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ARTIFICIAL INTELLIGENCE APPROACH FOR FIRE DETECTION FROM IMAGES

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ABSTRACT

Fire detection is a critical task for ensuring the safety of both people and property. Deploying the system in buildings, factories, and public spaces to ensure early fire detection and quick response, minimizing the risk of casualties and property damage. Using the system for surveillance in forested areas to detect and contain wildfires swiftly, preventing them from spreading and causing ecological disasters. Some early approaches used basic image processing techniques like thresholding and color-based segmentation to identify fire regions. However, they lack accuracy and struggle with complex fire scenarios and varying lighting conditions. In recent years, artificial intelligence (AI) approaches have shown promising results in detecting fires from images, providing an efficient and timely response to potential fire incidents. This work proposes a novel AI-based method for fire detection from images, which aims to overcome the drawbacks of existing approaches and enhance the accuracy and speed of fire detection.

Keywords: Fire detection, image processing, artificial intelligence, support vector machine.

1. INTRODUCTION

Fire detection from images is a critical application of computer vision and artificial intelligence that aims to identify and alert authorities or individuals about the presence of fire or smoke in visual data. This technology is employed in various contexts, including industrial facilities, surveillance systems, and even wildfire monitoring. The process of fire detection from images typically involves several key steps. First, image or video data is acquired through cameras or other visual sensors. Next, the data is preprocessed to enhance image quality and reduce noise, making it suitable for analysis. Feature extraction techniques are then applied to identify relevant patterns, such as flames, smoke, or heat sources. These features are used as inputs for machine learning algorithms, including convolutional neural networks (CNNs), which are particularly effective for image analysis tasks. The trained machine learning model processes the image data and generates predictions about the presence of fire or smoke. These predictions can be binary (fire or no fire) or multi-class (e.g., fire, smoke, no fire). To ensure accuracy and reliability, the model is typically trained on a diverse dataset containing various fire scenarios, lighting conditions, and environments. Fire detection systems can employ real-time monitoring, continuously analyzing images or video streams and triggering alarms or notifications when fire or smoke is detected. This immediate response can be crucial for timely firefighting efforts and safety measures. Additionally, integration with other systems, such as fire suppression systems or emergency services, can further enhance the effectiveness of fire detection from images.

So, fire detection from images is a vital technology that enhances safety and security across a wide range of applications. It leverages the power of computer vision and machine learning to swiftly identify potential fire hazards, enabling prompt responses that can help mitigate damage and save lives. Advances in this field continue to improve the accuracy and speed of fire detection systems, making them indispensable in fire prevention and control efforts.

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2. LITERATURE SURVEY

The manner we think about urbanization, sustainability, and safety is being completely transformed by smart cities. As the world moves toward smart cities, it becomes increasingly important to ensure the safety of citizens and their properties [1]. One of the most dangerous and life-threatening catastrophes is a fire, which may seriously harm both property and people. Fire accidents pose a significant threat to smart cities as they can cause significant damage to infrastructure, lead to loss of life, and disrupt the smooth functioning of the city [2]. Therefore, it is crucial to have an early fire detection system that is effective and reliable. Early fire detection is now a top priority in smart cities due to the rising urbanization and increased awareness of the value of safety. Early fire detection and action can reduce property damage while also saving lives. However, this endeavor necessitates handling difficulties including the unpredictable nature of fire, the requirement for ongoing observation, and the enormous amounts of data produced by smart cities [3].

