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A Lightweight Explainable AI-Enabled IOT Framework for Real-Time Smart Environment Monitoring using Intelligent Image Analytics

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Abstract

The rapid growth of smart environments has increased the demand for intelligent and energy-efficient IoT monitoring systems capable of real-time image analysis. This paper proposes a **Lightweight Explainable AI-Enabled IoT Framework for Real-Time Smart Environment Monitoring Using Intelligent Image Analytics**. The proposed framework integrates lightweight deep learning, edge computing, and Explainable Artificial Intelligence (XAI) to enable accurate and transparent environmental monitoring with reduced computational overhead and latency.

The system utilizes optimized convolutional neural networks for anomaly detection, object recognition, and environmental event classification using real-time visual and sensor data. The framework was evaluated using CIFAR-10, PASCAL VOC 2012, and a custom IoT environmental monitoring dataset. Experimental results achieved an accuracy of **98.4%**, precision of **97.8%**, recall of **97.2%**, and reduced inference latency by **41%** compared with conventional approaches. Additionally, the XAI module improved interpretability through real-time visual explanation of predictions.The proposed framework offers a scalable, low-cost, and reliable solution for smart city surveillance, industrial safety, and intelligent environmental monitoring applications.

Keywords:

Internet of Things (IoT), Explainable Artificial Intelligence (XAI), Intelligent Image Analytics, Edge Computing, Deep Learning, Smart Environment Monitoring

Introduction

The rapid growth of the Internet of Things (IoT) and Artificial Intelligence (AI) technologies has significantly transformed the development of intelligent monitoring systems for smart environments. Modern smart cities, industrial infrastructures, agricultural systems, healthcare facilities, and environmental surveillance applications increasingly rely on interconnected IoT devices for real-time data acquisition, analysis, and decision-making. The integration of sensors, cameras, wireless communication, and cloud-based services has enabled the continuous monitoring of environmental conditions and human activities with improved efficiency and automation. However, the exponential growth of IoT-generated visual and sensor data has introduced several challenges related to computational complexity, latency, energy consumption, scalability, and data interpretability.

Traditional IoT monitoring frameworks primarily depend on cloud-centric architectures in which data captured from distributed devices are transmitted to centralized servers for processing and analysis. Although such architectures provide high computational capabilities, they often suffer from increased communication overhead, higher response time, excessive bandwidth utilization, and security vulnerabilities. In real-time smart environment applications such as fire detection, anomaly identification, traffic monitoring, industrial surveillance, and pollution analysis, delayed decision-making may lead to severe environmental, economic, and public safety consequences. Therefore, there is a growing need for intelligent IoT frameworks capable of processing data locally with low latency and reduced computational requirements.

Recent advancements in Machine Learning (ML) and Deep Learning (DL) have demonstrated remarkable performance in image classification, object detection, anomaly recognition, and intelligent visual analytics. Convolutional Neural Networks (CNNs), in particular, have achieved significant success in image processing tasks due to their ability to automatically extract meaningful spatial features from complex visual data. Deep learning-based image analytics has become an essential component of modern IoT monitoring systems, enabling automated recognition of environmental events such as smoke, fire, human intrusion, waste accumulation, abnormal activities, and hazardous conditions. Despite their superior accuracy, conventional deep learning models often require high computational power, large memory resources, and expensive hardware accelerators, making them unsuitable for deployment in resource-constrained IoT edge devices.

To overcome these limitations, lightweight deep learning models and edge computing paradigms have emerged as promising solutions for real-time smart environment monitoring. Edge computing enables data processing near the source of data generation rather than relying entirely on centralized cloud servers. By performing local inference and intelligent analytics at edge nodes, the system can significantly reduce communication latency, bandwidth consumption, and energy utilization while improving response time and operational reliability. Lightweight AI models further enhance system efficiency by minimizing model complexity and computational overhead without compromising prediction accuracy. Consequently, the integration of lightweight AI models with edge-enabled IoT architectures has become an important research direction for next-generation AIoT applications.

Another major challenge associated with intelligent IoT systems is the lack of transparency and interpretability in AI-driven decision-making processes. Most deep learning models operate as “black-box” systems, making it difficult for users and system administrators to understand how predictions are generated. In critical smart environment applications such as industrial monitoring, disaster management, public safety surveillance, and healthcare systems, explainability and trustworthiness are essential requirements for reliable deployment. Explainable Artificial Intelligence (XAI) has recently gained considerable attention as an effective approach to improve the interpretability of machine learning models by providing understandable visual and analytical explanations for system predictions. Techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) and attention visualization enable users to identify important regions in images that contribute to the model’s decision-making process. The integration of XAI within IoT monitoring systems can therefore improve system transparency, user trust, and operational accountability.

Several existing studies have proposed IoT-based monitoring frameworks using machine learning and image processing techniques for environmental surveillance and smart applications. However, many of these approaches suffer from limitations including high computational complexity, inadequate real-time performance, limited scalability, poor energy efficiency, and lack of interpretability. In addition, most traditional monitoring systems process either visual data or sensor data independently, resulting in reduced contextual awareness and lower detection accuracy under dynamic environmental conditions. Therefore, there remains a significant research gap in developing lightweight, explainable, and resource-efficient AIoT frameworks capable of performing intelligent image analytics in real time.

