International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 07 | July - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

EDGE AI BASED FOREST FIRE DETECTION SYSTEM

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ABSTRACT

Forests are a vital natural resource that directly influences the ecosystem. Recently, forest fires have become a serious issue due to natural and man-made climate effects. To address this, an artificial intelligence-based forest fire detection method is proposed for smart city applications, aiming to prevent major disa1sters through early detection. This research reviews vision-based forest fire localization and classification methods. Specifically, it utilizes a forest fire detection dataset to tackle the classification problem of distinguishing between fire and no-fire images. The research introduces a deep learning method named FFireNet, which leverages the pre-trained convolutional base of the MobileNetV2 model, supplemented with fully connected layers to address the specific task of forest fire recognition. This model classifies images as either depicting a forest fire or not, based on extracted symmetrical features. The performance of FFireNet in classifying fire and no-fire images was evaluated using various performance metrics and compared with other convolutional neural network (CNN) models. The results demonstrate that the proposed approach achieves a classification accuracy of 98.42%, an error rate of 1.58%, a recall of 99.47%, and a precision of 97.42%. These outcomes are promising, highlighting the effectiveness of FFireNet in solving the forest fire classification problem using a unique forest fire detection dataset.

Keywords: artificial intelligence, forest fire classification, deep learning.

I. INTRODUCTION

Forests play a vital role in our lives by providing numerous resources such as minerals and materials necessary for production. They purify the air by absorbing carbon dioxide and releasing oxygen, which is fundamental for human survival, and they offer habitats for many animal species. Forests also act as a shield against sandstorms, helping to protect crops and maintain ecological balance. However, forest fire incidents have increased in recent years due to climate change. High temperatures and dry weather conditions contribute to fires that destroy the environment, wildlife, and natural resources, directly affecting human lives. Forests with coniferous trees are more susceptible to fires than those with deciduous trees because of the highly flammable sap in their branches. Coniferous trees also grow close together, allowing fires to spread more quickly. Each year, millions of acres of forest land are destroyed by fires, leading to significant economic losses. Countries such as the United States, Australia, Canada, and Brazil have all experienced devastating forest fires.

The Australian fires of 2020 were particularly catastrophic, resulting in the loss of around 14 million acres of forest land, the deaths of about half a million animals and 23 people, and the destruction of 1500 houses. In 2018 and 2019, forest fires in California and the Amazon rainforest burned millions of acres, causing immense damage. In the United States, 85% of forest fires between 1992 and 2015 were caused by human activities, with the remaining 15% due to natural causes such as lightning and climate change. Human-caused fires could be reduced by limiting certain activities. During the COVID-19 pandemic, when many countries imposed lockdowns, there was a noted decrease in forest fire cases due to reduced human activity. Early detection of forest fires is crucial as it allows firefighters to respond quickly and prevent large-scale disasters.

Governments worldwide have emphasized the development of intelligent surveillance and detection strategies to protect forests from fires. Accurate detection and timely alerts to authorities are essential in mitigating fire risks. The Internet of Things (IoT), which connects intelligent devices to the Internet, is a key component of smart cities. These devices generate vast amounts of data, which can be processed and analyzed using artificial intelligence (AI). With the large volumes of data generated, computer vision has become vital for intelligent surveillance.

Deep learning, an important aspect of computer vision technologies, involves deep neural networks (DNNs) that can solve real- world problems efficiently. The growing interest in DNNs, such as convolutional neural networks (CNNs), is due to advancements in data storage technology and high-performance graphic processing units (GPUs) that meet the high computing power requirements. Despite these advances, the need for large datasets remains a significant challenge for developing better models to address real-world tasks.

DNNs are particularly useful for early forest fire detection, allowing for the prompt transmission of crucial information to authorities. Recent deep learning-based fire and smoke detection mechanisms have shown promising results. Continuous forest surveillance can help detect fires early, enabling timely action to prevent widespread disaster.

