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Smoke Detection and Localization in Video Surveillance Applications Based on Efficient Deep CNN

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Abstract: Due to human causes and a dry climate, the number of forest fires reported has in-creased year after year. Many detection strategies have been extensively investigated and put into practise in order to avoid a horrific fire disaster. Their use in snoke detection systems will significantly enhance detection accuracy, resulting in fewer fire disasters and less ecological and social consequences. However, because of the large memory and processing requirements for inference, the application of CNN-based smoke detection systems in real-world surveillance networks is a serious challenge. in the proposed scheme, To create a classification model that utilizes Deep Learning to detect fires in images/video frames, allowing for early detection and saving manual work. This model can be used to detect smoke in surveillance videos. This method can also be used to reduce the number of accidents caused by fires in in- dustries, hospitals, and other locations. Furthermore, by taking into consideration the specific characteristics of the situation at hand as well as the variety of smoke data, this suggested system demonstrates how a balance between smoke detection accuracy and efficiency may be achieved

Keywords: Smoke detection , Fire detection, CNN, Deep learning, Image Processing etc.

I. INTRODUCTION

Rate of forest fires reports have increased yearly due to human causes and dry climate. To avoid terrible disaster of smoke, many detection techniques have been widely studied to apply in practice. Most of traditional method are based on sensors due to its low-cost and simple installation[1]. These systems are not applicable for using outdoor where energy of flame affected by fire materials and the burning process affected by environment that have potential cause of false alarms[2]. Visual-based approach of image or video processing was shown to be more reliable method to detect the smoke since the closed circuit television (CCTV) surveillance systems are now available at many public places, can help capture the smoke scenes. In order to detect smoke from scenes of color-videos, various schemes have been studied,mainly focus on the combination of static and dynamic characteristics of smoke such as color information, texture and motion orientation, etc[1].

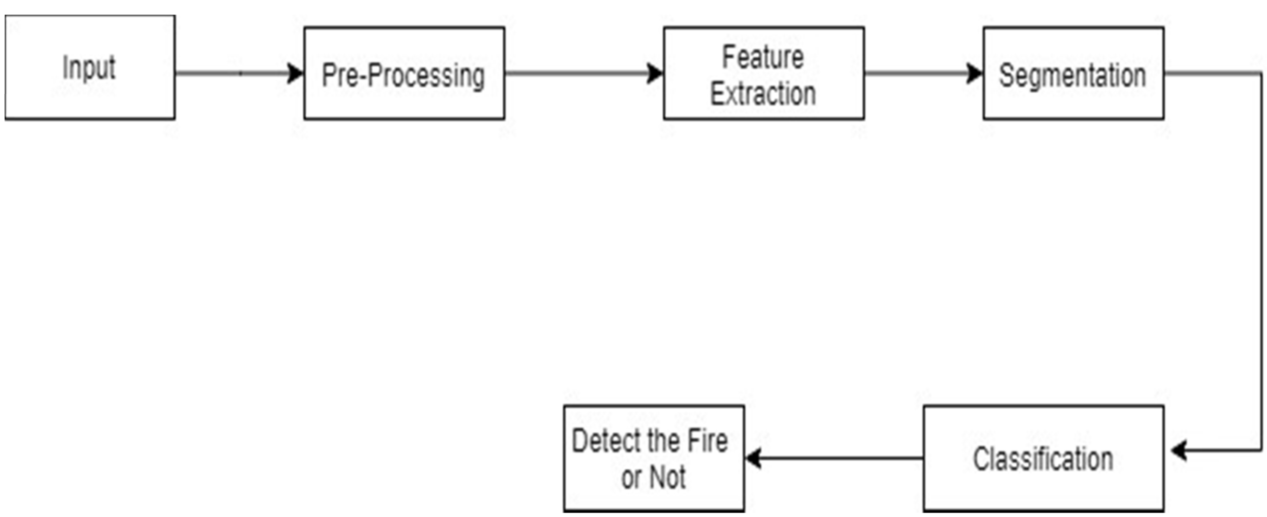

Fig.1

II. PROJECT MANAGEMENT COMPONENTS

A. Resource

The team of professionals involved in the project, such as deep learning engineers, data scientists, software developers, and project managers. Hardware and software tools like GPUs, cloud servers, deep learning frameworks (e.g., TensorFlow, PyTorch), and computer vision libraries (e.g.,OpenCV). Video datasets containing annotated footage of smoke in various conditions, used for training and testing the model**.** Budget allocation for software, hardware, personnel, and infrastructure required to support the project.