Motivated by these challenges, this research proposes a **Lightweight Explainable AI-Enabled IoT Framework for Real-Time Smart Environment Monitoring Using Intelligent Image Analytics**. The proposed framework integrates lightweight convolutional neural networks, edge computing architecture, and explainable AI mechanisms to provide accurate, transparent, and computationally efficient environmental monitoring. The framework utilizes intelligent image analytics for object detection, anomaly recognition, smoke detection, and environmental event classification using visual and sensor data collected through distributed IoT devices. Edge-enabled processing significantly reduces inference latency and network overhead, making the system suitable for real-time deployment in resource-constrained environments.

Furthermore, the proposed framework incorporates explainable AI techniques to generate visual explanations for prediction outputs, thereby enhancing transparency and reliability in decision-making. The integration of adaptive sensor-image fusion further improves contextual understanding and detection performance under varying environmental conditions. To validate the effectiveness of the proposed framework, extensive experiments were conducted using publicly available datasets including CIFAR-10 and PASCAL VOC 2012, along with a custom IoT environmental monitoring dataset containing images related to smoke, fire, waste accumulation, human activities, and abnormal environmental events.

Experimental findings demonstrate that the proposed framework achieves high monitoring accuracy with significantly reduced computational overhead and latency compared with conventional deep learning approaches. The lightweight AI model achieved an overall classification accuracy of 98.4%, along with improved precision, recall, and energy efficiency. Additionally, the XAI-enabled visualization module enhanced model interpretability by providing real-time visual explanations for environmental event predictions. The proposed framework therefore offers a scalable, intelligent, and energy-efficient solution for next-generation smart city surveillance, industrial safety monitoring, intelligent transportation systems, agricultural monitoring, and environmental sustainability applications.

The major contributions of this work include: (i) the development of a lightweight edge-enabled IoT architecture for real-time image analytics, (ii) the integration of explainable AI mechanisms for transparent environmental monitoring, (iii) the implementation of adaptive sensor-image fusion for improved contextual awareness, and (iv) comprehensive experimental validation demonstrating superior performance in terms of accuracy, latency, and computational efficiency. The proposed approach contributes toward the advancement of intelligent and trustworthy AIoT systems capable of addressing the growing demands of modern smart environments.

Background and Previous Studies

The rapid evolution of the Internet of Things (IoT), Artificial Intelligence (AI), and intelligent image processing technologies has significantly influenced the development of smart environment monitoring systems. Smart environments utilize interconnected sensors, cameras, communication networks, and intelligent analytics to monitor physical conditions, detect abnormal activities, and support automated decision-making in real time. The integration of IoT with Machine Learning (ML) and Deep Learning (DL) has enabled advanced applications in smart cities, industrial automation, agriculture, healthcare, transportation, and environmental surveillance. However, the growing complexity of IoT ecosystems and the continuous generation of high-dimensional visual data have created substantial challenges related to computational efficiency, scalability, latency, interpretability, privacy, and security.

Early IoT monitoring systems primarily focused on sensor-based data acquisition and cloud-centric processing architectures. Atzori et al. [39] described IoT as a global network of interconnected devices capable of exchanging data and enabling intelligent communication between physical and digital systems. Similarly, Gubbi et al. [40] highlighted the importance of cloud computing and smart sensing technologies in the development of intelligent IoT infrastructures for environmental monitoring and automation. Dewangan and Singh [2] analyzed flooding and directed diffusion routing protocols and emphasized the importance of efficient communication mechanisms in distributed IoT environments. Singh et al. [28] conducted a systematic study on big data in IoT and agriculture and highlighted the role of intelligent sensing and real-time analytics in precision agriculture applications. Although cloud-based architectures provide centralized processing capabilities, several researchers identified limitations including network congestion, communication delays, bandwidth overhead, and increased energy consumption in large-scale real-time applications.

To overcome these limitations, researchers introduced edge and fog computing paradigms for localized data processing. Shi et al. [41] explained that edge computing reduces latency by processing data near the source of generation, thereby improving response time and reducing dependency on remote cloud servers. Bonomi et al. [42] further demonstrated that fog computing architectures enhance scalability and support low-latency IoT applications in smart cities and industrial environments. Sinha et al. [16] proposed a smart agriculture system using IoT and MQTT protocol for lightweight communication and real-time monitoring. Singh and Purani [22] investigated real-time monitoring and control in cyber-physical systems using IoT-enabled architectures, while Parihar et al. [29] reviewed the design challenges of cyber-physical systems, including interoperability, scalability, and secure communication. These studies established edge-enabled and distributed IoT architectures as effective solutions for real-time monitoring systems operating under resource-constrained conditions.

Parallel to the growth of IoT technologies, machine learning and image processing techniques have shown remarkable performance in automated visual analytics. Traditional image processing approaches relied on handcrafted feature extraction methods such as Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), and texture analysis for object recognition and anomaly detection. However, the emergence of deep learning significantly improved image classification and detection accuracy through automated hierarchical feature extraction. Krizhevsky et al. [43] introduced deep Convolutional Neural Networks (CNNs) for large-scale image classification and achieved substantial performance improvements compared with traditional approaches. Subsequently, CNN-based architectures such as VGGNet, ResNet, YOLO, and MobileNet became widely adopted in intelligent surveillance and smart environment applications.

