safety systems like gas alarms, circuit breakers, and smoke detectors mainly work alone and react only after dangerous situations exceed set limits.

These systems often miss early signs of problems, such as small structural cracks, gradual gas leaks, insulation wear, or worsening indoor air quality. As a result, issues go unnoticed until they turn into serious failures. By connecting Internet of Things (IoT) devices with artificial intelligence, homes can operate as cyber-physical systems that monitor conditions and spot issues early.

Deep learning models are useful for pulling complex spatial and temporal features from different sensor and image data. Edge computing makes systems faster by allowing local data processing, which cuts down on delays and protects privacy. Continuous monitoring supports predictive maintenance, lowers repair costs, and increases overall safety. Despite these improvements, bringing together various safety areas into a single smart home monitoring system is still a research challenge.

2. BACKGROUND AND MOTIVATION

The demand for residential monitoring systems is increasing due to urban growth, aging infrastructure, and rising health concerns. Rapid construction and crowded living conditions raise exposure to safety risks like structural failures, gas leaks, electrical faults, and indoor air pollution. Over time, structural elements, electrical systems, and gas pipelines wear down because of environmental stress, material fatigue, and lack of proper maintenance. Catching

this damage early can significantly cut repair costs, prevent accidents, and improve safety for residents.

Urbanization has led to higher population density, often resulting in multi-story buildings with complicated electrical and plumbing systems. If these systems are not properly maintained or if damage goes unnoticed, it can lead to serious failures, such as electrical fires caused by damaged insulation or structural collapses due to hidden cracks. Therefore, preventive monitoring is crucial to create safe living environments and reduce emergency response costs.

Indoor environmental health has become a major concern in recent years due to lifestyle changes and spending more time indoors. Poor indoor air quality (IAQ) is linked to respiratory issues, allergies, asthma, and heart disease. Sicard et al. studied global urban air pollution trends over two decades and found ongoing exposure to particulate matter and gas pollutants. Since people spend much of their time indoors, it is essential to continuously monitor indoor air pollutants, including CO, CO₂, PM_{2.5}, PM₁₀, and volatile organic compounds (VOCs).

Smart monitoring systems help make data-driven choices that improve comfort, health, and energy efficiency indoors. These systems can provide real-time feedback, predictive insights, and automated actions, such as activating ventilation or managing electrical loads. Together, these factors drive the creation of integrated smart home monitoring solutions that can address multiple hazards at once.

Moreover, combining monitoring for structure, electrical systems, gas, and air quality allows for a comprehensive management of residential environments. Traditional systems often work separately and react only after a problem arises. A coordinated approach not only reduces risk but also increases convenience, lowers operating costs, and ensures long-term durability. Advanced sensors, machine learning, and edge-cloud computing support these smart monitoring systems, allowing for scalable, reliable, and real-time solutions.

3. VISION-BASED STRUCTURAL CRACK DETECTION

Structural Health Monitoring (SHM) is essential for keeping residential buildings safe and ensuring they last long. Cracks often signal early signs of structural failure. If not found, these can lead to serious damage or even collapse. Manual inspection methods are subjective, take a lot of time, and can be limited by access issues. Inspectors might overlook small cracks hidden in corners, behind furniture, or in poorly lit spaces.

Vision-based crack detection systems solve these problems by offering automated, non-contact inspections using cameras or mobile devices. These systems use computer vision algorithms to find, segment, and measure cracks, allowing for more frequent and thorough monitoring. High-resolution cameras, panoramic imaging, and 3D reconstruction also improve the ability to detect tiny cracks and hidden issues.

Recent research focuses on improving robustness under real-world conditions, including shadows, noise, reflections, and complex backgrounds. Ma et al. proposed a shadow-resistant neural network that significantly improves crack detection accuracy in challenging visual environments [1]. This is particularly relevant for indoor residential settings where lighting varies across rooms and natural sunlight interacts with artificial lighting. Vision-based systems also reduce labor cost, allow frequent inspection, and support predictive maintenance strategies.