B. Activity

Video frames are preprocessed, which can include resizing, grayscale conversion, and background subtraction to make the detection more robust.

Efficient deep CNNs, such as EfficientNet, MobileNet, or lightweight custom models, are often chosen for their ability to process images quickly with relatively low computational costs.

The CNN model processes each frame to detect the presence of smoke. This step involves using convolutional layers to extract features specific to smokeSmoke detection in outdoor surveillance for forest fire prevention, indoor fire detection in warehouses or homes, and industrial safety monitoring in facilities with potential fire hazards.

C. Objectives

Achieve rapid detection of smoke in video frames to allow early intervention and response to potential fire hazards. Pinpoint the exact location of smoke in video frames, allowing responders to know precisely where the smoke is emerging. Reduce the need for human monitoring by providing reliable automated alerts with minimal false alarms.

D. Schedule

In the context of "Identify and consult stakeholders to determine the specific requirements and schedule," schedule refers to the timeline or roadmap for the project's activities.

During this initial step, stakeholders and project planners discuss and outline how long each phase will take, key deadlines, and when certain deliverables should be completed. This helps ensure that every party involved has a clear understanding of project expectations, milestones, and overall timeframe. The schedule becomes a guiding tool to track progress and ensure that each phase aligns with the project’s goals and resources.

III. PROBLEM FACED IN PROJECT MANAGEMENT:

A. RCPSP- Resource Constrained Project Scheduling Problem

1) *Hardware Limitations:* Deep CNNs are computationally intensive, often requiring GPUs or specialized hardware for training and real-time processing. Budget or equipment limitations may restrict access to necessary hardware, slowing down development and affecting real-time deployment performance.
2) *Time Constraints:* Developing, training, and testing deep CNN models for smoke detection can be time-consuming. If there is a strict timeline for deploying the system, resource constraints may limit time available for optimizing the model, potentially affecting its accuracy and robustness[3].
3) *Data Availability and Labeling:* Collecting and labeling large datasets for training is resource-intensive. Limited data resources can reduce model accuracy, especially in varying lighting or environmental conditions, leading to potential inaccuracies in smoke detection and localization.
4) *Budget Constraints:* Funding limitations may restrict the ability to access high-quality datasets, hire skilled personnel, or acquire necessary software and hardware tools for efficient deep learning model development and deployment[2].
5) *Personnel and Skill Shortages:* Developing a deep learning-based surveillance system requires specialized skills in AI, computer vision, and system integration. A shortage of skilled personnel may slow down development or limit the ability to troubleshoot issues, especially with real-time optimization[5].
6) *Maintenance and Long-Term Scalability:* Resource constraints may impact the ability to support ongoing maintenance, updates, and potential scaling of the system across multiple sites, affecting the system's reliability over time[1].

