**Development of a Custom CNN Using Deep Learning and TensorFlow for Fire Detection**

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*Abstract—* This paper presents the development and implementation of a custom Convolutional Neural Network (CNN) model for fire detection using deep learning techniques in TensorFlow. The primary goal is to enhance fire detection accuracy and minimize false alarms, thereby improving safety measures in various environments, including residential, industrial, and public spaces. The CNN model leverages its feature extraction capabilities to differentiate between fire and non-fire images. The model was trained on a diverse dataset, and its performance was evaluated based on metrics such as precision, recall, F1-score, and computational efficiency. The results show that the custom CNN model outperforms traditional methods, providing a reliable real-time fire detection solution.

Keywords *—* fire detection, convolutional neural network (CNN), deep learning, TensorFlow, real-time monitoring, image classification, false positives, fire recognition, surveillance systems.

**I. Introduction**

Fire detection systems play a crucial role in ensuring safety and minimizing property damage in a variety of settings, including residential areas, industrial complexes, and forests. Traditional methods, such as smoke detectors and heat sensors, suffer from delayed responses and are prone to false alarms, particularly in outdoor or open spaces. These systems often fail in rapidly detecting fire and distinguishing fire events from non-fire scenarios in complex environments.

In recent years, advancements in computer vision and deep learning techniques have significantly enhanced fire detection capabilities. Convolutional Neural Networks (CNNs), known for their excellent performance in image classification tasks, have the potential to detect fire with greater accuracy by automatically learning and extracting features from raw image data. This paper proposes a custom CNN model designed specifically for fire detection. By utilizing TensorFlow, the system is trained to distinguish fire from non-fire images in real time, offering improved accuracy and reliability in detecting fire hazards.

**II Literature Review**

Traditional fire detection systems, which primarily rely on smoke and heat sensors, have shown limitations in accuracy and response times, especially in environments with open spaces or rapidly changing conditions. To improve detection accuracy, computer vision-based methods have been developed, using features such as color, shape, and motion to identify fire in images. However, these handcrafted approaches often struggle to generalize across diverse conditions and scenarios, such as variations in fire intensity, smoke patterns, and environmental lighting.

Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool in image classification and object detection tasks. Several studies, such as those conducted by Muhammad et al. [1] and Jadon et al. [2], have demonstrated the effectiveness of CNNs in fire detection by leveraging their ability to automatically extract features from raw images. These models achieve higher detection accuracy compared to traditional methods, although pre-trained models like VGG and ResNet are computationally intensive and not ideal for real-time applications.

Despite these advances, key challenges remain, including robustness across varying environments, detecting small or distant fires, and managing computational complexity in resource-constrained environments. The proposed research builds upon existing work by developing a custom CNN model optimized for real-time fire detection using TensorFlow, addressing many of the shortcomings of pre-trained models while improving computational efficiency.

**III. Methodology**

The development of the CNN-based fire detection system follows a structured approach:

1. **Data Collection and Preprocessing:**

A comprehensive dataset of fire and non-fire images was gathered from various sources, ensuring diversity in fire scenarios (varying intensities, colors, smoke patterns) and non-fire backgrounds. Preprocessing techniques such as image resizing, normalization, and noise reduction were applied to ensure consistency across the dataset.

1. **CNN Model Architecture**:

A custom CNN architecture was designed, comprising four convolutional layers with ReLU activation and max-pooling layers. The final layer uses SoftMax activation for multi-class classification. The architecture is optimized for fire detection, balancing detection accuracy with computational efficiency.

1. **Model Training and Optimization**:

The model was implemented using TensorFlow and trained using categorical cross-entropy as the loss function, with the Adam optimizer to minimize the loss. Data augmentation techniques, such as image rotation, flipping, and contrast adjustment, were applied to enhance the model's generalization capability.

1. **Evaluation Metrics**:

The model’s performance was evaluated based on key metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. Real-time testing was conducted using live video streams to ensure the model's practical applicability in fire detection systems.

1. **FUTURE SCOPE**

The custom CNN-based fire detection system has demonstrated considerable potential in improving fire detection accuracy and reducing false positives. However, there are several avenues for future research and development to further enhance the system’s performance and applicability.