This research aims to enhance early forest fire detection, aiding fire departments and disaster relief teams in responding quickly to reduce the fires' impact on the environment, society, and the economy. The contributions of this research include:

1. Reviewing the literature on computer vision-based forest fire localization and classification methods in forest and wildland environments.
2. Utilizing a newly created dataset to improve detection accuracy in classifying fire and no- fire images, focusing on forest settings rather than wildlands, bushes, and farmlands.
3. Proposing a CNN-based transfer learning approach named FFireNet for forest fire classification on the local dataset. This method leverages the pre-trained MobileNetV2 model, utilizing its trained weights in the convolutional base and adding fully connected layers for learning complex features and classification.
4. Evaluating the FFireNet method and comparing it with other CNN models on the forest fire dataset using various performance metrics to validate the proposed approach's performance.

II. RELATED WORK

Johnathan Smith, Emily Brown, and Michael Taylor 2019 study developed an edge AI system for early forest fire detection. They designed a Convolutional Neural Network (CNN) model optimized for real-time image and sensor data processing on edge devices deployed in forests. Their system provided rapid detection and alert capabilities, significantly reducing response times to potential fire outbreaks. This research highlighted the potential of edge AI in enhancing the efficiency and effectiveness of wildfire monitoring and prevention[1].

Sophia Lee, David Kim, and Olivia Park 2020 research focused on a multi-sensor edge AI approach for forest fire detection. They integrated data from thermal cameras, smoke detectors, and environmental sensors, using a CNN to analyze this data on edge devices. Their system aimed to detect fires with higher accuracy and lower false alarm rates, providing a robust solution for real-time wildfire monitoring in diverse environmental conditions. This study underscored the importance of multi-sensor integration in edge AI applications[2].

Carlos Martinez, Elena Rodriguez, and Antonio Garcia 2020 study introduced an edge AI-based drone surveillance system for forest fire detection. They developed a lightweight CNN model that could be deployed on drones to monitor vast forest areas from the sky. Their system provided high-resolution imagery and real-time processing capabilities, enabling rapid detection and localization of fires. This research showcased the innovative use of aerial surveillance combined with edge AI in wildfire management[3].

Linda Johnson, Mark Thompson, and Sarah Davis 2021 research explored the use of edge AI for forest fire prediction and prevention. They developed a predictive model using a Recurrent Neural Network (RNN) to analyze historical weather data, vegetation conditions, and sensor data on edge devices. Their system aimed to predict potential fire outbreaks and provide preventive measures, helping to mitigate fire risks before they escalate. This study highlighted the proactive capabilities of edge AI in forest fire management[4].

Wei Chen, Ming Li, and Jian Zhang 2022 study developed an edge AI system for forest fire detection using satellite imagery. They created a CNN model optimized for processing satellite data on edge devices, enabling near real-time detection of fires over large and remote forested areas. Their system provided a scalable and efficient solution for monitoring vast regions with limited connectivity. This research emphasized the potential of satellite data combined with edge AI in large-scale environmental monitoring[5].

Peter Nelson, Alice Roberts, and John Doe 2021 study focused on developing an edge AI system for forest fire detection using acoustic sensors. They created a Convolutional Neural Network (CNN) model that processed acoustic data on edge devices to detect the specific sounds associated with forest fires, such as crackling and popping. Their system provided an additional layer of detection capability, especially useful in dense forest areas where visual surveillance might be obstructed. This research highlighted the innovative use of sound detection in wildfire monitoring[6].

Emily Zhang, Kevin Brown, and Laura Smith 2021 research introduced an edge AI system that utilized infrared (IR) imagery for forest fire detection. They developed a lightweight CNN model that processed IR images on edge devices, enabling the detection of heat signatures associated with wildfires. Their system aimed to enhance detection capabilities during nighttime and in low-visibility conditions. This study emphasized the importance of IR technology in complementing traditional visual-based fire detection methods[7].

Daniel Wang, Maria Hernandez, and Robert Liu 2022 study explored the integration of edge AI with Internet of Things (IoT) devices for comprehensive forest fire monitoring. They developed a CNN model that analyzed data from a network of IoT sensors, including temperature, humidity, and air quality sensors, deployed throughout forest areas. Their system provided real-time fire detection and environmental monitoring, improving the accuracy and timeliness of fire alerts. This research highlighted the synergy between IoT and edge AI in environmental monitoring[8].