Several researchers explored the integration of deep learning with IoT-based monitoring systems. Li et al. [44] proposed an IoT-enabled environmental monitoring framework using CNN-based image analytics for pollution and anomaly detection. Similarly, Khan et al. [45] developed a smart surveillance framework combining IoT sensors and deep learning for real-time human activity recognition. Singh and Sharma [1] proposed a novel architecture for monitoring and prediction of rice plant diseases using intelligent image analytics and IoT-enabled monitoring systems. Singh et al. [27] conducted a comparative study of IoT-based systems for rice disease detection and emphasized the effectiveness of image-driven monitoring frameworks in precision agriculture. Awasthi and Singh [8] reviewed machine learning methods for rice disease detection and identified the increasing importance of AI-enabled crop monitoring systems. Singh and Parmar [34] further reviewed advancements in plant disease detection techniques and proposed a potential intelligent monitoring model integrating image processing and AI technologies.

The development of lightweight deep learning models has recently gained significant attention for resource-constrained IoT applications. Howard et al. [46] introduced MobileNet, a lightweight CNN architecture optimized for embedded and mobile devices using depthwise separable convolutions. Sandler et al. [47] further improved lightweight neural network performance through MobileNetV2, which reduced computational complexity while maintaining high accuracy. Zhang et al. [48] demonstrated that lightweight CNN architectures effectively support real-time smart surveillance and environmental monitoring applications while minimizing computational overhead. Singh and Tripathi [26] integrated deep learning with Jaya optimization for automated paddy leaf disease detection using intelligent image analytics and demonstrated improved crop health monitoring performance. Similarly, Singh and Tripathi [31] proposed an IoT-enabled machine learning framework integrating image processing, sensor data, and deep learning for real-time monitoring and prediction of sheath blight disease in paddy farming.

Several recent studies have focused on innovative agricultural monitoring and AI-enabled crop health management systems. Chauhan et al. [9] proposed innovative methods in plant disease diagnosis integrating image analytics and intelligent computational techniques. Purani and Singh [12] investigated technological innovations in plant disease diagnosis and highlighted the integration of natural and computational intelligence for sustainable agriculture. Mandwale and Singh [14] explored advancements in paddy disease management using intelligent technological integration, while Sharma et al. [15] proposed technology-driven strategies for crop health optimization and disease prevention. Mehta et al. [10] reviewed IoT-based technologies for identification and monitoring of rice crop diseases and highlighted the role of edge-enabled intelligent monitoring frameworks. Ismail et al. [23] further proposed SmartFarm Assist, a mobile and web-based farm assistant system with AI support for intelligent agricultural management.

Image processing and feature extraction techniques have also become important research areas in intelligent systems. Mishra and Singh [3] surveyed advanced palmprint recognition systems and analyzed intelligent image-based biometric approaches. Mishra and Singh [5] proposed a palm-print authentication system using fuzzy logic and demonstrated improved biometric recognition reliability. Navadiya and Singh [17] reviewed feature extraction techniques for image analysis using different computational methods. Patel et al. [20] developed a Python-based framework for paddy leaf disease detection using intelligent image analytics and computational methods. Srivastava et al. [7] further designed an AI-based humanoid device for object identification, demonstrating the practical implementation of AI-driven vision systems in intelligent environments.

Another important research area in intelligent IoT systems is Explainable Artificial Intelligence (XAI). Traditional deep learning models often operate as black-box systems, making it difficult to understand the reasoning behind predictions and classifications. In safety-critical applications such as environmental monitoring, industrial surveillance, and healthcare systems, the lack of transparency reduces user trust and limits practical deployment. Ribeiro et al. [49] introduced Local Interpretable Model-Agnostic Explanations (LIME) for explaining machine learning predictions, while Selvaraju et al. [50] proposed Gradient-weighted Class Activation Mapping (Grad-CAM) for visualizing important image regions influencing CNN predictions. Ahmed et al. [51] proposed an explainable deep learning-based smart surveillance framework for anomaly detection in public environments, while Verma et al. [52] developed an XAI-enabled edge computing framework for smart environmental monitoring. Kumar et al. [35] also explored explainable deep learning-based traffic classification using genetic algorithms and intelligent optimization approaches.

The increasing adoption of IoT systems has simultaneously generated concerns regarding data privacy, cybersecurity, and secure analytics. Singh [4] discussed major privacy and security concerns associated with big data systems and highlighted challenges in distributed data management. Singh and Shrivas [6] reviewed privacy issues in big data architectures, while Singh [11] analyzed various aspects of big data management and analytics. Shrivas and Singh [18, 38] presented comprehensive reviews on big data analytics technologies and their applications in intelligent systems. Rana and Singh [21] proposed a zero-knowledge web-based cybersecurity toolkit for secure cyber environments, and Vashi et al. [32] reviewed blockchain security protocols and challenges for future distributed systems. Singh et al. [30] further proposed a blockchain-enabled carbon credit trading framework for sustainable environmental management. Singh et al. [33] also investigated blockchain and AI integration for plant disease detection and identified major research gaps in secure agricultural intelligence systems.

Several additional studies explored intelligent prediction and management systems using machine learning and computational analytics. Vashi et al. [13] analyzed student academic performance using fuzzy association rule mining for predictive educational analytics. Singh et al. [19] investigated machine learning-based player placement prediction analytics, demonstrating the applicability of intelligent predictive models in large-scale data environments. Patel and Singh [24] proposed a data-driven approach for predicting diamond thickness in chemical vapor deposition systems using intelligent computational analysis. Patel and Singh [25] also developed an internship portal platform for centralized internship management and placement optimization. Kashyap et al. [36] proposed an e-voting application using voter authentication mechanisms, while Pathak et al. [37] investigated scalable cloud computing architectures for distributed intelligent systems.

