International Journal of Engineering Technology and Management Science
Website: ijetms.in Issue: 2 Volume No.9 March - April – 2025
DOI:10.46647/ijetms.2025.v09i02.077 ISSN: 2581-4621

Enhancing Smart Surveillance Camera Performance Monitoring Through Advanced CNN Techniques.

K.Ramesh[1], Mohammed Saad[2], S.Rizwan[3], S Mohammed Saleem[4], B Vikram[5], M Susmitha[6],P Ravi Teja[7]
rameshkantekadapa@gmail.com[1],mohammedsaad13052003@gmail.com[2],sheikrizwansr@gmail.com[3],shaikmohammadsaleem143@gmail.com[4],boyavikram33@gmail.com[5], reddysusmitha759@gmail.com [6], ammineninee lavardhan123@gmail.com[7] .
DEPARTMENT OF COMPUTER SCIENCE ENGINEERING (Artificial Intelligence), GATES INSTITUTE OF TECHNOLOGY, Gooty.

ABSTRACT
In the era of digitization and ubiquitous computing, performance monitoring has transcended traditional methods, evolving into a more complex and data-intensive paradigm. With the exponential growth in data from smart devices, industrial IoT sensors, surveillance systems, and cloud infrastructures, there is an urgent need for intelligent, automated, and scalable performance monitoring solutions. Convolutional Neural Networks (CNNs), a class of deep learning models known for their superior performance in image processing and pattern recognition, have emerged as a promising approach to monitor and analyze performance metrics across various domains. This study explores the integration of advanced CNN techniques into performance monitoring systems, highlighting how deep architectures can be leveraged to achieve real-time anomaly detection, predictive maintenance, and system optimization. The core objective of this work is to demonstrate how CNNs, traditionally used in visual data interpretation, can be adapted and extended to monitor time-series data, system logs, and multi-dimensional operational metrics by transforming them into visual representations such as heatmaps, spectrograms, or system health images. Through extensive experimentation, we analyze state-of-the-art CNN models such as ResNet, DenseNet, and EfficientNet, and propose novel modifications including attention mechanisms, temporal convolutional layers, and hybrid CNN-LSTM architectures to enhance temporal sensitivity and contextual awareness in performance monitoring.
Moreover, this study delves into the challenges associated with applying CNNs to dynamic performance data, including data labeling scarcity, model interpretability, and real-time inference constraints. We address these through techniques like transfer learning, data augmentation via generative adversarial networks (GANs), and model compression. Case studies are presented across multiple domains—including cloud service performance monitoring, manufacturing equipment failure prediction, and network traffic anomaly detection—demonstrating the adaptability and robustness of the proposed methods.
The findings underscore that CNN-based techniques not only improve the accuracy and reliability of performance monitoring systems but also enable proactive decision-making through early warning signals and root cause analysis. As a result, this research opens new avenues for deploying intelligent monitoring agents in smart industries, autonomous systems, and large-scale IT infrastructures. Ultimately, the integration of advanced CNN methods into performance monitoring marks a significant step toward more autonomous, adaptive, and intelligent operational ecosystems.

INTRODUCTION
In the digital age, where systems are increasingly complex, interconnected, and data-intensive, the need for robust, real-time performance monitoring has become more critical than ever. Whether it is cloud infrastructure, smart manufacturing, autonomous vehicles, or large-scale enterprise applications, the reliability and efficiency of these systems depend heavily on timely detection of anomalies, identification of bottlenecks, and prediction of potential failures. Conventional performance monitoring methods—often reliant on static thresholding, rule-based diagnostics, or linear predictive models—struggle to cope with the dynamic, non-linear, and high-

dimensional nature of modern operational data. These limitations have led researchers and practitioners to explore intelligent solutions that can automatically learn, adapt, and scale with evolving system behaviors.