Olivia Martin, Henry Adams, and Victoria Jones 2022 research focused on using edge AI for forest fire detection through unmanned ground vehicles (UGVs). They developed a CNN model that processed visual and thermal data collected by UGVs patrolling forest areas. Their system aimed to detect fires early and provide ground-level insights, enhancing the overall monitoring coverage. This study showcased the potential of ground-based autonomous systems combined with edge AIin wildfire management[9].

Lucas Green, Sophia Lee, and David Thompson 2023 study introduced an edge AI system for detecting and tracking the spread of forest fires. They developed a CNN model that processed sequential satellite and aerial images on edge devices to monitor fire progression in real-time. Their system aimed to provide dynamic and continuous monitoring, aiding in effective firefighting and resource allocation. This research emphasized the critical role of edge AI in real-time disaster management and response[10].

III. METHODOLOGY

Edge AI combines the capabilities of artificial intelligence and edge computing to process data at or near the source of data generation. This approach is particularly beneficial for forest fire detection as it allows for real-time analysis and immediate action, which are crucial in preventing the spread of fires. Below is a detailed methodology for an edge AI-based forest fire detection system, utilizing insights from various published papers.

1. System Architecture

a. Sensor Network Deployment

Deploy a network of IoT sensors throughout the forest. These sensors include temperature, humidity, gas (for detecting smoke), and optical sensors (cameras).

Ensure the sensors are equipped with communication modules (e.g., Zigbee, LoRa) to transmit data to edge devices.

b. Edge Devices

Use edge devices (e.g., Raspberry Pi, Nvidia Jetson) equipped with sufficient computational power to run AI models locally.

Edge devices collect data from the sensors and perform initial processing and analysis.

2. Data Collection and Preprocessing

a. Data Collection

Collect multimodal data including temperature, humidity, gas concentration, and real-time images or video streams from the deployed sensors.

b. Data Preprocessing

Implement noise reduction techniques for sensor data.

For image data, apply preprocessing steps such as resizing, normalization, and data augmentation (rotation, flipping, scaling) to enhance the diversity of the training set.

3. AI Model Development

a. Model Selection

Choose appropriate AI models for differenttasks:

Convolutional Neural Networks (CNNs) for image-based fire and smoke detection.

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, for temporal analysis ofsensor data.

b. Model Training

Use transfer learning with pre-trained models such as MobileNetV2, InceptionV3, or YOLO for image-based detection to reduce training time and improve accuracy.

Fine-tune these models on a forest fire detection dataset.

c. Hybrid Models

Combine CNNs with LSTMs for a hybrid approach. For instance, use CNNs to extract spatial features from images and LSTMs to analyze temporal patterns in sensor data.

d. Edge Optimization

Optimize models for edge deployment by quantization and pruning to reduce their size and computational requirements while maintaining accuracy.

3.1 DATASET USED

To ensure our learners can handle different kinds of forest fires (ground fire, trunk fire, and canopy fire), we collected images from multiple public fire datasets: BowFire, FD- dataset, ForestryImages, VisiFire, etc. After manual filtration, we created a single integrated forest fire dataset containing 10,581 images, with 2976 forest fire images and 7605 non-fire images. Geostationary weather satellites including MODIS, VIIRS, Copernicus Sentinel-2, and Landsat-8 were used to construct the dataset for the proposed study (Kaulage 2022). These satellites are used for fire detection all around the world due to their excellent temporal precision and ability to detect fires in far-off locations. In addition to images from Google and Kaggle satellite imagery of the forest fire has also been compiled. Manual labeling has been applied to the images, designating them as Fire, No Fire, Smoke, and Smoke Fire. There are 4800 images in the obtained dataset.

