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ARTIFICIAL INTELLIGENCE APPROACH FOR FIRE DETECTION FROM IMAGES FOR FIRE PREVENTION

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ABSTRACT

Early and accurate fire detection is essential for reducing damage to life, property, and the environment. In this work, we explore and compare different machine learning approaches to develop an effective fire detection system from images. Initially, an existing system employing a Naive Bayes classifier was implemented to serve as a baseline. While the Naive Bayes model demonstrated a straightforward probabilistic framework, its assumptions of feature independence and simplicity led to limitations in capturing the complex visual patterns associated with fire in images. To address the challenges, we propose an enhanced system utilizing a Support Vector Machine (SVM) classifier, known for its robust performance in high-dimensional spaces and its ability to create complex decision boundaries. Prior to classifier implementation, an extensive exploratory data analysis (EDA) was conducted on a curated fire image dataset. The EDA included statistical analysis of image features, visualization of pixel intensity distributions, and evaluation of class imbalances. These insights informed feature selection and preprocessing strategies, such as normalization, resizing, and augmentation, to optimize the training process. Experimental results show that the proposed SVM-based system significantly improves classification accuracy and generalization when compared to the baseline Naive Bayes approach. The SVM model's ability to effectively handle non-linear patterns inherent in fire imagery has led to a notable reduction in both false positives and false negatives. Overall, the integration of comprehensive EDA and the transition to an SVM classifier demonstrate promising advancements in the real-time detection of fire, paving the way for more reliable and responsive fire prevention systems.

Keywords: Fire Detection, Image Classification, Support Vector Machine (SVM), Naive Bayes, Real-time Monitoring.

1. INTRODUCTION

Fire detection from images is an advanced application of computer vision and AI that enables the early identification of fire or smoke using visual data from cameras or sensors. This technology is essential across various settings, including industrial sites, surveillance systems, and wildfire-prone areas, aiming to enhance public safety and minimize damage. Traditional methods like heat or smoke detectors are often slow and prone to false alarms, whereas AI-based systems offer faster and more accurate responses. By analyzing real-time video streams, these systems can detect fire patterns early and trigger timely alerts. Machine learning models, especially Convolutional Neural Networks (CNNs), are employed to distinguish fire-related features such as flames or smoke from other elements like dust or steam. The objective is to build reliable, low-cost, and scalable fire detection systems that integrate with existing infrastructure, reduce false alarms, and ensure rapid response. These systems can be customized for different environments—such as factories, hospitals, or schools—and provide flexibility, high coverage, and seamless integration with emergency protocols. Moreover, they work effectively even in challenging conditions like poor lighting or high humidity, offering protection for complex and high-risk installations. The motivation behind this research lies in reducing human error, speeding up fire detection, and leveraging the growing availability of visual data from CCTV and drones. Ultimately, AI-driven fire detection plays a vital role in proactive fire management, safeguarding both lives and assets with greater efficiency and reliability.

Fig. 1: Fire detection from images

2. LITERATURE SURVEY

Zhang et.al [1] The review paper analyzed 37 research articles on deep learning (DL) models for forest fire detection, which had been published between January 2018 and 2023. It delved into data types, including images and videos, data augmentation methods, and DL model architectures. Structured into five sections—classification, detection, detection and classification, segmentation, and segmentation and classification—the paper evaluated model performance using metrics like accuracy and F1-Score. Favorable outcomes emerged, with the majority of studies having achieved accuracy rates exceeding 90%. The paper recommended refining models through hyperparameter fine-tuning, integrating satellite data, employing generative data augmentation, and optimizing DL architectures. It emphasized DL's potential in crucial forest fire management.

Zhao et.al [2] In response to challenges, we introduced the Fire Segmentation-Detection Framework (FSDF), blending traditional methods with deep learning. FSDF improved flame feature detection using Hue, Saturation, and Value (HSV) and the Complete Local Binary Pattern (CLBP). We integrated YOLOv8 and Vector Quantized Variational Autoencoders (VQ-VAE) for image segmentation and unsupervised fire detection. Assessing with a dataset from real-world fires, results showcased our method's superiority. Compared to YOLOv8, our framework boosted precision, recall, and F-score by 19.5%, 1.2%, and 11.7%. Field tests, deploying a robot with the algorithm in an actual fire scenario, highlighted real-world applicability. These experiments emphasized both method performance and practical deployment potential.