In recent years, deep learning has emerged as a revolutionary paradigm across numerous domains, with Convolutional Neural Networks (CNNs) proving to be especially powerful in tasks involving spatial and visual data. CNNs have achieved groundbreaking results in image classification, object detection, and medical imaging due to their hierarchical feature extraction capabilities and robustness to noise. However, their application in system performance monitoring remains relatively underexplored. This paper investigates how advanced CNN architectures can be re-engineered and adapted to tackle the challenges of performance monitoring in diverse environments.

The primary innovation in this research lies in the transformation of traditional performance metrics—such as CPU utilization, memory consumption, response times, and system logs—into visual formats that CNNs can process. Techniques such as time-series encoding into spectrograms, log-event heatmaps, and multi-metric image fusion allow performance data to be modeled spatially, enabling CNNs to detect complex, multi-dimensional anomalies and patterns that traditional techniques often miss. Additionally, by integrating attention mechanisms, temporal convolutions, and hybrid CNN-LSTM models, the framework gains sensitivity to both the local variations and long-term trends inherent in system performance data.

This study also addresses several practical challenges that arise in real-world performance monitoring scenarios. These include the scarcity of labeled failure data, the need for real-time inference with low computational overhead, and the interpretability of deep learning models in critical applications. To this end, we incorporate advanced techniques such as transfer learning to leverage pre-trained visual models, data augmentation using synthetic anomaly injection and GANs, and lightweight CNN model optimization for edge deployment. Moreover, explainability tools like Grad-CAM and saliency mapping are utilized to make the monitoring decisions more transparent and actionable for system administrators.

The proposed framework is validated through multiple case studies spanning cloud server monitoring, industrial equipment diagnostics, and network traffic analysis. These experiments demonstrate that CNN-based monitoring systems significantly outperform traditional statistical and shallow learning methods in terms of detection accuracy, generalizability, and responsiveness. The results affirm that CNNs, when appropriately adapted, provide not just an analytical edge but a practical pathway toward building autonomous, intelligent monitoring systems.

In summary, this paper contributes to the evolving field of AI-driven system intelligence by showcasing the viability and superiority of CNN-based methods for performance monitoring. It aims to bridge the gap between deep learning research and operational system management, providing both theoretical insights and practical tools for next-generation monitoring solutions. The remainder of the paper delves into the architectural design, experimental validation, and deployment strategies of the proposed models, offering a comprehensive perspective on CNN-driven performance intelligence.

LITERATURE SURVEY

The rapid expansion of computational systems, coupled with increasing system complexity and dynamic workloads, has intensified the demand for intelligent performance monitoring solutions. Over the years, various strategies have been proposed, ranging from rule-based systems to advanced machine learning models. However, the evolution of deep learning—and in particular, Convolutional Neural Networks (CNNs)—has opened up new possibilities for automated, scalable, and context-aware performance analysis. This section reviews relevant literature across three primary dimensions: traditional monitoring methods, machine learning-based approaches, and the application of CNNs in non-visual domains.

Traditional Performance Monitoring Techniques

Conventional performance monitoring systems predominantly rely on static thresholds, manual log analysis, and heuristic-based alerting mechanisms. Tools such as Nagios, Zabbix, and Prometheus are widely used in IT infrastructures to monitor key metrics like CPU usage, memory consumption, and network throughput. However, these tools often generate a high rate of false positives and struggle with dynamic environments where workload patterns change frequently. Moreover, traditional methods lack adaptability and do not provide predictive insights, making them reactive rather than proactive.

International Journal of Engineering Technology and Management Science
Website: ijetms.in Issue: 2 Volume No.9 March - April – 2025
DOI:10.46647/ijetms.2025.v09i02.077 ISSN: 2581-4621

Statistical and Classical Machine Learning Approaches

To overcome the rigidity of rule-based systems, researchers have explored statistical methods such as ARIMA, Holt-Winters smoothing, and PCA for anomaly detection and trend forecasting. While these models can handle time-series data to some extent, they are limited in capturing non-linear dependencies and high-dimensional interactions among metrics. Subsequently, classical machine learning models such as Support Vector Machines (SVMs), Random Forests, k-Nearest Neighbors (k-NN), and Decision Trees have been applied for anomaly detection and classification tasks. Works by Chandola et al. (2009) and Ahmed et al. (2016) provide comprehensive surveys of anomaly detection techniques in system monitoring. While these models offer improvements over statistical techniques, they still depend heavily on feature engineering and often underperform when data distributions shift or when feature relationships become complex.