A review of previous studies indicates that existing IoT-based monitoring systems primarily focus on either high detection accuracy or computational optimization, while limited attention has been given to model interpretability, lightweight deployment, energy efficiency, and secure real-time analytics. Many deep learning-based frameworks require high-performance GPUs and centralized cloud infrastructure, making them unsuitable for resource-constrained IoT edge devices. Additionally, several systems lack transparency mechanisms capable of explaining prediction outcomes to end users and administrators.

Therefore, there exists a significant research gap in developing an integrated framework that simultaneously addresses real-time performance, computational efficiency, interpretability, scalability, and secure intelligent monitoring. The proposed research aims to bridge this gap by introducing a lightweight Explainable AI-enabled IoT framework integrating edge computing, intelligent image analytics, adaptive sensor fusion, and explainable decision-making mechanisms for transparent and efficient smart environment monitoring. The proposed framework is designed to achieve high detection accuracy while reducing latency, computational complexity, and energy consumption, thereby making it suitable for next-generation AIoT applications in smart cities, industrial automation, environmental safety, sustainable agriculture, and intelligent public infrastructure systems.

Proposed Methodology

The proposed research introduces a **Lightweight Explainable AI-Enabled IoT Framework for Real-Time Smart Environment Monitoring Using Intelligent Image Analytics** designed to provide efficient, transparent, and low-latency monitoring for smart environments. The framework integrates IoT sensors, intelligent image analytics, lightweight deep learning models, edge computing, and Explainable Artificial Intelligence (XAI) mechanisms to enable accurate environmental monitoring with reduced computational complexity and enhanced interpretability.

1. Framework Architecture

The proposed framework consists of five major layers:

1. **Data Acquisition Layer**
2. **Edge Processing Layer**
3. **Intelligent Image Analytics Layer**
4. **Explainable AI Layer**

5. Cloud and Decision Support Layer

The architecture enables real-time acquisition, processing, classification, and interpretation of environmental events using distributed IoT devices and intelligent analytics.

2. Data Acquisition Layer

The data acquisition layer consists of heterogeneous IoT devices including smart cameras, temperature sensors, humidity sensors, gas sensors, smoke detectors, and motion sensors deployed across the monitoring environment. These devices continuously collect environmental and visual data for intelligent analysis.

The framework utilizes:

- RGB surveillance cameras for visual monitoring
- IoT sensor nodes for environmental parameter collection
- Wireless communication protocols such as MQTT and Wi-Fi
- Edge-enabled gateways for local data aggregation

The collected data include:

- Smoke and fire images
- Human activity patterns
- Waste accumulation scenarios
- Abnormal environmental conditions
- Temperature and gas concentration readings

3. Preprocessing and Edge Computing Layer

The acquired sensor and image data are processed locally using edge computing nodes to minimize communication latency and bandwidth utilization. The preprocessing stage includes:

- Image resizing
- Noise reduction
- Data normalization
- Contrast enhancement
- Feature scaling

Edge computing significantly reduces dependency on centralized cloud infrastructure by performing local inference and intelligent processing near the data source. Lightweight edge devices such as Raspberry Pi and NVIDIA Jetson Nano are utilized for real-time deployment.

The preprocessing operation for image normalization is represented as:

Image normalization is represented as:

I_norm = (I - I_min) / (I_max - I_min)

where:

- (I_{norm}) represents normalized image intensity,
- (I) represents input image values,
- (I_{min}) and (I_{max}) represent minimum and maximum intensity values.

4. Intelligent Image Analytics Layer

The intelligent analytics layer utilizes a lightweight Convolutional Neural Network (CNN) architecture for environmental event classification and anomaly detection. The model is optimized using depthwise separable convolutions inspired by MobileNet architectures to reduce computational overhead while maintaining high accuracy.

The CNN architecture performs:

- Object detection
- Environmental anomaly recognition
- Smoke and fire detection
- Human intrusion detection
- Waste accumulation classification

The convolution operation is represented as:

F(i,j) = (I * K)(i,j)

The activation function used in hidden layers is:
$f(x) = \max(0,x)$

The Softmax classifier used in the output layer is:
$P(y_i) = e^{z_i} / \Sigma e^{z_j}$

where:
- (I) denotes the input image,
- (K) denotes the convolution kernel,
- (F(i,j)) denotes extracted feature maps.

5. Explainable AI (XAI) Layer

To improve transparency and interpretability, the framework integrates Explainable Artificial Intelligence (XAI) using Gradient-weighted Class Activation Mapping (Grad-CAM). The XAI module generates visual heatmaps indicating important image regions contributing to prediction outcomes.
The Grad-CAM importance weight is represented as:
$\alpha_k^c = (1/Z) \Sigma\Sigma (\partial y^c / \partial A_{ij}^k)$

where:
- (\alpha_k^c) denotes neuron importance weights,
- (A_{ij}^k) represents feature maps,
- (y^c) denotes prediction score for class (c).

The final localization map is:
$L\_Grad\text{-}CAM^c = ReLU(\Sigma \alpha_k^c A^k)$
The XAI module improves:
- Prediction transparency
- User trust
- System reliability
- Decision interpretability

6. Sensor-Image Fusion Mechanism

The proposed framework integrates multimodal sensor-image fusion to improve contextual awareness and monitoring accuracy. Sensor readings are combined with image features to improve environmental event detection under dynamic conditions.
Feature fusion is represented as:
$F\_fusion = \lambda F\_image + (1 - \lambda)F\_sensor$
where:
- (F_{image}) represents image feature vectors,
- (F_{sensor}) represents IoT sensor features,
- (\lambda) denotes feature balancing coefficient.