In addition, image-based monitoring allows for tracking crack progression over weeks or months. This gives insights into how fast structures degrade, helping with maintenance schedules and risk

assessments. Connecting with IoT platforms enables remote monitoring, centralized data storage, and real-time alerts to homeowners or building managers, improving both safety and convenience.

The use of computer vision and deep learning has changed structural inspection into a process that is scalable, efficient, and accurate. As residential buildings get older, using automated visual monitoring becomes more important to ensure safety, lower maintenance costs, and extend the lifespan of structures.

3.1 Deep Learning Models

Deep learning has become the main method for crack detection because it can effectively extract important features from complex image data. Convolutional Neural Networks (CNNs) learn spatial patterns on their own. This helps them tell cracks apart from background textures, shadows, and surface irregularities. Unlike traditional image processing methods, deep models can adapt to different materials, lighting conditions, and camera angles.

A major challenge in crack detection is the class imbalance between crack pixels, which are the minority, and non-crack pixels, which are the majority. Standard loss functions can lead to bias in the network toward the majority class; this can result in fine cracks being missed. Tian et al. addressed this issue using an adaptive cost-sensitive loss function that improves detection of thin and subtle cracks [2].

Unsupervised learning techniques reduce reliance on large labeled datasets, which are time-consuming and costly to generate. Xie et al. introduced UP-CrackNet, employing adversarial image restoration for pixel-wise crack detection without manual annotations [3]. These techniques improve scalability, allowing deployment in multiple residential environments with minimal labeling effort.

Lightweight deep learning models are being tested for use in smart homes. These models allow real-time processing on embedded devices that have limited computing power, which makes them ideal for continuous monitoring on-site. Methods such as model pruning, quantization, and knowledge distillation lower computational complexity while keeping accuracy high.

Additionally, researchers are developing hybrid models that combine CNNs with recurrent networks or attention mechanisms to capture both spatial and temporal features. Temporal modeling helps track crack growth over time, which supports predictive maintenance and early intervention. The combination of supervised, unsupervised, and lightweight edge-friendly architectures forms the foundation of modern vision-based SHM systems for residential buildings.

3.2 Image Acquisition and Enhancement

Reliable crack detection depends greatly on image quality. Indoor environments pose challenges like uneven lighting, shadows, different surface textures, reflections, cluttered backgrounds, and obstructions. The camera angle, resolution, and distance also affect image consistency. Changes in lighting during the day, like morning sunlight or artificial light at night, can hide small cracks and lead to false negatives.

Lu et al. proposed an augmented crack segmentation framework that explicitly addresses background interference, significantly improving segmentation accuracy in complex scenes [4]. Pre-processing techniques like grayscale normalization, histogram equalization, and adaptive contrast improvement increase differences between damaged and intact surfaces. Noise reduction with Gaussian and median filters removes artifacts from textured walls and construction materials. Morphological operations

sharpen crack boundaries, get rid of isolated noise, and improve contour continuity.

Data augmentation techniques like rotation, scaling, flipping, brightness adjustment, and cropping improve how well models generalize in different residential settings. Synthetic data generation helps deal with class imbalance, especially for rare fine cracks. Temporal image acquisition enables monitoring of crack development over time. This allows for strategies that predict maintenance needs.

Better image acquisition pipelines make systems more resistant to changes in the environment, lighting shifts, and camera misalignment. Automated calibration, multi-angle imaging, and high dynamic range (HDR) imaging improve the ability to detect subtle or partially hidden cracks. When paired with deep learning models, these improvements support accurate, dependable, and continuous monitoring of structural health in smart homes.

4. CRACK CLASSIFICATION AND SEGMENTATION

Crack detection methods usually fall into two categories: classification-based and segmentation-based. Classification models identify if cracks are present or not at the image or patch level, giving a rough safety evaluation. Segmentation models focus on pixel-level detail, allowing for exact identification of crack shape, length, width, and growth direction.

Zhou *et al.* introduced DUCTNet, a segmentation network designed for UAV-based crack detection that demonstrates high accuracy in capturing fine crack structures [5]. Despite being developed for outdoor use, its encoder-decoder architecture with skip connections preserves spatial context while maintaining high-resolution localization, making it transferable to indoor residential settings.