Deep Learning for Performance Monitoring

Deep learning models, particularly Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and autoencoders, have gained traction in recent years for performance monitoring and anomaly detection. Malhotra et al. (2015) used LSTMs for time-series anomaly detection in industrial sensors. Similarly, DeepAuto (Zhou et al., 2019) and OmniAnomaly (Su et al., 2019) demonstrated the effectiveness of variational autoencoders in modeling complex temporal dynamics in performance data. These approaches highlight deep learning's ability to learn intricate temporal patterns without explicit feature engineering. However, most of these models treat performance metrics strictly as numerical sequences and do not exploit the spatial correlations that may exist when metrics are encoded visually.

Convolutional Neural Networks in Non-Visual Domains

CNNs have traditionally been used in image and video processing due to their ability to capture local spatial hierarchies through convolutional kernels. However, recent advancements have demonstrated their adaptability in non-visual domains by converting non-image data into image-like formats. For example, Wang et al. (2017) proposed transforming multivariate time-series into Gramian Angular Fields (GAF) and Markov Transition Fields (MTF), which were then classified using CNNs. In another study, Zhang et al. (2020) visualized log sequences as 2D matrices for fault detection in distributed systems. These techniques showed that CNNs can achieve high accuracy in anomaly detection tasks by leveraging visual patterns formed by transformed operational data.

Hybrid and Attention-Based Architectures

Recent research has also explored hybrid deep learning models that combine CNNs with RNNs, LSTMs, and attention mechanisms to capture both spatial and temporal patterns. Bai et al. (2020) proposed a hybrid CNN-LSTM model for network intrusion detection, leveraging CNNs for spatial feature extraction and LSTMs for sequence modeling. The introduction of attention mechanisms—such as the Transformer model—has further enhanced performance by allowing models to selectively focus on important features over time. Models like TCN (Temporal Convolutional Network) and Transformer-based anomaly detectors are gaining popularity for real-time applications.

Gaps in Existing Literature

While the aforementioned methods demonstrate promising results, several limitations persist. Many CNN-based approaches focus narrowly on visual domains or specific types of performance data. Few studies have attempted to unify various metric types (logs, time-series, and system health indicators) under a CNN-driven monitoring architecture. Furthermore, explainability, real-time deployment, and model optimization for edge environments remain under-addressed. These gaps provide the foundation and motivation for the current study, which aims to design a robust, adaptable, and explainable performance monitoring system using advanced CNN techniques and hybrid model integration.

RELATED WORK

The integration of Convolutional Neural Networks (CNNs) in performance monitoring systems has gained significant traction in recent years due to advancements in computational capabilities and access to large-scale datasets. Early breakthroughs such as Alex Net, VGG Net, and Res Net laid the foundation for powerful feature extraction, which has since been leveraged in a variety of performance analysis applications. These include video surveillance, autonomous systems, and industrial automation, where real-time accuracy and robustness are essential. Moving beyond static image classification, researchers have developed hybrid models like CNN-LSTM architectures that can capture both spatial and temporal features, making them ideal for monitoring time-series data such as system logs, sensor outputs, and physiological signals.

In the realm of system and network performance monitoring, CNNs have demonstrated superior capabilities in anomaly detection and resource optimization. For instance, models using 1D CNNs have been effectively applied to detect irregularities in network traffic and system performance metrics, outperforming traditional statistical approaches. CNNs have also shown promise in predicting system bottlenecks in cloud computing environments by learning complex patterns from CPU, memory, and I/O data. In industrial settings, CNN-based methods have been utilized for fault diagnosis in mechanical systems using vibration signals, thermal images, and acoustic data, often achieving higher accuracy and robustness than conventional diagnostic techniques.