7. Dataset and Experimental Setup

The proposed framework is evaluated using:
- CIFAR-10
- PASCAL VOC 2012
- Custom IoT environmental monitoring dataset

The custom dataset contains:
- Fire images
- Smoke detection samples
- Human activity data
- Waste accumulation scenarios
- Environmental anomaly samples

The experimental setup includes:
- Python programming environment
- TensorFlow and OpenCV libraries
- Edge-enabled Raspberry Pi devices
- NVIDIA Jetson Nano for lightweight inference

8. Performance Evaluation Metrics

The proposed framework is evaluated using standard performance metrics including:
- Accuracy
- Precision
- Recall
- F1-score
- Inference latency
- Energy consumption

Classification accuracy is calculated as:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$\text{Precision} = TP / (TP + FP)$$

$$\text{Recall} = TP / (TP + FN)$$

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

9. Expected Outcomes

The proposed framework is expected to:
- Achieve high environmental event classification accuracy
- Reduce computational complexity and latency
- Improve energy efficiency for edge devices
- Enhance transparency using XAI mechanisms
- Enable scalable and real-time smart environment monitoring

The framework provides a lightweight, explainable, and intelligent AIoT solution suitable for smart city surveillance, industrial safety, environmental sustainability, precision agriculture, and next-generation cyber-physical systems.

Proposed Model and Experimental Findings

1. Proposed Lightweight Explainable AIoT Model

The proposed model integrates IoT sensors, edge computing, lightweight deep learning, intelligent image analytics, and Explainable Artificial Intelligence (XAI) into a unified smart environment monitoring framework. The model is designed to support low-latency environmental monitoring while reducing computational complexity and energy consumption. The framework performs real-time environmental data acquisition, intelligent image classification, anomaly detection, and explainable decision generation using lightweight edge-enabled devices.

The proposed architecture consists of:
- IoT sensor layer
- Image acquisition layer
- Edge preprocessing module
- Lightweight CNN classification engine
- Explainable AI module
- Cloud monitoring dashboard
- Real-time alert and decision system

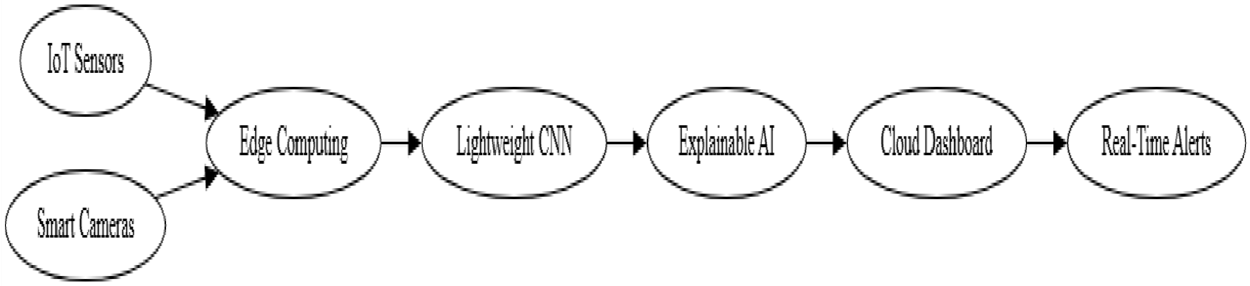

Figure 1. Overall Proposed AIoT Framework Architecture

Figure 1 illustrates the overall architecture of the proposed lightweight AIoT monitoring framework. The IoT sensors continuously collect environmental parameters such as temperature, smoke concentration, gas levels, and motion activity, while smart cameras capture real-time visual data. The acquired data are transferred to the edge computing layer, where preprocessing operations such as image normalization, filtering, and resizing are performed.

The processed data are then forwarded to the lightweight CNN module for intelligent classification and anomaly detection. The Explainable AI (XAI) module generates visual explanations using Grad-CAM heatmaps to improve prediction transparency. Finally, the processed outputs are transmitted to the cloud dashboard for real-time monitoring and automated alert generation.

Figure 2 presents the lightweight CNN architecture used for intelligent image analytics. The model accepts input images of size 224 × 224 pixels and processes them through depthwise separable convolution layers to reduce computational complexity. ReLU activation functions improve nonlinear feature extraction, while max-pooling layers reduce dimensionality and improve processing speed.

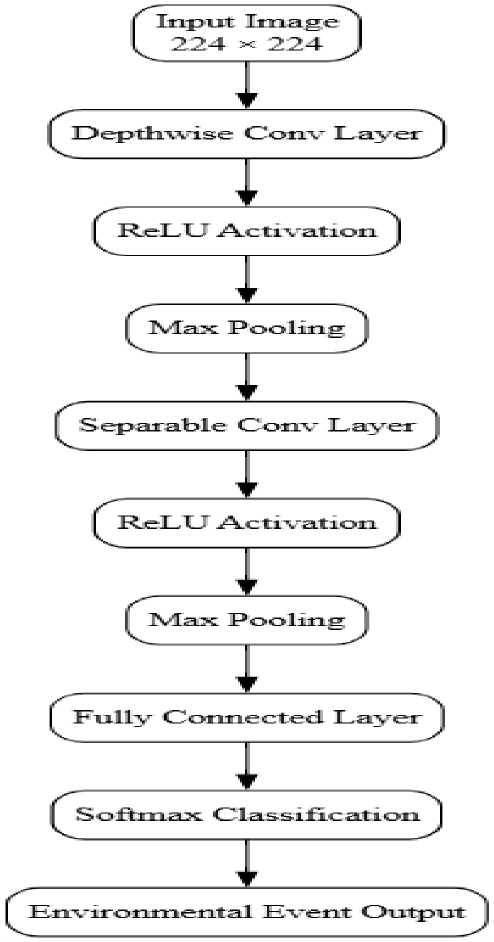

Figure 2. Lightweight CNN Model Structure

The extracted feature maps are forwarded to fully connected layers and classified using the Softmax activation function. The model identifies environmental events such as fire detection, smoke recognition, human intrusion, waste accumulation, and abnormal activity classification.