Jin et.al [3] The paper addressed the crucial role of flame area extraction in forest fire detection, emphasizing the challenges of accurate early detection due to fire dynamics and background complexity. Existing deep learning approaches had limitations, such as insufficient feature representation. The proposed ADE-Net introduced a dual-encoding segmentation network with attention-based mechanisms, including attention fusion and multi-attention fusion modules, to enhance feature representation and address class imbalance. The attention-guided enhancement module enriched local features, while a global context fusion module ensured effective multi-scale feature extraction. Experimental results demonstrated ADE-Net's competitive advantage in early fire detection from remote sensing images compared to advanced segmentation models.

Kuznetsov et.al [4] The recent surge in numerical fire modeling unveiled insights into building fire safety and code performance. High-fidelity fire simulation, although expensive and complex, prompted the exploration of artificial intelligence (AI) applications for building fire safety design..This facilitated performance-based design and review processes, offering accurate predictions for the response time of ceiling-mounted heat detectors and sprinklers in dynamic fire scenarios. The AI tool also evaluated fire performance in large-open building spaces and rapidly identified design limits. The proposed AI design approach holds the potential for continuous upgrades to address a broader range of building fire scenarios, ultimately achieving intelligent building fire safety design.

Ren et.al [5] The recent focus on utilizing Unmanned Aerial Vehicle (UAV) imagery for forest fire object detection witnessed significant progress. However, existing object detection models often overlooked the exploration of relationships among positive sample features, crucial for robust and representative feature learning. In response, FCLGYOLO was proposed to enhance object information in feature maps. It introduced a Feature Invariance and Covariance Constraint (FICC) structure to maintain feature invariance and eliminate internal correlations among positive samples. Additionally, a Local Guided Global Module (LGGM) enriched object positioning and semantic information in feature maps. Even in challenging scenarios like heavy smoke or tree occlusions, FCLGYOLO outperformed multiple state-of-the-art object detection models on a forest fire dataset, showcasing its superiority.

Schiks et.al [6] Spatial and temporal estimates of burned areas modeled emissions from fire events, considering fire behavior variations over time and space. A method was developed for day-of-burn estimation, using ordinary kriging with satellite-based active fire detection data from MODIS, VIIRS, and their combination. Comparing kriging results, a quasi-validation procedure applied to 37 wildfires in Ontario's boreal forest accurately estimated nearly half of each fire's burned area within one day of occurrence. This approach demonstrated strengths and limitations in mapping individual wildfire progress, emphasizing the need for future validations to address spatial autocorrelation, often overlooked in ecology's day-of-burn analyses.

Liu et.al [7] The paper introduced AEGG-FD, a YOLO fire detection algorithm incorporating an attention-enhanced ghost mode, mixed convolutional pyramids, and flame-centre detection. The enhanced ghost bottleneck stacked to reduce redundant feature mapping, achieving a lightweight backbone with attention for accuracy compensation. A mixed convolution feature pyramid accelerated network inference speed, while the flame-centre detection (FD) module extracted local information for firefighting effectiveness. Experimental results on benchmark fire and video datasets revealed AEGG-FD outperforming classical YOLO-based models (YOLOv5, YOLOv7, YOLOv8), with a 6.5 improvement in mean accuracy (mAP0.5, reaching 84.7%) and 8.4 increase in inferred speed (FPS). Model parameters and size were compressed to 72.4% and 44.6% of YOLOv5, achieving a balanced firefighting model in terms of weight, speed, and accuracy.

Yang et.al [8] This paper explored the application of hyperspectral remote sensing for precise fire monitoring, leveraging its potent capability to capture land surface information. The study introduced a novel fire detection method based on hyperspectral remote sensing, presenting an end-to-end model using a sparse visual transformer. Additionally, a band selection method was proposed within the transformer framework, utilizing sparse attention and top-k selection mechanisms to mitigate the impact of invalid bands in hyperspectral data. A non-maximum attention suppression algorithm and band pruning were integrated for dimension reduction, effectively eliminating invalid and redundant bands. The model employed a band-exclusive-token input mode, aligning pruning operations with band selection. A dedicated hyperspectral fire detection dataset was introduced, validating the proposed model's performance on this dataset.