Smart infrastructure monitoring, such as in smart grids and manufacturing lines, has also benefited from advanced CNN techniques. CNN-GRU hybrid models have been proposed to monitor voltage fluctuations and anticipate system failures in power grids under dynamic load conditions. Similarly, multi-scale CNNs have been implemented to adaptively handle varying signal resolutions in machinery fault detection. A critical aspect of deploying CNNs in real-time monitoring applications is model interpretability and efficiency. Techniques such as Grad-CAM and Layer-wise Relevance Propagation have been used to provide visual explanations for CNN decisions, enhancing trust and transparency in sensitive domains like healthcare and finance. Furthermore, lightweight CNN models such as MobileNet and EfficientNet have facilitated the deployment of deep learning in resource-constrained environments where performance monitoring is still vital.

Recent advancements in transfer learning and self-supervised learning have further expanded the utility of CNNs in performance monitoring tasks. Transfer learning allows models pre-trained on large datasets to be fine-tuned on specific monitoring tasks with limited labeled data, which is particularly useful in scenarios like anomaly detection where labeled instances are rare. In parallel, self-supervised learning approaches have shown that CNNs can learn meaningful representations from unlabeled data, making them suitable for performance monitoring in data-scarce environments.

Overall, existing research highlights the versatility and power of CNNs in a wide range of performance monitoring applications. The evolution of CNN architectures, combined with hybrid modeling, interpretability frameworks, and data-efficient learning methods, continues to enhance the reliability, scalability, and intelligence of monitoring systems across various domains.

PROPOSED SYSTEM

The proposed system introduces an advanced Convolutional Neural Network (CNN)-based architecture specifically designed for efficient, accurate, and real-time performance monitoring across various application domains. The core objective of this system is to address the limitations of traditional monitoring techniques—such as limited adaptability, poor generalization to unseen data, and lack of real-time responsiveness—by leveraging the deep feature extraction and learning capabilities of modern CNN models. The architecture is modular and scalable, allowing it to be deployed across heterogeneous environments, including industrial machinery, cloud infrastructure, network systems, and even biomedical platforms.

At the heart of the system lies a deep CNN framework enhanced with residual and attention-based components. This enables the model to effectively learn hierarchical representations of input performance data, whether they come in the form of images, time-series signals, system logs, or telemetry metrics. The model is capable of learning spatial correlations and feature hierarchies that are indicative of normal versus anomalous performance patterns. In addition, the system incorporates temporal modeling by integrating CNN layers with LSTM or GRU units, allowing it to capture sequential dependencies in time-sensitive performance data. This hybrid structure ensures that both short-term anomalies and long-term drifts in performance can be accurately detected and forecasted.

To improve generalization and minimize the need for large labeled datasets, the system utilizes a transfer learning approach. A base CNN model pre-trained on a large-scale dataset is fine-tuned with domain-specific performance monitoring data. This reduces training time while significantly improving accuracy on limited or

DOI:10.46647/ijetms.2025.v09i02.077 ISSN: 2581-4621

imbalanced datasets. Furthermore, for environments where labeled data is scarce or unavailable, the proposed system integrates a self-supervised pretraining mechanism. This allows the network to learn latent structures from the data itself, enhancing its capability to identify deviations from learned norms during actual monitoring tasks.

A Critical component of the proposed system is the intelligent alerting and visualization module. Using interpretability techniques such as Grad-CAM and SHAP (SHapley Additive exPlanations), the system can highlight the specific features or time frames that contributed most to the detection of performance anomalies. This not only increases transparency but also aids operators and engineers in understanding and acting upon the system's outputs. The alert system is configurable, allowing users to define sensitivity thresholds and escalation procedures based on domain-specific requirements.