Segmentation-based methods allow for a quantitative assessment of structural degradation. By tracking the development of cracks over time, these methods support predictive maintenance, lower inspection costs, and enable automated safety evaluations. Advanced segmentation networks can tell cracks apart from noise, shadows, and other distractions, which improves reliability.

Integrating with IoT platforms permits centralized monitoring, historical trend analysis, real-time alert generation, and scheduling for predictive maintenance. Automated dashboards give homeowners or building managers visual representations of crack locations, severity, and progression, helping them make informed decisions. Overall, these approaches change traditional structural inspection into a scalable, data-focused, and highly reliable process suitable for modern residential safety management.

5. GAS LEAKAGE DETECTION SYSTEMS

Gas leakage remains a major safety issue in residential buildings because of the widespread use of LPG, natural gas, and other flammable gases. Undetected leaks can result in disasters such as fires, explosions, and asphyxiation. Long-term health risks can include respiratory irritation and chronic exposure effects. Standard gas detectors depend on fixed alarms, which can miss small leaks or cause false alarms due to changing conditions like temperature, humidity, and air flow.

Modern smart gas leakage detection systems use continuous sensing, data-driven detection of problems, and automated responses. These systems gather time-series data from multiple sensors to spot unusual gas buildup before it reaches dangerous levels. By examining temporal patterns, they differentiate between real leak events

and temporary environmental changes caused by cooking, ventilation, or humidity.

These systems can connect with home automation platforms to trigger quick safety measures. Automated responses might involve shutting off gas valves, turning on ventilation fans, sounding alarms, and sending immediate notifications to residents and emergency responders. Cloud connectivity allows for remote monitoring, historical data analysis, and predictive insights, improving safety and convenience.

Machine learning techniques further boost reliability by learning specific gas usage patterns in households. Models adjust to changes in appliance use, occupancy, and environmental conditions, which helps lessen false alarms. More advanced frameworks use deep learning for multi-sensor data fusion, combining information from gas, temperature, and humidity sensors to create strong leak detection alerts.

New research is looking at lightweight models that run on edge devices for real-time analysis. This reduces reliance on cloud access and ensures quick responses. Predictive analytics can also anticipate potential leaks based on past patterns, which helps improve maintenance strategies. By blending continuous monitoring, adaptive learning, and automated actions, smart gas detection systems greatly improve safety, reliability, and residents' confidence.

5.1 Gas Sensor Technologies

Metal-oxide semiconductor (MOS) sensors, like MQ-series sensors, are popular for home gas monitoring because they are affordable, compact, and sensitive to combustible gases. These sensors detect gas concentration by measuring changes in resistance caused by chemical reactions on their surface. However, their performance can be impacted by temperature, humidity, sensitivity to other gases, and aging, which can lead to drift or inaccurate readings.

To improve reliability, multi-sensor fusion is used. By combining data from gas, temperature, and humidity sensors, we can adjust for environmental changes. Adaptive calibration routines update how sensors respond based on past usage, reducing drift and enhancing long-term stability. Machine learning models can recognize typical household gas usage patterns and spot deviations that might suggest leaks.

Some systems use multiple sensing methods, including electrochemical, catalytic, and infrared sensors, to boost detection accuracy and lower false positives. Automated diagnostics can identify when a sensor is degrading, allowing for maintenance before any failures happen. Connecting with cloud platforms facilitates remote calibration, performance logging, and firmware updates. Together, these approaches help ensure high reliability, low maintenance, and quick responses, making smart gas monitoring safe and effective for homes.

6. ELECTRICAL LEAKAGE AND FAULT DETECTION

Electrical faults like insulation wear, loose connections, overloads, short circuits, and arc faults are major causes of residential fires and appliance damage. Many of these problems develop slowly and go unnoticed by regular protective devices. Standard circuit breakers or fuses only react after too much current flows, which limits early action and increases the risk of damage to equipment or property. Smart electrical monitoring systems use non-invasive current sensors, voltage monitoring, and signal analysis to spot unusual behavior. High-frequency sampling helps detect brief events like micro-

arcing, leakage currents, or harmonic distortions, which traditional protection systems often miss. These systems offer ongoing insights into the health of the electrical network, aiding in preventive maintenance and energy efficiency.