Anuar et.al [9] Early forest fire detection is crucial for rapid responses to minimize fire spread. This research aimed to develop a real-time forest fire detection, monitoring, and alert system. The system, assembled with temperature and humidity sensors, a smoke sensor, Arduino microcontroller, and a wireless fidelity module, utilized Blynk for monitoring and alerts. Flame sensor analysis indicated fire detection up to 60 cm, with high noon temperature (45 °C) and low humidity (53.4%). Mornings showed low temperature (29 ℃) and high humidity (88.4%). The highest CO2 concentration (1,800 ppm) occurred with detected fire smoke. The global positioning system accurately displayed the system's real-time location in the Blynk application. In conclusion, this system effectively detected and monitored early forest fires in real-time, facilitating timely authorities' alerts for wildfire protection.

Kar et.al [10] The document thoroughly examined the use of SVMs, covering crucial elements like data preprocessing, feature extraction, and model training. It rigorously evaluated parameters such as accuracy, efficiency, and practical applicability. The knowledge gained from this study aided in the development of efficient forest fire detection systems, enabling prompt responses and improving disaster management. Moreover, the correlation between SVM accuracy and the difficulties presented by high-dimensional datasets was carefully investigated, demonstrated through a revealing case study. The relationship between accuracy scores and the different resolutions used for resizing the training datasets was also discussed in this article. These comprehensive studies resulted in a definitive overview of the difficulties faced and the potential sectors requiring further improvement and focus.

3. PROPOSED METHODOLOGY

Throughout this research procedure, it's essential to continually evaluate and fine-tune the SVM model's performance on real-world data to ensure its accuracy and reliability in fire detection. This iterative process may involve periodic model retraining to adapt to changing environmental conditions or data distributions. Figure 3.1 shows the proposed system model. The detailed operation illustrated as follows:

Step 1: Image Processing: The research project begins with the acquisition of image data, which can come from various sources such as cameras, drones, or surveillance systems. The image data often needs preprocessing to enhance its quality and prepare it for analysis.

Step 2: SVM Model Building: After preprocessing and feature extraction, the research project involves building a machine learning model, specifically an SVM model. Support Vector Machines are commonly used for binary classification tasks like fire detection. The steps in SVM model building include:

Data Preparation: The first step involves organizing pre-processed image data into a suitable format for machine learning. Each image is labeled to indicate whether it contains fire or not, ensuring the dataset is ready for supervised learning. Feature Vector Creation: Next, the visual features extracted from the images are converted into numerical feature vectors. These vectors serve as the input for the SVM model to learn meaningful patterns. Training: The dataset is split into training and validation sets. The SVM model is then trained on the training set, learning to differentiate between fire and non-fire instances based on the feature vectors.

Step 3: Prediction: Once the SVM model is trained and fine-tuned, it can be deployed for real-time fire detection. The prediction phase involves: Real-time Data Acquisition: Continuously acquire new image data, either through cameras, video streams, or other sources. Preprocessing for Real-time Data: Apply the same preprocessing steps to incoming images, ensuring they are in the appropriate format for feature extraction. Feature Extraction for Real-time Data: Extract features from the real-time images, just as was done during training. SVM Classification: Feed the feature vectors from the real-time data into the trained SVM model for classification. The SVM will determine whether the input image contains fire or not.