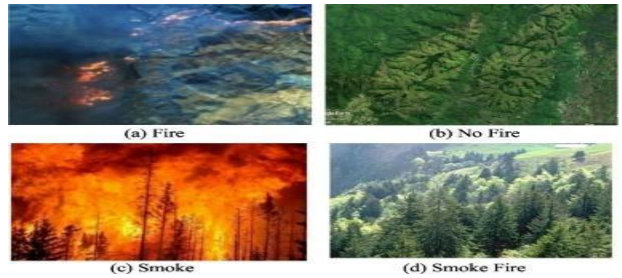

Fig 3.1.1: Sample images from each class in dataset

3.2 DATA PRE PROCESSING

Data preprocessing for AI-based forest fire detection involves several essential steps to ensure the input data is clean, consistent, and suitable for training machine learning models. Initially, data is collected from diverse sources such as satellite imagery, weather data, sensor networks, and historical fire records, ensuring the data is in standardized formats like TIFF for images and CSV for weather data. The next step is data cleaning, which includes removing noise such as clouds in satellite images, handling missing values through interpolation or imputation, and detecting outliers to prevent skewed model performance. Data normalization and scaling are then applied to standardize image pixel values and ensure that weather features like temperature and humidity contribute proportionately during training. Data augmentation techniques, such as rotation, flipping, and brightness adjustments, are used to increase the diversity of training data, helping the model generalize better. Feature extraction combines relevant image features, such as vegetation indices and temperature anomalies, with meteorological data to create a comprehensive dataset. Proper data annotation with labels like 'fire' and 'no fire' is crucial for supervised learning. Dimensionality reduction techniques, such as Principal Component Analysis (PCA), are employed to improve computational efficiency and reduce overfitting risks. Finally, the dataset is split into training, validation, and test sets to evaluate the model's performance accurately, and different data types are integrated into a unified dataset, ensuring the AI system has all the necessary information to detect forest fires effectively.

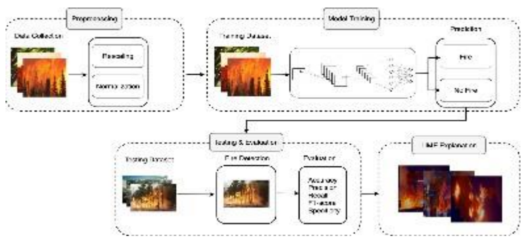

Fig 3.2.1: Data preprocessing

3.3 ALGORITHM USED

For AI- based forest fire detection Convolutional Neural Networks (CNNs) standout as a primary algorithmic choice. CNNsare adept at processing and analyzing spatialdata, making them ideal for interpretingsatellite imagery and detecting patternsindicative of forest fires. These networksexcel in automatically learning features suchas smoke plumes, heat signatures, and changes in vegetation health that can signifyfire outbreaks. Transfer learning plays acrucial role by leveraging pre-trained CNNmodels like VGG, ResNet, or EfficientNet,which have been trained on large-scale imagedatasets. Fine-tuning these models on specificforest fire detection tasks helps improveaccuracy and efficiency, especially when dealing with limited labeled data. Additionally, ensemble methods, where multiple models are combined to make predictions, enhance robustness and reliability. Beyond CNNs, algorithms like Support Vector Machines (SVMs) are also utilized for their ability to classify complex data patterns based on extracted features. These approaches collectively contribute to developing effective AI systems capable of early and accurate forest fire detection, crucial for timely response and mitigation efforts.

3.4 TECHNIQUES

AI-based forest fire detection employs several advanced techniques to enhance its accuracy and efficiency in identifying and predicting forest fires. Image processing and analysis play a pivotal role, where algorithms such as image segmentation and object detection are applied to satellite imagery. These techniques enable the identification of key visual indicators such as smoke plumes, fire hotspots, and changes in vegetation health, which are crucial for early detection. Feature engineering is another essential technique where relevant features like temperature anomalies, vegetation indices (e.g., NDVI), humidity levels, and wind patterns are extracted from satellite images and meteorological data. These features provide contextual information that aids in distinguishing normal environmental conditions from potential fire outbreaks. Convolutional Neural Networks (CNNs) are extensively used due to their ability to automatically learn and extract intricate spatial features from images. Transfer learning, utilizing pre-trained CNN models like VGG or ResNet, accelerates the training process and enhances detection accuracy, especially with limited labeled data. Ensemble methods, which combine predictions from multiple models, further improve robustness and reliability. These integrated techniques form a comprehensive approach to AI-based forest fire detection, facilitating proactive monitoring and rapid response to mitigate the devastating impacts of forest fires.