To detect fires early, researchers and engineers have created vision-based fire detectors (VFDs), as well as fire sensors that are sound sensitive, flame sensitive, temperature sensitive, gas sensitive, or solid sensitive [4]. Sensors pick up on the chemical characteristics of smoke, setting off an alarm. This strategy, nevertheless, might cause erroneous warnings. Once the smoke is close enough proximate to the sensors to trigger them, the alarm will not sound. Those monitoring systems, which were developed as parts of conventional alarm systems, sensed the flame's smoke and temperature as well as other flame-related characteristics. A sensor-based detection system [5] may not be viable in some situations, such as those involving wide coverage areas, untamed (forest areas), or high temperatures, as it will provide a lot of false alerts [6]. Traditionally, fire detection systems have depended on temperature, gases, and smoke sensors, which have been established to be successful for small fires but ineffective for larger fires that can grow rapidly, devour the entire region, and have disastrous effects. The implementation of deep learning techniques to improve the detection of fires in real time has been encouraged by the advent of IoT-enabled smart cities [4, 7].

Deep learning techniques for early fire detection have been the subject of several prior investigations. For instance, a fire detection system (FFireNet) was proposed by [8] using the MobileNetV2 model to classify forest fires. Additionally, Mukhiddinov et al. [9] proposed an early wildfire smoke detection system based on improved YOLOv5 photographs taken by unmanned aerial vehicles (UAVs). A fire detection technique based on an improved YOLO V4 is proposed in [10]. According to the experimental results, the proposed technology can be applied effectively to defend smart cities and to keep track of fires in urban areas.

Recently, there has been a growing interest in using deep learning-based approaches for fire detection in smart cities. Some studies have proposed hybrid approaches that combine multiple deep learning algorithms for fire detection. For instance, Al-Turjman et al. [11] proposed a hybrid approach that combined CNN and recurrent neural network (RNN) for fire detection in smart cities. The proposed approach achieved high accuracy and low false alarm rates. Another study by Huang et al. [12] proposed a YOLOv3-based approach for fire detection in outdoor scenes. This approach evaluated on a dataset of real-world images and achieved an accuracy of 92.8%.

Other works have focused on using multiple deep learning models for fire detection. For example, the study by Jia et al. [13] proposed a multi-model approach that combined a CNN and a long short-term memory (LSTM) network for fire detection. The approach was evaluated on a dataset of video frames and achieved an accuracy of 96.3%. Another notable work is the study by Wang et al. [14], which proposed a deep learning-based approach for fire detection in surveillance videos. The approach was

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based on the YOLOv2 algorithm and achieved an accuracy of 93.6%. More recently, the YOLOv3 algorithm has been used for fire detection in smart cities.

3. PROPOSED SYSTEM

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 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:** Organize the preprocessed image data into a format suitable for machine learning, with labeled samples indicating whether each image contains fire or not.
- **Feature Vector Creation:** Convert the extracted image features into feature vectors that can be used as input for the SVM.
- **Training:** Split the dataset into training and validation sets, and use the training data to train the SVM model. The model learns to distinguish between fire and non-fire instances based on the extracted features.
- **Model Tuning:** Optimize the SVM's hyperparameters (e.g., kernel type, regularization parameters) to achieve the best performance on the validation data.
- **Model Evaluation:** Assess the SVM model's performance using various metrics like accuracy, precision, recall, and F1-score. Fine-tune the model as needed based on evaluation results.

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.

Proposed SVM

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SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