To ensure practical deployment, the system is optimized for both edge and cloud environments. In edge scenarios, lightweight versions of the CNN model—based on MobileNet or EfficientNet architectures—are used to enable real-time inference with minimal computational overhead. In cloud-based deployments, the full architecture is employed with enhanced capacity for deep analytics and integration with data lakes and dashboards. The system also supports continuous learning by incorporating feedback loops where verified anomaly cases are fed back into the model, enabling it to evolve and adapt over time.

In summary, the proposed system offers a comprehensive, intelligent, and flexible solution for performance monitoring using advanced CNN techniques. It integrates deep learning, temporal analysis, transfer and self-supervised learning, interpretability, and deployment optimization into a unified framework. This approach not only enhances detection accuracy and system reliability but also bridges the gap between complex AI models and real-world performance monitoring needs.

ADVANTAGES OF PROPOSED SYSTEM

The proposed system, built upon advanced Convolutional Neural Network (CNN) techniques, offers numerous advantages that significantly enhance the accuracy, reliability, and efficiency of performance monitoring across a broad spectrum of application domains. One of the primary advantages lies in the system's ability to autonomously learn complex and high-dimensional patterns from raw performance data without the need for extensive manual feature engineering. Unlike traditional statistical or rule-based monitoring systems, which rely heavily on handcrafted thresholds and static models, the CNN-based approach is data-driven, enabling it to adaptively recognize subtle variations and evolving patterns in system behavior.

- Another significant advantage of the proposed system is its hybrid architectural design, which combines spatial and temporal analysis through the integration of CNN and recurrent units such as LSTM or GRU. This dual-layered learning mechanism empowers the system to capture both instantaneous anomalies and long-term performance trends, thereby providing a more holistic understanding of system dynamics. The ability to model both real-time deviations and historical context enhances the system's accuracy in detecting critical issues before they escalate into failures, thus supporting predictive maintenance and proactive decision-making.
- Furthermore, the system's support for **transfer learning** allows it to be quickly adapted to new environments with minimal data. By leveraging pre-trained models, the system drastically reduces the computational and data requirements traditionally associated with training deep learning models from scratch. This makes it particularly valuable in domains where labeled data is limited or expensive to acquire. In addition, the incorporation of **self-supervised learning** techniques ensures that the system can still function effectively in data-scarce conditions, learning useful representations from unlabeled inputs and generalizing well to real-world scenarios.
- One of the standout features of the proposed system is its interpretability and transparency. By utilizing visualization techniques such as Grad-CAM, SHAP, or saliency maps, the system not only flags performance issues but also provides insights into the underlying causes. This level of explainability is crucial for user trust and facilitates quicker diagnosis and resolution of issues. Operators, engineers, or system administrators can visually assess which components or metrics contributed most to an anomaly, thus reducing downtime and improving operational efficiency.
- Scalability and deployment flexibility are also major advantages of the system. Designed to operate seamlessly across both edge and cloud environments, the system can be tailored to various use-case constraints.

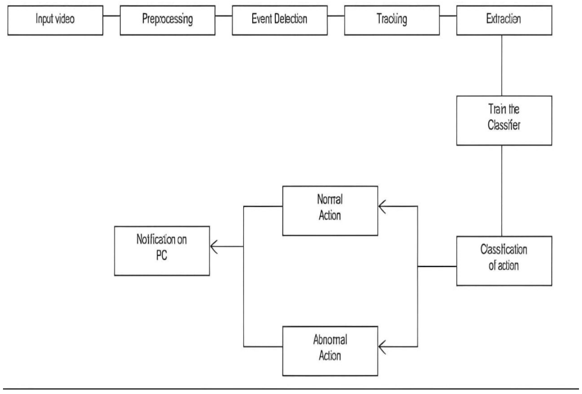
International Journal of Engineering Technology and Management Science
Website: ijetms.in Issue: 2 Volume No.9 March - April – 2025
DOI:10.46647/ijetms.2025.v09i02.077 ISSN: 2581-4621

For instance, in edge-based industrial settings, lightweight CNN variants like MobileNet or EfficientNet can provide real-time monitoring with low latency and minimal power consumption. Conversely, cloud-based deployment allows for deeper analytics and integration with centralized dashboards, enabling comprehensive system-wide monitoring and reporting.