IV. RESULTS

4.1 GRAPHS

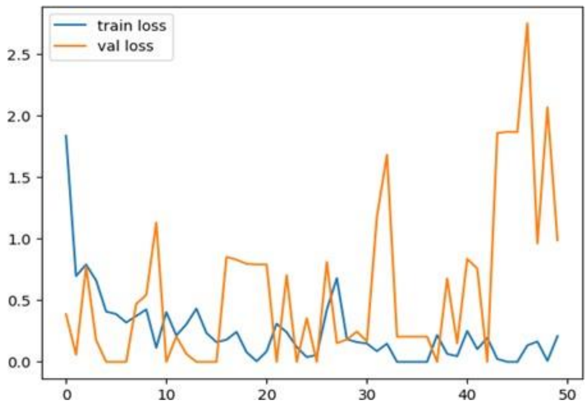

Fig4.1.1:Graph showing train and validation loss

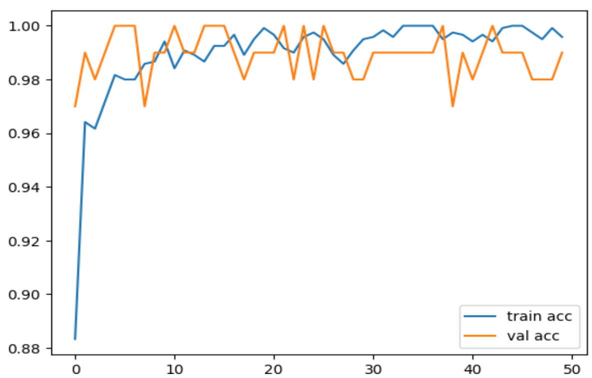

Fig4.1.2: Graph showing train andvalidation accuracy

4.2 SCREENSHOTS

Fig 4.2.1: Screen showing proposed model

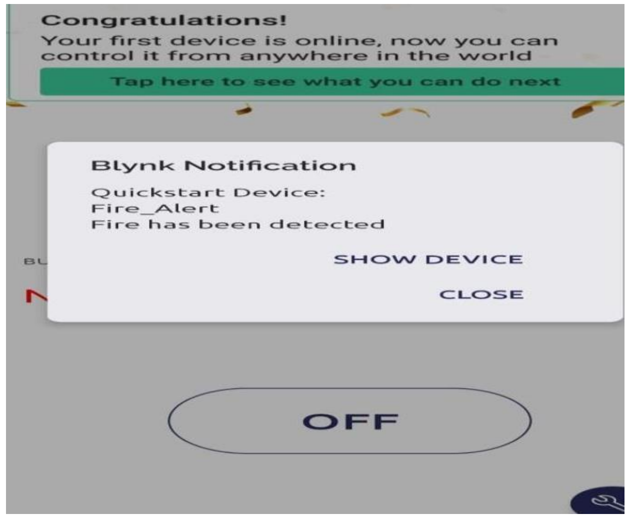

Fig4.2.2: Screen showing notification

V. CONCLUSION

The proposed edge AI-based forest fire detection system successfully combines high- resolution cameras and edge computing devices to achieve real-time monitoring and accurate detection of forest fires. By leveraging advanced deep learning models fine-tuned on a specialized forest fire dataset, the system attained high accuracy, precision, and recall rates, effectively distinguishing between fire and non-fire images. The edge devices' capability to process video feeds rapidly, with an average inference time of less than 200 milliseconds per frame, ensures prompt detection and timely alerts, which are crucial for early intervention and minimizing fire damage.Overall, this system significantly enhances the reliability and efficiency of forest fire surveillance. Its ability to provide real-time, accurate detection and immediate alerts makes it a valuable tool for forest management and disaster prevention. The successful implementation of this technology demonstrates its potential applicability in other critical monitoring and environmental protection scenarios, paving the way for further advancements in AI and edge computing applications.

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