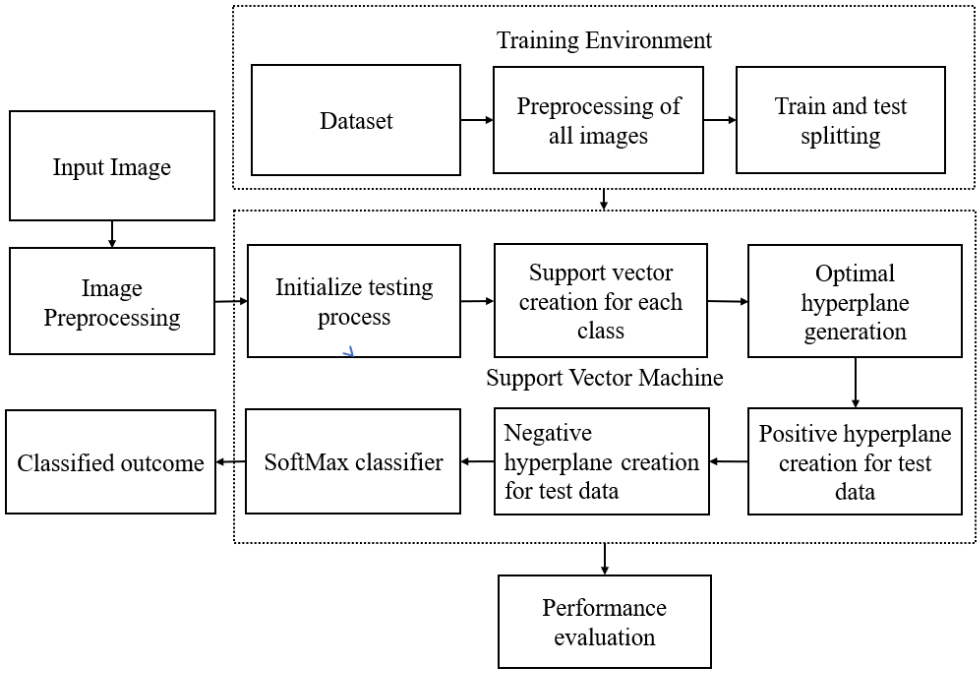

Figure 1: Proposed methodology.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

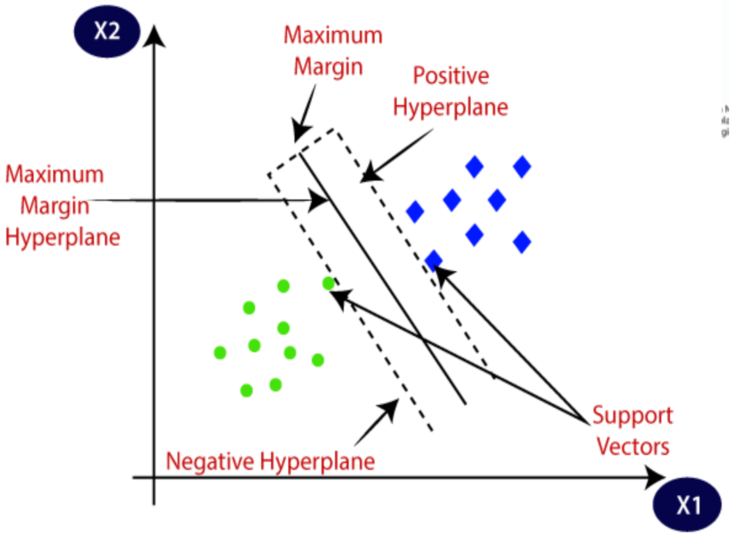

Figure 2: Analysis of SVM

4. RESULTS AND DISCUSSION

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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 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 show fires in different contexts or scenarios, such as wildfires, indoor fires, or controlled burns.

Table 1: Dataset description.