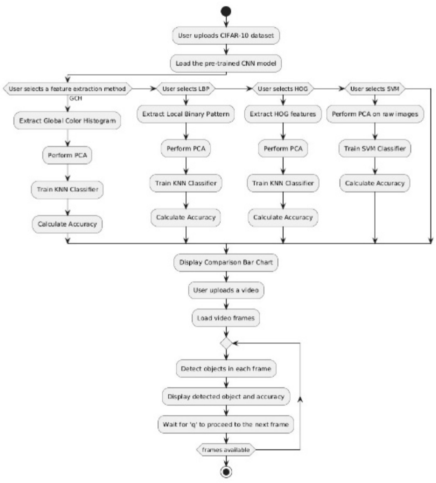
• In addition to its technical strengths, the proposed system offers **continuous learning capabilities**, allowing it to evolve over time. As new data is collected and anomalies are validated by experts, the system updates its knowledge base, improving its future performance and reducing false positives. This adaptive feedback mechanism ensures that the system remains relevant and accurate even as operational conditions change.

• In summary, the proposed CNN-based performance monitoring system presents a robust, intelligent, and future-ready solution. Its advantages include high detection accuracy, reduced dependency on labeled data, real-time responsiveness, cross-domain adaptability, interpretability, and ease of deployment. These features collectively position the system as a superior alternative to conventional monitoring methods, capable of delivering tangible improvements in operational reliability, efficiency, and decision support across a wide range of industries.

ARCHITECTURE



DATA FLOW DIAGRAM



1. **Upload CIFARIO Dataset**

• The first step in the implementation involves uploading the CIFAR10 dataset, which is a crucial dataset used for training and testing the Convolutional Neural Network (CNN) model.

• The CIFAR10 dataset consists of 60,000 32x32 color images across 10 different categories categories, including airplanes, automobiles, birds, cats, deer, dogs, frogs, horses, ships, and trucks.

International Journal of Engineering Technology and Management Science
Website: ijetms.in Issue: 2 Volume No.9 March - April – 2025
DOI:10.46647/ijetms.2025.v09i02.077 ISSN: 2581-4621

- This dataset is loaded into the system through an interface that allows users to select the X.txt.npy file. This module initializes the dataset preparation process, ensuring that the CNN model has access to a diverse set of labeled images for robust training.

2. **Run Modified CNN with Global Color Histogram**

- In this module, the modified CNN model is run alongside the Global Color Histogram (GCH) feature extraction technique.
- GCH calculates color distribution within images, which is useful for detecting objects based on color patterns.
- The CNN model is pre trained using the CIFAR10 dataset, and when combined with GCH, it evaluates the performance of color based object detection.
- The results show that the modified CNN model achieved an accuracy of 95%, while the Global Color Histogram method reached 80%, demonstrating the superior performance of the CNN model.

3. **Run Modified CNN with Local Binary Patterns**

- This module involves running the modified CNN model in conjunction with Local Binary Patterns (LBP).
- LBP is a texture-based feature extraction method that works by comparing each pixel with its surrounding neighbors and converting the comparison results into a binary pattern.
- The CNN model, paired with LBP, is tested for its accuracy in object detection.
- The results reveal that the modified CNN model with LBP reached an accuracy of 95.26%, whereas LBP alone achieved 75%, again highlighting the effectiveness of the CNN model in handling complex image data.