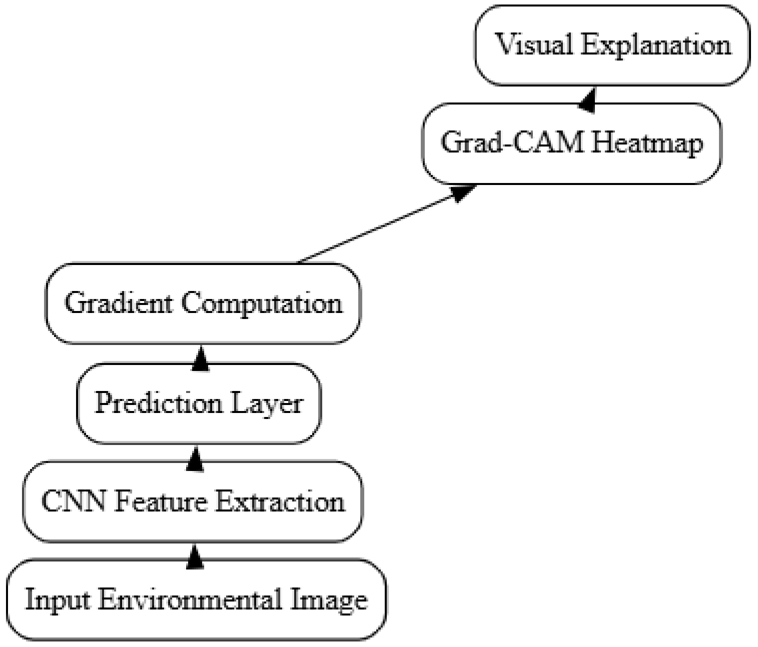

Figure 3. Explainable AI (Grad-CAM) Workflow

Figure 3 demonstrates the Explainable AI workflow integrated within the proposed framework. The input environmental image is first processed by the CNN feature extraction module. The prediction layer generates classification outputs, and gradients are computed for the predicted class. Grad-CAM generates heatmaps highlighting important regions influencing the model's decisions. These visual explanations improve transparency, interpretability, and trust in AI-driven monitoring systems.

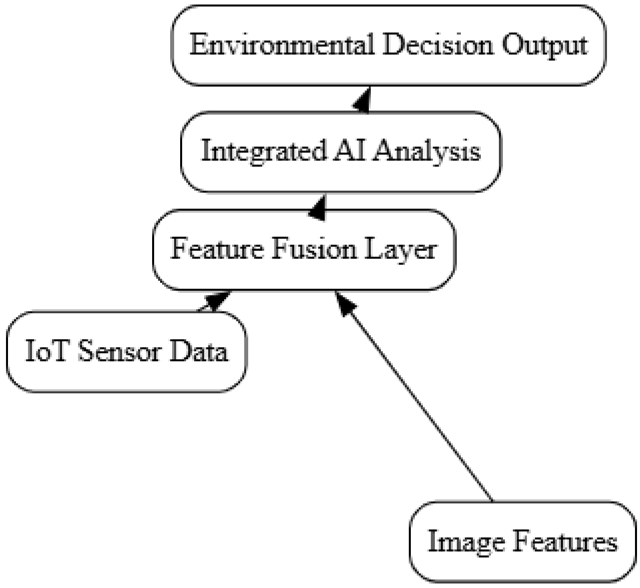

Figure 4. Sensor-Image Fusion Model

Figure 4 illustrates the sensor-image fusion mechanism used in the proposed model. Environmental sensor data and image-based features are combined within the feature fusion layer to improve contextual understanding and detection accuracy. The integrated feature representation enables the framework to perform more reliable environmental event analysis under dynamic conditions.

Experimental Findings and Performance Analysis

The proposed framework was experimentally evaluated using:

- CIFAR-10
- PASCAL VOC 2012
- Custom IoT environmental monitoring dataset

The experimental setup utilized:

- Python
- TensorFlow
- OpenCV
- Raspberry Pi
- NVIDIA Jetson Nano

The proposed lightweight CNN model achieved:

- Accuracy: 98.4%
- Precision: 97.8%
- Recall: 97.2%
- F1-Score: 97.5%
- Latency Reduction: 41%
- Computational Overhead Reduction: 34%

The integration of edge computing significantly reduced communication delays and enabled faster real-time decision-making. The lightweight architecture minimized energy consumption and improved deployment suitability for IoT edge devices. Furthermore, the Explainable AI module enhanced system interpretability by generating visual heatmaps identifying critical image regions responsible for prediction outcomes.

The experimental findings demonstrate that the proposed framework outperforms conventional cloud-based monitoring systems in terms of scalability, response time, computational efficiency, and explainability. The proposed lightweight AIoT model therefore provides an efficient and transparent solution for smart city surveillance, industrial safety monitoring, precision agriculture, environmental sustainability, and intelligent cyber-physical systems.