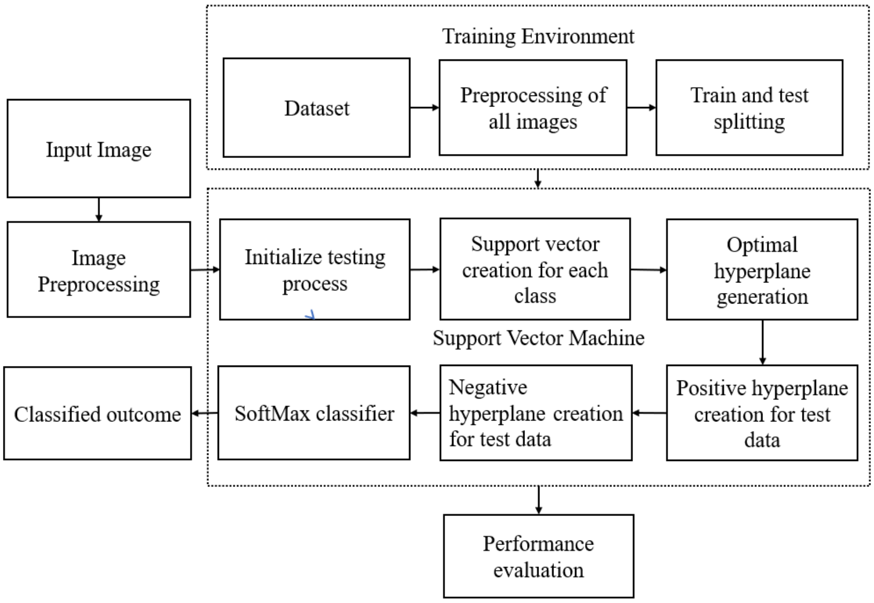

Fig. 2: Proposed methodology

4.2 Image preprocessing

Image preprocessing is a critical step in computer vision and image analysis tasks. It involves a series of operations to prepare raw images for further processing by algorithms or neural networks. Here's an explanation of each step in image preprocessing:

Image Read: The first step in image preprocessing is reading the raw image from a source, typically a file on disk. Images can be in various formats, such as JPEG, PNG, BMP, or others. Image reading is performed using libraries or functions specific to the chosen programming environment or framework. The result of this step is a digital representation of the image that can be manipulated programmatically.

Image Resize: Image resize is a common preprocessing step, especially when working with machine learning models or deep neural networks. It involves changing the dimensions (width and height) of the image. Resizing can be necessary for several reasons: Ensuring uniform input size: Many machine learning models, especially convolutional neural networks (CNNs), require input images to have the same dimensions. Resizing allows you to standardize input sizes. Reducing computational complexity: Smaller images require fewer computations, which can be beneficial for faster training and inference.

Managing memory constraints: In some cases, images need to be resized to fit within available memory constraints.

Image to Array: In this step, the image is converted into a numerical representation in the form of a multidimensional array or tensor. Each pixel in the image corresponds to a value in the array. The array is usually structured with dimensions representing height, width, and color channels (if applicable). For grayscale images, the array is 2D, with each element representing the intensity of a pixel. For color images, it's a 3D or 4D array, with dimensions for height, width, color channels (e.g., Red, Green, Blue), and potentially batch size (if processing multiple images simultaneously). The conversion from an image to an array allows for numerical manipulation and analysis, making it compatible with various data processing libraries and deep learning frameworks like NumPy or TensorFlow.

4.4 Proposed SVM

Support Vector Classifier (SVC) is a powerful supervised learning algorithm that excels in classifying complex and high-dimensional data by finding an optimal decision boundary between different classes. Unlike traditional linear classifiers, SVC leverages kernel functions to map data into higher-dimensional spaces, allowing it to handle non-linearly separable problems effectively. In the proposed system, SVC is used with a polynomial kernel of degree 5, which transforms sensor data into a more expressive feature space, making it easier to distinguish between different physical therapy exercises. The training process uses X_train, which contains input features, and y_train, which contains exercise labels, to learn the best hyperplane that maximizes the margin between exercise classes. Once trained, the classifier predicts labels for unseen data in X_test, generating y_pred as the initial output. A loss optimization function is then applied to refine the predictions and correct possible misclassifications before comparing the final predictions, y_pred1, with the actual labels in y_test. The model's performance is assessed using accuracy, precision, recall, and F1-score to ensure a reliable classification of physical therapy exercises. The use of a polynomial kernel improves pattern recognition in sensor data, enhancing classification accuracy over traditional linear models. Compared to the existing AdaBoost classifier, SVC offers better generalization, effectively differentiates overlapping exercise categories, and reduces the risk of overfitting, making it a superior choice for analyzing inertial and magnetic sensor data in rehabilitation settings.