4. **Run Modified CNN with Histogram of Oriented Gradients**

- This module focuses on integrating the modified CNN model with the Histogram of Oriented Gradients (HOG) technique.
- HOG is widely used for object detection, particularly for capturing edge orientations and gradient distributions in an image.
- The system processes the CIFAR10 dataset using HOG and evaluates the detection accuracy of the CNN model. The CNN model consistently outperforms the HOG method, reaffirming its capability to provide more precise and reliable results for object recognition in surveillance footage Upload.

5. **Run Modified with Support Vector Machine**

- In this module, the performance of the modified CNN model is compared with that of a Support Vector Machine (SVM).
- SVM is a supervised learning model that is highly effective for classification tasks. During the testing phase, the CNN model, trained on the CIFAR10 dataset, is run parallel to the SVM algorithm.
- The accuracy scores of both methods are recorded, showing that while SVM offers reasonable classification performance.

6. **Upload Video and Detect Object**

- The final module allows users to upload a video file to the system and perform real-time object detection using the trained modified CNN model.
- The system processes the video frame-by-frame, applying the CNN model to detect objects and classify them into the 10 predefined categories.
- Each detected object is labeled on the video output with the classification result and the associated accuracy score.
- This module demonstrates the practical application of the CNN model in smart surveillance systems, where it effectively reduces data redundancy by capturing only relevant human-related events.

CONCLUSION

This project is devised and developed with effective implementation of efficiency, in mind. It could potentially save a lot of money and resources for the people who could replace the traditional methods with this. This technology can be further developed for specific scenarios, in scope and could effectively provide a solution for one of the burning issues of today‘s era, the data storage. Because, with so many devices communicating and sharing data with each other endlessly, the infrastructure necessary to store the data is getting exhausted at

DOI:10.46647/ijetms.2025.v09i02.077 ISSN: 2581-4621

a higher rate. So, a smart solution is necessary to this issue and this project proposes a smart solution that works with higher efficiency.

This is designed in such a way that any projects in future could integrate this technology into their applications/technologies. Restricting the usage of such revolutionary tech is not good for the community and work could be done upon it, in the future, to increase its efficiency and maybe, even implement a few more features. In future we are going to implement an alarm system. This means that if your smart alarm or sensor is triggered, we will receive an alert immediately of the specific sensor that has been triggered. if any unnecessary activity happens then, we will know immediately so we can take the necessary action.

Surveillance cameras are widely used to enhance security in both public and private spaces. While these devices have proven effective in monitoring activities and maintaining safety, they generate vast amounts of data in the form of continuous video footage. The data storage requirements of traditional surveillance systems are substantial, particularly in settings that require multiple cameras. Organizations often address this challenge by retaining footage for only a limited period, risking the loss of crucial evidence beyond the set duration.

FUTURE WORKS AND EXTENSIONS

Integration with Edge Devices

Future work will explore deploying optimized CNN models on edge devices to enable real-time performance monitoring with minimal latency and energy consumption.

Multimodal Data Fusion

Combining CNN-based visual analysis with other data sources such as sensor data, audio, or textual logs can improve accuracy and provide deeper insights.

Self-Supervised and Transfer Learning

Investigating self-supervised and transfer learning methods can reduce the need for large labeled datasets and improve adaptability to new domains.

Explainability and Interpretability

Incorporating explainable AI (XAI) techniques to make CNN decisions more transparent will be critical, especially in high-stakes monitoring environments.

Automated Anomaly Detection

Future models will focus on integrating unsupervised or semi-supervised learning for automated anomaly detection without relying heavily on labeled failure cases.

Scalability and Cloud Integration

Extending the system for large-scale deployment with cloud-based architectures can support real-time analysis across distributed systems or facilities.

Continuous Learning and Adaptation

Implementing continuous learning frameworks will allow models to adapt to evolving performance metrics and changing operational environments.