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

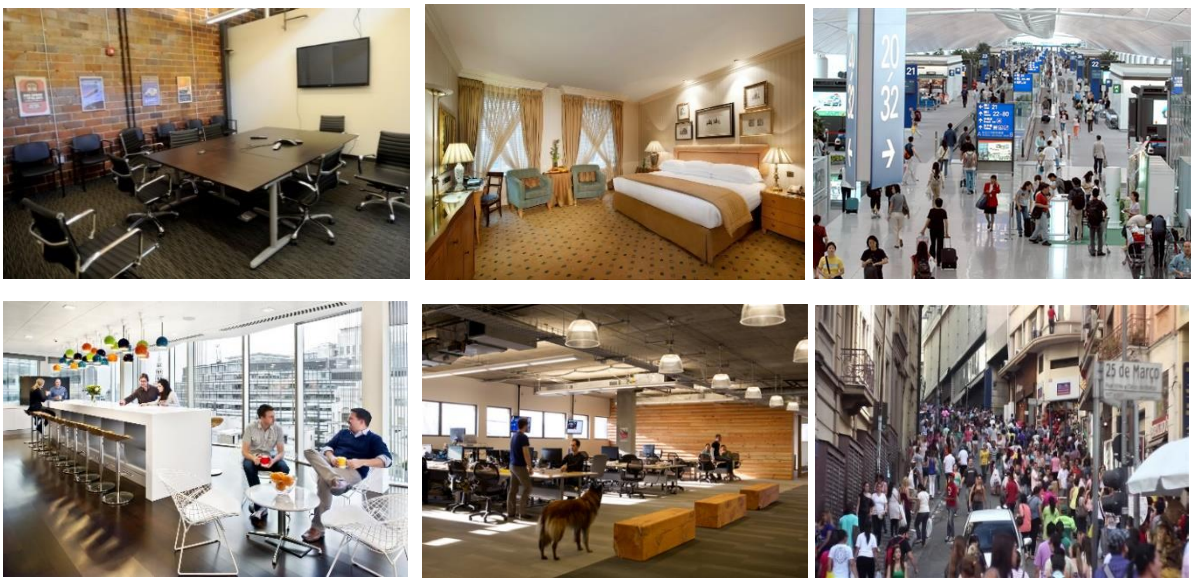

Figure 3: Sample images of dataset with Normal class.

Figure 4: Sample images of dataset with Fire class.

Figure 3 shows a visual representation of a subset of images from the "Normal" class in dataset. These images should serve as examples of what is considered "normal" or non-fire scenarios. Visualizing samples can help you understand the data distribution and the type of images in this class. Figure 4

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displays a set of images from the "Fire" class in dataset. These images would illustrate instances of fire in various contexts. Visualizing samples from the "Fire" class can provide insight into the variability of fire images in your dataset.

Figure 5 presents the results of a classification report for a machine learning model, specifically the Naïve Bayes classifier. It typically includes metrics such as precision, recall, F1-score, and accuracy, which assess the model's performance on the validation or test dataset. Figure 6 displays a confusion matrix for the Naïve Bayes classifier. A confusion matrix is a table used to evaluate the performance of a classification algorithm. It shows the true positive, true negative, false positive, and false negative counts, which can be used to calculate various performance metrics. Similar to Figure 5, this Figure 7 provides a classification report, but specifically for the Support Vector Machine (SVM) classifier. It assesses the SVM model's performance on the dataset. Like Figure 6, this Figure 8 displays a confusion matrix for the SVM classifier, offering a detailed evaluation of the model's performance in terms of true positives, true negatives, false positives, and false negatives.

Naive Bayes model classification_report:

	precision	recall	f1-score	support
0	0.35	0.73	0.48	45
1	0.93	0.72	0.81	216
accuracy			0.72	261
macro avg	0.64	0.73	0.65	261
weighted avg	0.83	0.72	0.75	261