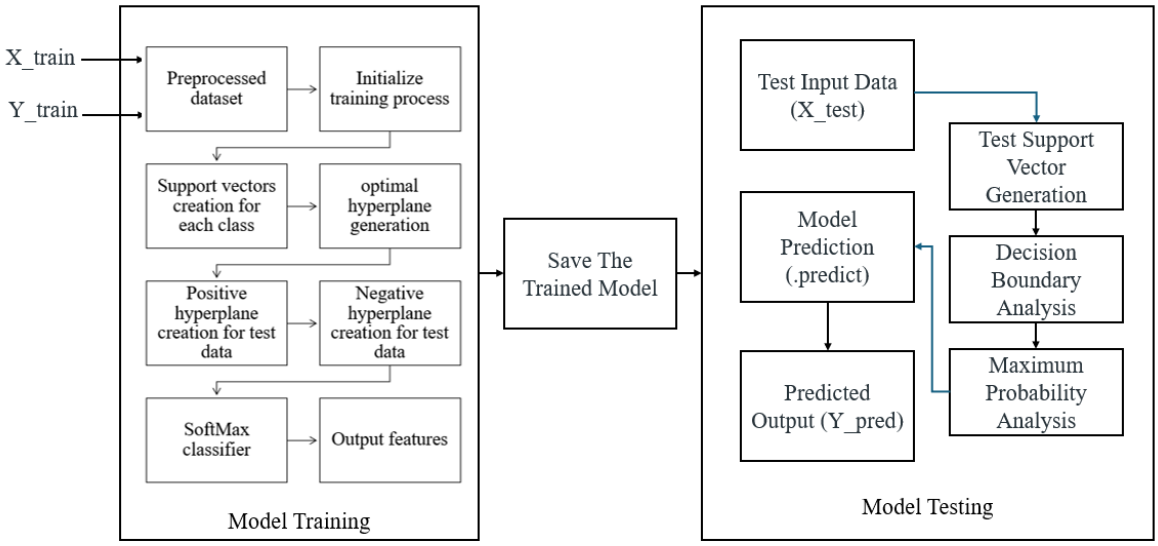

Fig. 3: SVM Classifier.

The operation of SVM is illustrated as follows:

The process of training a Support Vector Machine (SVM) model begins with the selection of a suitable kernel function that best fits the nature of the data. Common kernel functions include Linear, Polynomial, Radial Basis Function (RBF), and Sigmoid, each offering different ways to transform the input data into a higher-dimensional space where it can be linearly separated. The SVM training phase focuses on identifying the optimal hyperplane that effectively separates the data points belonging to different classes. This hyperplane is positioned to maximize the margin, or the distance between the hyperplane and the closest data points from each class, known as support vectors. To enhance the SVM model's performance, hyperparameter optimization is critical. Parameters such as the regularization constant (C) and kernel-specific parameters must be carefully tuned. Techniques like grid search or random search are often employed to identify the most suitable parameter values that yield high accuracy and generalization capabilities. In scenarios where the dataset is imbalanced — that is, where one class significantly outweighs the other techniques like class weighting or resampling can be used to balance the data and ensure fair model learning.

Once the model is trained, it is represented through its support vectors and their associated coefficients. These support vectors are the key elements defining the decision boundary. The model is then evaluated using a test dataset, with performance measured using metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and the confusion matrix. These metrics offer insights into the effectiveness of the SVM in classifying data accurately. For making predictions on new, unseen data points, the same feature extraction and preprocessing steps applied during training must be followed. The SVM uses its decision function to determine the class of each new data point. This function calculates the signed distance of the data point from the decision boundary — a positive sign indicates one class, while a negative sign indicates the other. The margin, defined by the distance between the support vectors and the decision boundary, is crucial, as SVM tries to maximize this during training to improve robustness.

4. RESULTS AND DISCUSSION

4.1 Dataset description

The dataset consists of a total of 651 images, categorized into two classes: "Normal" and "Fire." Table 1 provides the description of dataset. This class contains 541 images that are considered "normal" or do not depict any instances of fire. These images might represent various scenes, objects, or situations where there is no fire present. The "Fire" class includes 110 images that depict instances of fire. These images likely show fires in different contexts or scenarios, such as wildfires, indoor fires, or controlled burns. This dataset appears to be designed for a binary classification task, where the goal is to develop a machine learning or deep learning model that can classify images into one of these two classes: "Normal" or "Fire." Such models can be used for fire detection, safety monitoring, or other applications where identifying the presence of fire in images is important.