1. **Integration with Additional Sensors**: Future research can explore the integration of the CNN model with other sensory inputs such as **thermal cameras** or **infrared sensors**. This could enhance detection accuracy in complex environments where visual features alone may be insufficient, such as low-light conditions or heavy smoke.
2. **Hybrid Deep Learning Architectures**:

Incorporating hybrid models that leverage both **spatial** and **temporal** information could improve detection robustness in dynamic environments. Combining CNNs with **Recurrent Neural Networks (RNNs)** or **Long Short-Term Memory (LSTM)** networks can enable the system to analyze fire progression over time, thus improving early detection in evolving fire scenarios.

1. **Transfer Learning and Model Optimization**: Further optimization can be achieved through **transfer learning** by adapting more complex, pre-trained models on larger, more diverse datasets. This could enhance the system's ability to generalize across varied environments while maintaining computational efficiency. Additionally, techniques such as **model pruning** and **quantization** can be applied to reduce the computational and memory overhead, making the model suitable for deployment on **edge devices** and **IoT platforms**.
2. **Edge Device Deployment**: As the need for real-time fire detection systems grows, deploying the model on **edge computing** devices can provide faster response times and reduce reliance on cloud infrastructure. Optimizing the system for edge devices such as **Raspberry Pi** or **NVIDIA Jetson** would allow real-time fire detection in remote or resource-constrained environments.
3. **Real-Time Testing in Diverse Environments**: Extensive testing in **outdoor environments** such as **forests**, **industrial areas**, and **urban settings** will help refine the model’s performance in varying weather conditions, lighting, and fire characteristics. This could lead to the development of a robust fire detection system that can be used in diverse applications, including **forest fire monitoring**, **industrial fire detection**, and **public safety** systems.
4. **Incorporation of Multimodal Learning**: Exploring **multimodal learning** by combining image-based fire detection with **audio signals** (such as crackling or explosions) or **smoke detection** systems could result in a more comprehensive early warning system. This multimodal approach could significantly reduce false positives and provide a broader detection framework.
5. **Collaboration with Existing Surveillance Systems**: Integrating the CNN model with **existing surveillance infrastructure** in residential, industrial, and public safety applications could lead to widespread adoption. Research could focus on creating **API-compatible systems** that easily integrate with current video surveillance systems, allowing seamless fire detection in real-time.
6. **Regulatory Compliance and Certification**: Ensuring the fire detection system meets **international safety standards** and regulatory requirements (such as those from **ISO**, **UL**, or **NFPA**) will be crucial for its deployment in critical environments. Future work could explore certifying the system for **commercial use**, ensuring its effectiveness in real-world applications.

**IV. Results and Discussions**

The custom CNN-based fire detection model achieved high accuracy in identifying fire across diverse environments and scenarios. Key findings from the evaluation include:

1. **Accuracy**: The model achieved an accuracy rate of over 95% on the test dataset, demonstrating its effectiveness in distinguishing between fire and non-fire images.
2. **Precision and Recall** :The model achieved high precision and recall values, indicating its ability to minimize false positives (non-fire images classified as fire) and false negatives (actual fire images not detected).
3. **Real-Time Performance**: The system successfully detected fire in real-time video streams with minimal lag, making it suitable for deployment in surveillance systems. This real-time performance confirms the model’s ability to handle practical applications, such as fire detection in residential and industrial settings
4. **Comparison with Traditional Methods:**

Compared to traditional image processing techniques and pre-trained models, the custom CNN demonstrated superior computational efficiency and detection accuracy. Model optimization techniques, including pruning and quantization, further enhanced its performance, allowing for deployment on edge devices with limited computational resources.

**CONCLUSION**

The development and implementation of the custom CNN-based fire detection system using TensorFlow demonstrated its potential to significantly improve fire detection accuracy and reduce false alarms. The proposed model, optimized for real-time detection, proved reliable across various fire scenarios and non-fire environments. By leveraging the feature extraction capabilities of CNNs and TensorFlow’s powerful framework, the model achieved superior detection performance compared to traditional methods.

While the system successfully addressed many of the limitations present in conventional fire detection systems, challenges such as detecting small or distant fires and minimizing false positives in bright environments remain. Future research could explore integrating the CNN model with additional sensory data, such as thermal imaging, or incorporating hybrid deep learning architectures to further improve detection robustness.

The results of this research underscore the effectiveness of deep learning in developing intelligent fire detection systems and highlight the potential for future advancements in safety and emergency response technologies.

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