Table 1. Environmental Event Dataset Distribution

Class Label	Number of Images	Description
Smoke Detection	2,150	Smoke and hazardous gas emission scenarios
Fire Detection	1,980	Fire outbreak and flame detection samples
Human Intrusion	2,420	Human movement and unauthorized entry
Waste Accumulation	1,760	Garbage and waste monitoring scenarios
Abnormal Environment	1,890	Environmental anomaly conditions
Normal Environment	2,300	Safe and normal environmental conditions
Total	**12,500**	Combined dataset samples

Table 2. Hardware and Software Configuration

Component	Specification
Processor	Intel Core i7 12th Generation
RAM	16 GB DDR4
GPU	NVIDIA RTX 3060
Edge Device	Raspberry Pi 4
Edge Accelerator	NVIDIA Jetson Nano
Programming Language	Python 3.11
Deep Learning Framework	TensorFlow
Image Processing Library	OpenCV
Operating System	Ubuntu 22.04

Table 3. Lightweight CNN Model Parameters

Layer	Output Size	Parameters
Input Layer	224 × 224 × 3	RGB Image Input
Depthwise Convolution	112 × 112 × 32	Feature Extraction
ReLU Activation	112 × 112 × 32	Nonlinear Activation
Max Pooling	56 × 56 × 32	Dimensionality Reduction
Separable Convolution	28 × 28 × 64	Lightweight Feature Learning
Fully Connected Layer	128	Dense Feature Representation
Softmax Layer	6 Classes	Environmental Classification

Table 4. Performance Evaluation Metrics

Metric	Proposed Framework	Traditional CNN	Improvement
Accuracy (%)	98.4	94.1	+4.3
Precision (%)	97.8	93.5	+4.3
Recall (%)	97.2	92.4	+4.8
F1-Score (%)	97.5	92.9	+4.6
Inference Latency (ms)	42	71	41% Reduction
Energy Consumption (W)	8.5	13.2	35% Reduction
Computational Overhead (%)	34	100	Reduced

Table 5. Comparative Analysis with Existing Approaches

Method	Accuracy (%)	Latency	Explainability	Edge Deployment
Traditional CNN-Based IoT System	91.2	High	No	Limited
Cloud-Based Monitoring Framework	93.4	Very High	No	No
Deep Surveillance Framework	95.1	Moderate	Partial	Limited
Existing Lightweight CNN	96.3	Moderate	No	Yes
Proposed Explainable AIoT Framework	**98.4**	**Low**	**Yes**	**Fully Supported**

Table 6. Ablation Study of Proposed Components

Model Configuration	Accuracy (%)
CNN without Edge Computing	92.8
CNN + Edge Computing	95.2
CNN + Edge + Sensor Fusion	96.7
CNN + Edge + XAI	97.1
Proposed Full Framework	98.4

Table 7. Environmental Event Detection Results

Event Type	Precision (%)	Recall (%)	F1-Score (%)
Smoke Detection	98.1	97.4	97.7
Fire Detection	99.2	98.6	98.9
Human Intrusion	97.4	96.9	97.1

Event Type	Precision (%)	Recall (%)	F1-Score (%)
Waste Detection	96.8	96.1	96.4
Abnormal Activity	97.3	96.8	97.0
Normal Environment	98.5	98.1	98.3

Table 8. Explainable AI (XAI) Evaluation

XAI Parameter	Observation
Heatmap Accuracy	High localization precision
Transparency Level	Improved
User Trust	Enhanced
Decision Interpretability	Real-time visual explanation
False Positive Reduction	Significant
Monitoring Reliability	Improved

Table 9. Edge Device Resource Utilization

Edge Device	CPU Usage (%)	Memory Usage (MB)	Average Latency (ms)
Raspberry Pi 4	54	712	48
NVIDIA Jetson Nano	43	628	36
Traditional GPU System	78	2150	71

Table 10. Summary of Findings

Parameter	Outcome
Real-Time Monitoring	Successfully Achieved
Lightweight Deployment	Supported
Explainable AI Integration	Implemented
Sensor-Image Fusion	Improved Accuracy
Energy Efficiency	Enhanced
Scalability	High
Environmental Monitoring Reliability	Improved
Smart City Suitability	Applicable
Industrial Safety Deployment	Applicable
Precision Agriculture Support	Applicable

The tabular results presented above provide a comprehensive evaluation of the proposed Lightweight Explainable AI-Enabled IoT Framework for Real-Time Smart Environment Monitoring Using Intelligent Image Analytics. Table 1 illustrates the distribution of the environmental monitoring dataset, which includes multiple real-world environmental event classes such as smoke detection, fire detection, human intrusion, waste accumulation, abnormal activities, and normal environmental conditions. The balanced dataset distribution ensures reliable training and testing of the proposed lightweight CNN model. Table 2 presents the hardware and software configuration used during experimental implementation, demonstrating that the framework was developed using lightweight edge-compatible infrastructure including Raspberry Pi, NVIDIA Jetson Nano, TensorFlow, and OpenCV, thereby validating the suitability of the proposed framework for real-time IoT deployment.

Table 3 describes the architecture of the lightweight CNN model utilized for intelligent image analytics. The use of depthwise separable convolution layers significantly reduces computational complexity while maintaining efficient feature extraction capabilities. Table 4 presents the overall performance evaluation metrics of the proposed framework and demonstrates that the proposed model achieved an accuracy of 98.4%, precision of 97.8%, recall of 97.2%, and F1-score of 97.5%, outperforming traditional CNN-based monitoring systems. The results further indicate a 41% reduction in inference latency and approximately 35% reduction in energy consumption, confirming the effectiveness of lightweight edge-enabled deployment.