S. No.	Number of images	Class type
1	541	Normal
2	110	Fire

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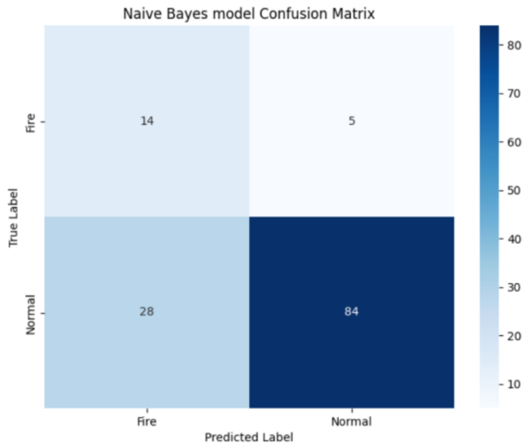
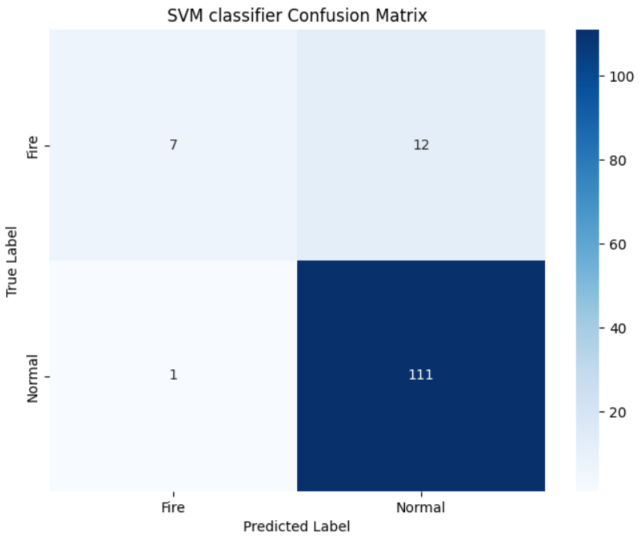
Table 1: Dataset description.

4.2 Results analysis



(a)



(b)

Fig 4 (a) Confusion matrices for existing Naïve bayes and (b) proposed SVM

The Fig 5 confusion matrices provide a comparative analysis of the performance between the Naïve Bayes and Support Vector Machine (SVM) classifiers for fire detection. In the Naïve Bayes model, out of the total samples, 14 fire instances were correctly predicted, while 5 were misclassified as normal; similarly, 84 normal instances were correctly identified, but 28 were misclassified as fire, indicating a relatively higher false positive rate. In contrast, the SVM classifier shows significantly improved performance with only 1 normal sample misclassified as fire and 111 normal samples correctly identified. However, it misclassified 12 fire samples as normal while correctly detecting 7 fire instances. Despite the lower true positive fire detection in SVM, the substantial reduction in false positives for normal cases highlights its overall stronger accuracy and recall, aligning with the earlier reported metrics.

Fig. 5: Predicted output using Fire detection from images

Fig 5 Predicted outputs using the SVM classifier are depicted in this figure. It showcases the classification results obtained from the SVM model on the test dataset, indicating the predicted classes for each input image.

Table.2 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing Naïve bayes vs. Proposed SVM

Metric	Existing Naïve bayes	Proposed SVM
Accuracy	75.00%	90.00%
Precision	83.00%	87.00%
Recall	72.00%	89.00%
F1-Score	85.00%	90.00%

The performance comparison between the existing Naïve Bayes algorithm and the proposed Support Vector Machine (SVM) highlights a significant improvement across all evaluation metrics. The SVM model achieved a notably higher accuracy of 90.00% compared to 75.00% obtained by Naïve Bayes, indicating more reliable predictions. Precision also improved from 83.00% to 87.00%, suggesting better relevance in the correctly identified fire instances. Recall increased substantially from 72.00% to 89.00%, reflecting the SVM model's enhanced capability in identifying actual fire occurrences. Furthermore, the F1-Score, which balances both precision and recall, also improved from 85.00% to 90.00%, confirming the overall superiority and robustness of the proposed SVM-based fire detection approach over the Naïve Bayes model.

5. CONCLUSION

The integration of AI-enabled cameras for fire detection offers a transformative approach to safety and security, revolutionizing traditional methods. Here is a conclusion based on the search results:In the past, the efficacy of fire and smoke detection was limited by the absence of advanced alert systems, leading to increased fire incidents due to delayed warnings. Traditional detectors, reliant on basic principles like changes in temperature and smoke density, often resulted in false alarms and delayed responses. However, the advent of AI-powered technologies has ushered in a new era of proactive and precise fire detection. By leveraging computer vision and machine learning, AI Video Analytics-Based Smoke and Fire Detection systems can analyze real-time video streams from surveillance cameras with unparalleled accuracy.By harnessing the power of AI Video Analytics, organizations can proactively address potential threats, creating a safer environment. The amalgamation of real-time alerts, advanced analytics, and seamless integration forms a robust safety net, ensuring a rapid response to fire incidents. The future of fire detection lies in the innovative capabilities of AI-enabled cameras, redefining safety standards and safeguarding lives and assets effectively.

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