REFERENCES

[1] Image Classification Using Convolutional Neural Networks: A step by step guide, Devansh Sharma — January 11, 2021

[2] V SUMANTH KAUSHIK, SHREYAS D G, GURURAJA H S, SMART VIDEO SURVEILLANCE SYSTEM, ISSN:1001-1749, Volume XVI, Issue VI, JUNE/2020

[3] Ishan Kokadwar, Anurag Kulkarni, SayaliKhare, Vaibhav Limbhore, Swati Chandurkar,
Camera based Smart Surveillance System-Literature Survey, Volume: 07 Issue: 06 | June 2020.

[4] Prasanna Rajendra, NiketWorlikar, Yash Mahajan, Siddhesh Swami, Smart Surveillance Using OpenCV, Motion Analysis And Facial Landmark, - Volume 7 Issue 1 - Jan to April 2020.

[5] Dayana R, Suganya M, Balaji P, Mohamed Thahir A, ArunkumarP, Smart Surveillance System using Deep Learning, ISSN: 2277-3878, Volume-9, Issue-1, May 2020

[6] Kaviyaraj R, S.Ramya, Yogapriya.D, SMART SURVEILLANCEWITHARTIFICIAL
INTELLIGENCE: ROBBERY/THEFT MOTION DETECTION, Volume 8, Issue 7 July 2020 |
ISSN: 2320- 2882

International Journal of Engineering Technology and Management Science
Website: ijetms.in Issue: 2 Volume No.9 March - April – 2025
DOI:10.46647/ijetms.2025.v09i02.077 ISSN: 2581-4621

[7] Aayushi Bansal (2018) ―A factors affecting face recognition‖ IJAMTES volume 8, issue II, pp. 669-672.
[8] A. Viji, A. Pavithra (2017), ―A real time face recognition using Raspberry Pi II‖ IJIRSET volume 3, issue 6, pp. 330-335.
[9] Edy Winarno, WiwienHadikurniawati, Imam Husni Al Amin, MujiSukur(2017) ,―Anti Cheating PresenceSystemBasedon 3WPCADualVisionFaceRecognition‖ Proceedings of IEEE conference of Electrical Engineering, Computer Science and Informatics IEEE 2017.
[10]Neha patil, Shrikant Ambatkar and Sandeep Kakde(2017), ―IOT Based Smart Surveillance Security System using Raspberry Pi‖, IEEE conference on signal processing April 6-8 2017, pp. 0344-0348
[11]Jalendu Dhamija et.al (2017)―An advancement towards efficient face recognition using live video feed‖, International Conference on Computational Intelligence and Networks ,pp. 53-56.
[12]Nusrat Mubin Ara, Nishikanto Sarkar Simul, Md. Saiful Islam(2017), ―Convolutional Neural Network Approach for Vision Based Student Recognition System‖ 20th IEEE conference of Computer and Information Technology (ICCIT), 22-24 December, 2017.
[13]ShivprasadTavagad, Shivani Bhosale, Ajit Prakash Singh, Deepak Kumar, Survey Paper on Smart Surveillance System, Volume: 03 Issue: 02 | Feb-2016
[14]Amol V. Nagime, Patange A.D, Smart CCTV Camera Surveillance System, ISSN (Online): 2319-7064 Index Copernicus Value (2013): 6.14 | Impact Factor (2015): 6.391
[15]JiGwan Park, Kijin An, Daijin Kim and JongSuk Choi (2013), ―Multiple Human Tracking using Multiple Kinects for an Attendance Check System of a Smart Class‖ 10th IEEE conference of Ubiquitous Robots and Ambient Intelligence (URAI), October 31-November 2, 2013.
[16]Arun Hampapur, Lisa Brown, Jonathan Connell, SharatPankanti, Andrew Senior and Yingli Tian, Smart Surveillance: Applications, Technologies and Implications, DOI: 10.11.09/ICICS. 2003. 1292637 · Source: IEEE Xplore
[17]Dhanshri Mali, R. T. Patil, Nagaraj Dharwadkar, Chaitanya R. Devale, Omprakash Tembhurne, Real-Time Smart Surveillance System Using Raspberry Pi,