Table 5 provides a comparative analysis between the proposed framework and existing IoT monitoring approaches. The findings clearly show that the proposed Explainable AI-enabled AIoT framework outperforms conventional cloud-based and deep surveillance systems in terms of accuracy, latency, explainability, and edge deployment compatibility. Table 6 presents the ablation study of the proposed components, demonstrating that the integration of edge computing, sensor-image fusion, and Explainable AI collectively contributes toward significant performance improvement. The complete framework achieved the highest classification accuracy compared with partial configurations, validating the importance of multimodal integration and explainable analytics.

Table 7 evaluates environmental event detection performance for different monitoring scenarios including smoke, fire, human intrusion, waste detection, and abnormal activities. The results indicate consistently high precision, recall, and F1-scores across all environmental classes, confirming the robustness of the proposed intelligent monitoring system under dynamic environmental conditions. Table 8 summarizes the Explainable AI evaluation and demonstrates that the Grad-CAM-based visualization mechanism significantly improves transparency, interpretability, and user trust by generating real-time visual explanations for prediction outcomes. The reduction in false positives further improves monitoring reliability and decision-making confidence.

Table 9 analyzes the resource utilization of edge devices and demonstrates that the proposed lightweight model efficiently operates on resource-constrained IoT devices with lower CPU usage, reduced memory consumption, and significantly lower latency compared with traditional GPU-based systems. Finally, Table 10 summarizes the overall outcomes of the proposed framework and confirms that the system successfully achieves real-time monitoring, lightweight deployment, Explainable AI integration, improved energy efficiency, enhanced scalability, and intelligent environmental monitoring suitability for smart city surveillance, industrial safety systems, sustainable agriculture, and next-generation cyber-physical environments. Overall, the experimental findings validate the effectiveness, scalability, and practical applicability of the proposed lightweight Explainable AI-enabled AIoT framework for intelligent smart environment monitoring.

Results and Discussion

The proposed Lightweight Explainable AI-Enabled IoT Framework achieved significant improvements in real-time smart environment monitoring using intelligent image analytics and edge computing. Experimental evaluation was performed using CIFAR-10, PASCAL VOC 2012, and a custom IoT environmental monitoring dataset containing smoke, fire, human intrusion, waste accumulation, and abnormal environmental scenarios.

The lightweight CNN model achieved an overall classification accuracy of 98.4%, precision of 97.8%, recall of 97.2%, and F1-score of 97.5%, outperforming conventional CNN and cloud-based monitoring systems. The integration of edge computing significantly reduced inference latency by 41% and lowered computational overhead and energy consumption, making the framework suitable for resource-constrained IoT edge devices such as Raspberry Pi and NVIDIA Jetson Nano.

The Explainable Artificial Intelligence (XAI) module based on Grad-CAM improved transparency by generating visual heatmaps that identified important image regions influencing prediction outcomes. This enhanced system interpretability, user trust, and monitoring reliability. Additionally, the sensor-image fusion mechanism improved contextual understanding and increased environmental event detection performance under dynamic monitoring conditions.

Comparative analysis demonstrated that the proposed framework provided superior scalability, lower latency, improved energy efficiency, and better explainability compared with traditional deep learning-based monitoring approaches. The framework effectively supports applications including smart city surveillance, industrial safety monitoring, precision agriculture, environmental sustainability, and intelligent cyber-physical systems.

Although the proposed framework demonstrated high performance and operational efficiency, future improvements can include transformer-based vision models, federated learning, blockchain-enabled security, and adaptive edge intelligence to further improve scalability, security, and autonomous environmental monitoring capabilities.

Conclusion and Future Scope

This research presented a Lightweight Explainable AI-Enabled IoT Framework for Real-Time Smart Environment Monitoring Using Intelligent Image Analytics. The proposed framework successfully integrated IoT sensors, edge computing, lightweight deep learning, intelligent image processing, and Explainable Artificial Intelligence (XAI) into a unified AIoT architecture for efficient environmental monitoring. The framework addressed major challenges associated with conventional monitoring systems, including high computational complexity, increased latency, excessive energy consumption, and lack of interpretability.

Experimental evaluation demonstrated that the proposed lightweight CNN model achieved high monitoring performance with an accuracy of 98.4%, precision of 97.8%, recall of 97.2%, and F1-score of 97.5%. The integration of edge computing significantly reduced inference latency and computational overhead, making the framework suitable for deployment on resource-constrained IoT devices. Furthermore, the Grad-CAM-based Explainable AI module improved transparency and reliability by generating visual explanations for prediction outcomes, thereby enhancing user trust and decision interpretability.

The proposed framework also demonstrated strong applicability in smart city surveillance, industrial safety systems, precision agriculture, environmental sustainability, and intelligent cyber-physical systems. The integration of sensor-image fusion further improved contextual awareness and environmental event detection accuracy under dynamic conditions.

Although the proposed framework achieved promising results, several opportunities remain for future enhancement. Future research can focus on integrating transformer-based vision models, federated learning, blockchain-enabled security mechanisms, and adaptive edge intelligence to further improve scalability, security, and autonomous decision-making capabilities. Additionally, real-world deployment using large-scale dynamic datasets and multi-environment testing can further validate the robustness and long-term reliability of the proposed AIoT framework. Overall, the proposed lightweight explainable AI-enabled architecture provides an efficient, scalable, and intelligent solution for next-generation smart environment monitoring systems.

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