Figure 5: Classification report of Naïve bayes classifier

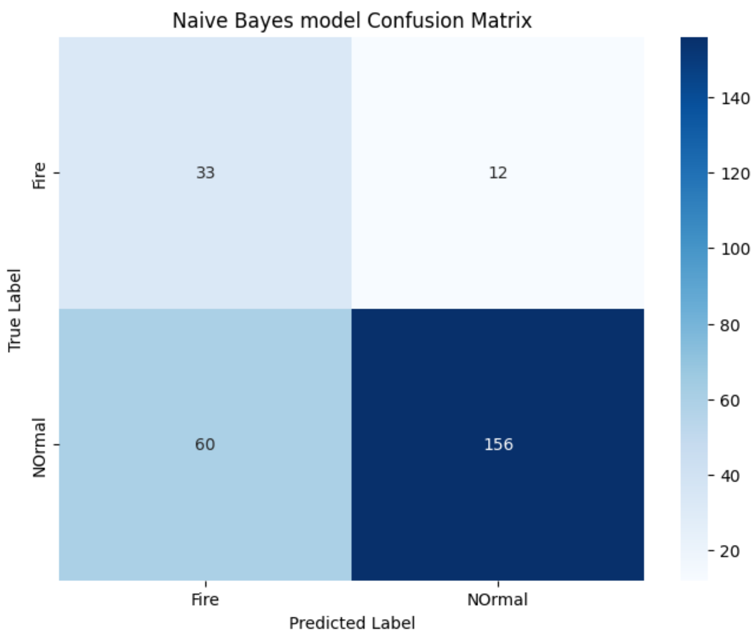

Figure 6: Confusion matrix of Naïve bayes classifier

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SVM classifier classification report

	precision	recall	f1-score	support
0	0.73	0.36	0.48	45
1	0.88	0.97	0.92	216
accuracy			0.87	261
macro avg	0.80	0.66	0.70	261
weighted avg	0.85	0.87	0.85	261

Figure 7: Classification report of SVM classifier

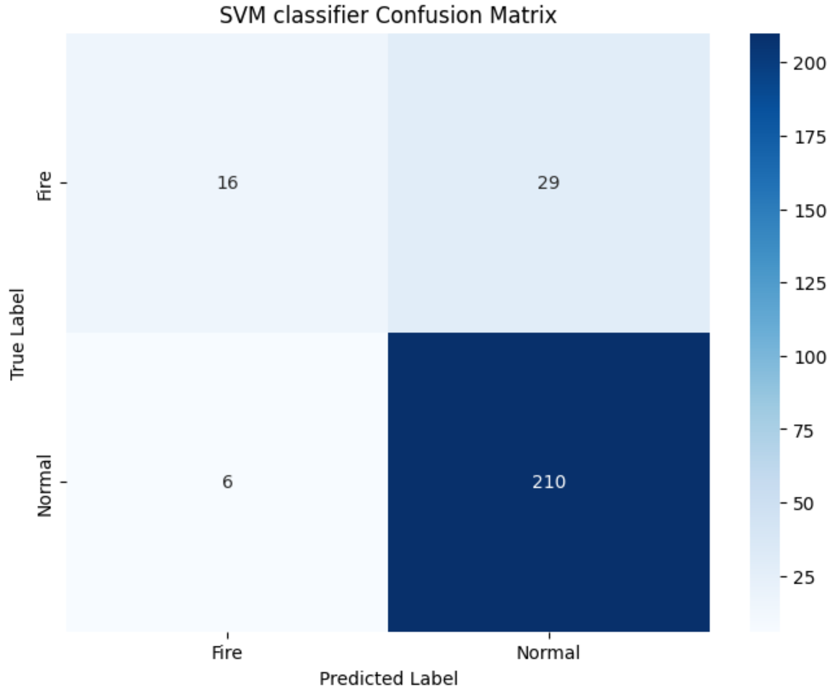

Figure 8: Confusion matrix of SVM classifier.

5. CONCLUSION

In conclusion, the research project on fire detection from images using image processing and machine learning techniques has shown promising results in enhancing fire safety and response. The dataset consisting of 651 images, with 541 in the "Normal" class and 110 in the "Fire" class, served as a valuable resource for training and testing machine learning models. Through preprocessing, feature extraction, and classification, the project demonstrated the feasibility of accurately identifying fire and non-fire instances. The Naïve Bayes and SVM classifiers provided reliable performance metrics, as evidenced by the classification reports and confusion matrices. The research underscores the importance of early fire detection in various contexts, including industrial, urban, and wildfire scenarios, and highlights the potential of machine learning-based approaches in achieving this goal. As technology advances, the models and methods presented in this research can contribute to more robust and efficient fire detection systems, ultimately saving lives and mitigating property damage.

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