B. Software Project Scheduling Problem (SPSP)

1) *Task Dependencies:* This project requires sequential phases such as data collection, model training, testing, and integration. Dependencies between these tasks (e.g., data preprocessing must be complete before model training) can complicate scheduling, as delays in one phase can cascade and affect the entire project timeline.
2) *Resource Allocation:* Efficient scheduling must consider resource limitations, such as availability of skilled personnel, hardware (e.g., GPUs for model training), and budget. For example, allocating GPU resources efficiently between training and testing phases can reduce idle time, but limited hardware could still create bottlenecks, delaying the project[4][1].
3) *Time Constraints for Iterative Development:* Deep CNN projects often require iterative tuning and testing to optimize model performance, but each iteration takes time and resources. Scheduling these iterations is challenging, as it's difficult to predict how many rounds of optimization may be needed to reach desired accuracy.
4) *Balancing Task Duration and Quality:* Some tasks, like hyperparameter tuning or model optimization (e.g., pruning or quantization for efficiency), could take longer to perfect. Project scheduling must balance these tasks' time constraints with the need for a highperforming system[4]. Cutting down time here could compromise the model's accuracy or real-time processing capability.
5) *Risk of Task Overlaps:* Due to time constraints, some tasks might need to overlap, such as beginning model integration with the surveillance system before testing is complete. This can introduce risks, as undetected bugs or issues in the model might complicate the integration process and require rework[6].
6) *Contingency Planning for Potential Delays:* Unexpected delays, such as extended model training times, unavailability of datasets, or difficulties in collecting smoke-related video footage, can disrupt the schedule. SPSP involves building flexibility into the schedule, allowing adjustments for unforeseen delays while staying within project deadlines.
7) *Skill-Specific Scheduling:* Different phases require specific skills (e.g., data science for model training, software engineering for system integration). Scheduling in a way that efficiently utilizes available personnel with the right skills is essential but challenging, especially if certain personnel are only available for limited times or shared with other projects[2].

IV. METHODOLOGIES FOR SOLVING SPSP

A. Genetic Algorithm

Genetic Algorithm (GA) refers to an optimization technique inspired by the process of natural selection. It is used to find the most efficient solutions for improving the performance of the deep learning model, particularly when dealing with complex and large solution spaces, such as optimizing hyperparameters, model architecture, or feature selection.

Key Aspects of Genetic Algorithm in this Context:

1) *Optimization of Hyperparameters:* In deep CNNs, the performance of the model depends heavily on hyperparameters like learning rate, batch size, number of layers, and kernel sizes. A GA can evolve different combinations of these parameters to find the most optimal set for smoke detection[7].
2) *Model Architecture Search:* GA can be used to discover the best structure for the CNN (such as the number of layers, the size of filters, and the type of layers used). It generates a population of different architectures, evaluates their performance, and iterates on the best solutions.
3) *Feature Selection:* Smoke detection models need to differentiate between various objects and environmental factors. GA can help in selecting the most relevant features or filters, discarding unnecessary ones, and improving the model's ability to accurately detect and localize smoke while maintaining efficiency[1].
4) *Optimization of Pruning and Quantization:* Once a CNN model is trained, GA can optimize pruning (removing unimportant connections) and quantization (reducing the precision of model parameters) to make the model more lightweight for real-time deployment on surveillance devices, without losing much accuracy.
5) *Improvement of Detection and Localization:* GA can fine-tune the thresholds for detecting and localizing smoke in video frames. This involves adjusting parameters that balance sensitivity (detecting all smoke) with specificity (minimizing false positives) to ensure high-quality results[4].

V. PREEMPTABILITY

Imagine a video surveillance system running on an edge device with limited CPU power. The system is continuously analyzing video frames for smoke detection. If the system is in the middle of processing background tasks (e.g., logging data or analyzing historical video), it may "preempt" these tasks to allocate resources to analyzing new video frames for smoke detection.

Once the smoke detection task is completed, the system can resume the background tasks without losing data or functionality.In summary, preemptability in this context ensures that the smoke detection and localization system remains responsive and can prioritize urgent tasks in a time-sensitive environment while efficiently managing resources[5][2].

VI. CONCLUSION

The integration of efficient deep convolutional neural networks (CNNs) for smoke detection and localization in video surveillance applications has proven to be a promising solution for enhancing safety and automation in various environments, including industrial sites, public buildings, and urban monitoring systems. This approach leverages the power of deep learning to not only detect smoke patterns in video streams but also to accurately localize the smoke within frames, providing valuable insights for real-time decision-making.In conclusion, deep CNNs offer a robust solution for smoke detection and localization in video surveillance applications, with the potential to greatly enhance safety protocols and improve response times in critical situations. By addressing resource constraints, optimizing model efficiency, and refining the system's ability to operate in real-time, these systems can be deployed effectively across various applications, ensuring a safer and more automated monitoring environment.

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