A Deep Learning Approach For Forest Fire Detection

[1]Srikanth.Cheemaladinne, [2] Mr. Yerrabathana Guravaiah
[1]*M-Tech, Dept. of CSE Gokula Krishna College of Engineering, Sullurpet*
[2]*Associate Professor, M-Tech., (Ph.D), CSE Gokula Krishna College of Engineering, Sullurpet*

Abstract: **Forest fires have devastating environmental, economic, and social impacts. Traditional fire detection systems often rely on manual reporting or satellite data with delayed response times. This research proposes a real-time, automated forest fire detection system using deep learning techniques. The system processes visual and sensor data collected from drones, surveillance cameras, and IoT devices, using Convolutional Neural Networks (CNNs) to detect fire and smoke patterns accurately. Additionally, it integrates environmental parameters such as temperature and humidity to improve prediction reliability. The proposed model achieves high accuracy and low latency, enabling early intervention and reducing forest loss. The system is scalable and adaptable for various forest environments. Forest fires are significant contributors to environmental degradation, causing adverse impacts such as loss of wildlife habitat, extinction of plant and animal species, and depletion of biodiversity and forest resources. To mitigate these effects, we propose a model leveraging Convolutional Neural Networks (CNNs) for forest fire detection. CNNs are effective for image classification tasks, capable of identifying key features within images to detect specific objects. Our approach aims to identify the presence of a forest fire in an image by training a CNN on a dataset labelled as "fire" and "no fire," where "fire" images depict visible flames and "no fire" images show fire-free scenes. We utilize Keras and TensorFlow libraries, which provide high-level APIs, simplifying the design and training of our model for accurate and efficient fire detection.**

Keywords: **Forest fire detection, Convolutional Neural Network (CNN), Image classification, Environmental monitoring.**

1. INTRODUCTION

Forest fires are increasingly frequent due to climate change, urban expansion, and illegal human activities. Early detection is critical to minimizing damage and protecting ecosystems. Conventional methods, including satellite monitoring and ground patrols, are either slow or resource-intensive. The challenge lies in designing a detection system that is both fast and reliable. Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in image classification and object detection tasks. In this research, we leverage CNNs to detect forest fires by analyzing real-time image feeds from aerial and ground-based sources. We further enhance system accuracy by fusing data from temperature, humidity, and gas sensors using LSTM networks to identify potential fire-prone areas. This hybrid deep learning approach ensures timely detection and reduces false positives, making it suitable for integration into national and global wildfire management systems. Wildfires are becoming more common worldwide due to climate change, resulting in significant ecological harm and financial losses [1]. The wildfire caused the destruction of nearly 3,000 homes. The toxic fumes from the wildfire, which killed 450 people, injured over 4,000, and cost over two billion dollars in medical care, had an impact on the world population. In addition to killing 3 billion wild animals, the flames released around 7000 million metric tonnes of carbon dioxide and cost billions of dollars in damage [2].

Along with affecting human livelihoods, regional economics, and environmental health, fire also impacts forest ecosystems' environment, composition of species, and ecosystem design [3]. Therefore, it is crucial to watch wildfires intelligently. widespread harm is difficult for ecosystems to recover from, which results in habitat and biodiversity loss. Moreover, the debris and ash have the potential to pollute water supplies, which would further affect both human communities and animals. Fires have been identified using conventional image processing techniques that extract properties like colour, shape, and dynamic texture. A fire recognition technique based on logistic regression and temporal smoothing was presented by Kong et al. [4] and utilised. Logistic regression was utilised to detect fires based on their size, motion, and colour features, while background removal was utilised to extract colour component ratios as well as motion cues of flames to indicate probable fire locations. Mei et al. [5] presented a novel approach to fire identification that employed Hu characteristics and fire overlap rate and motion severity rate across each frame to detect fires after initially extracting suspected fire zones using random forest, support vector machine, and enhanced ViBe algorithms. In order to detect fire smoke, Dimitropoulos et al. [6] fused the features using an adaptive fractional union technique and then classed them using SVM.