When combined with machine learning, these systems can detect anomalies based on past patterns. The models can tell the difference between normal appliance usage and unusual electrical signatures, catching early signs of faults before they worsen. Predictive alerts notify homeowners about potential hazards, allowing for timely action. Cloud-based dashboards enable remote monitoring, historical trend analysis, and optimization of energy consumption.

6.1 Non-Invasive Current Monitoring

Non-invasive current transformers (CTs) and clamp-on sensors offer continuous electrical monitoring without changing existing wiring. These sensors record real-time current waveforms across circuits. This allows the measurement of load patterns, leakage currents, and transient events. Non-intrusive monitoring works well for retrofitting residential buildings. It removes the need for rewiring or disruptive installation.

The captured signals are analyzed using statistical methods, frequency-domain techniques, and learning-based approaches to find anomalies. Edge computing devices detect issues quickly and send alerts with minimal delay. This ensures an immediate response to dangerous conditions. Long-term data logging helps with predictive maintenance, assessing appliance health, and optimizing energy use. Continuous monitoring boosts electrical safety and supports proactive energy management and efficient operations.

6.2 Electrical Signature Analysis

Non-Intrusive Load Monitoring (NILM) techniques identify the electrical signatures of specific appliances, such as RMS current, harmonic distortion, transient response, and power factor. Each device generates a unique electrical pattern that supervised or unsupervised machine learning models can learn.

These models identify which devices are in use and spot deviations due to faults, wear, or unusual usage. By linking electrical signatures with environmental factors, occupancy patterns, and appliance usage schedules, we can improve diagnostic accuracy. Automated dashboards display energy consumption, device health, and potential risks. Alerts prompted by unusual signatures allow for preventive action, which helps reduce fire hazards, equipment damage, and unnecessary energy costs.

7. INDOOR AIR QUALITY MONITORING

Indoor air quality (IAQ) affects occupant health, comfort, productivity, and cognitive performance. Pollutants come from indoor sources like cooking, cleaning agents, furniture, paints, building materials, and poor ventilation. Bad IAQ is closely linked to respiratory disorders, allergies, asthma, and heart diseases.

Long-term studies show that city residents are exposed to harmful pollutants, even with outdoor air regulations in place. Sicard *et al.* highlighted persistent urban air pollution trends, emphasizing the need for continuous indoor monitoring [10]. Smart IAQ systems give real-time information about pollutant levels and environmental conditions. Ongoing monitoring leads to healthier indoor spaces, helps occupants make better choices, and supports energy-efficient ventilation management.

7.1 Pollutant Measurement

IAQ monitoring systems measure particulate matter ($PM_{2.5}$, PM_{10}), carbon dioxide (CO_2), carbon monoxide (CO), and volatile organic compounds (VOCs). They collect data on temperature, humidity, and air flow, which helps interpret pollutant levels and find their sources. Multi-parameter sensing helps calculate the Air Quality Index (AQI), detect pollution sources, and assess compliance.

Continuous data logging enables trend analysis, predictive modeling, and identification of patterns linked to human activity, outdoor pollution, or HVAC performance. Integrating with smart home platforms allows for automated alerts, ventilation control, and better air purifier management for healthier living environments.

8. RESILIENCE AND AUTOMATION

Table: Summary of Sensors, Analysis Techniques for Smart Monitoring Systems

Domain	Sensor/Hardware	Analysis/Algorithm	Techniques
Structural Safety	Camera Modules	CNN, Segmentation, Temporal Analysis	Fault Detection, Crack Identification
Gas Monitoring	MQ Sensors, Environmental Sensors	Thresholding, Sensor Fusion	Leak Detection, Predictive Alerts
Electrical Safety	Current Sensors, NILM	RMS, Pattern Recognition	Fault Detection, Predictive Maintenance
Air Quality	Particulate Sensors, VOC Sensors	Data Fusion, Predictive Modeling	IAQ Monitoring, Health-aware Analytics

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