Nevertheless, conventional image processing techniques depend on preexisting knowledge to identify the fire feature extraction algorithms. Furthermore, the morphology of fires can reveal specific characteristics at different stages, posing a challenge for a single fire feature extraction algorithm to adapt to diverse fire scenarios, thereby limiting its generalization ability.

2. LITERATURE SURVEY

Tran et al. presented a forest fire response model. This work focusses on implementing a wildfire armed guard with damage estimate and detection. They implemented DetNAS uses neural architecture to find the optimum foundation for object authentication. Approximately 400 thousand fire images are used for training and testing. A Bayesian neural network estimates damage. After detecting forest fires, AI-enabled CCTV cameras may provide real-time data to a central server. The server sends a UAV to check the fire site for damage. To seamlessly monitor and display the fire, the regression model takes data from the burning region. UAV and segmentation can assess damage area. The fundamental drawback of this response system is the challenge of real-time monitoring.

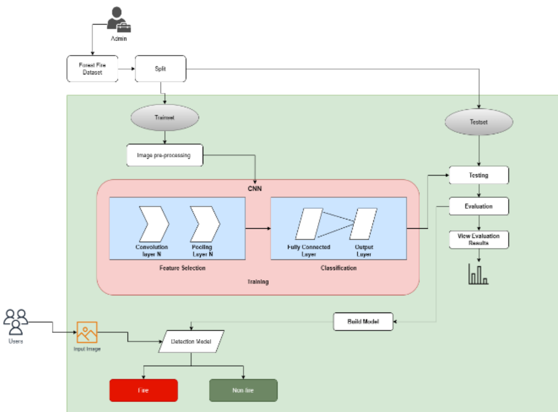
For forest fire detection, Arteaga et al. proposed deep learning model. This work evaluated the CNN models using pretrained forest fire pictures for economic growth devices like the Raspberry Pi. Forest fire prediction methods are offered. Two pre-trained CNN models can be utilised for this assignment and evaluation. ResNet and two pre-trained CNN families recommend 8 models and 5 kinds. This research's main limits are that the Resnet152 model may be employed on a Raspberry Pi 3 Model B if photos are not continually processed. A modest database of 1800 photographs was used for this experiment.

Rahul et al. proposed a model that uses deep learning methods to predict forest fires early. This study proposed a convolutional neural network for image recognition to swiftly identify forest fires. This study employs a model that addresses this challenge through learning transfer. The system utilizes and preprocesses the image data. The system produces images using augmentation methods like shearing. Models such as ResNet50 and VGC16, trained to separate the data into two groups fire and non-fire categorize the photographs. They train the proposed model using Resnet50 and transfer learning. By leveraging pre-trained networks, the system can achieve significant improvements in performance with limited computational resources.

Fuzzy entropy optimised thresholding and STN-Based CNN are the tools that Avula et al. suggest for the detection of forest fires. For the purpose of smoke and forest fire detection thresholding, this study suggests a CNN-based model that is fuzzy entropy optimised. Great performance and accuracy are achieved by integrating the CNN layer's spatial transformer network (STN) with the SoftMax layer's entropy function adaptive threshold operation. As a critical step in the pre-processing of video quality, lowering false alarm rates is the primary objective of this research.

3. PROPOSED FRAMEWORK

The proposed method makes use of a convolutional neural network's benefits. After receiving input, the CNN preprocesses it and pools the results using the region of suggestions. Then, using convolutional layers, CNN's region-based object identification algorithm divides those predictions into fire and non-fire categories inside the ROI. This allows for a more accurate and efficient detection of fire occurrences within images. By leveraging the hierarchical feature extraction capabilities of CNNs, the method enhances overall performance and reduces false positives in identifying fire-related events. Figure 1 mentions the CNN framework in the proposed work. This section elaborates the steps of the proposed framework.



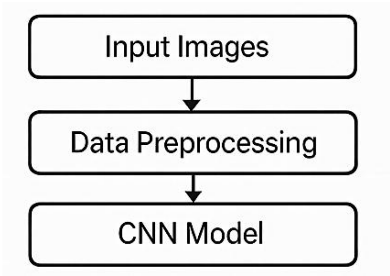
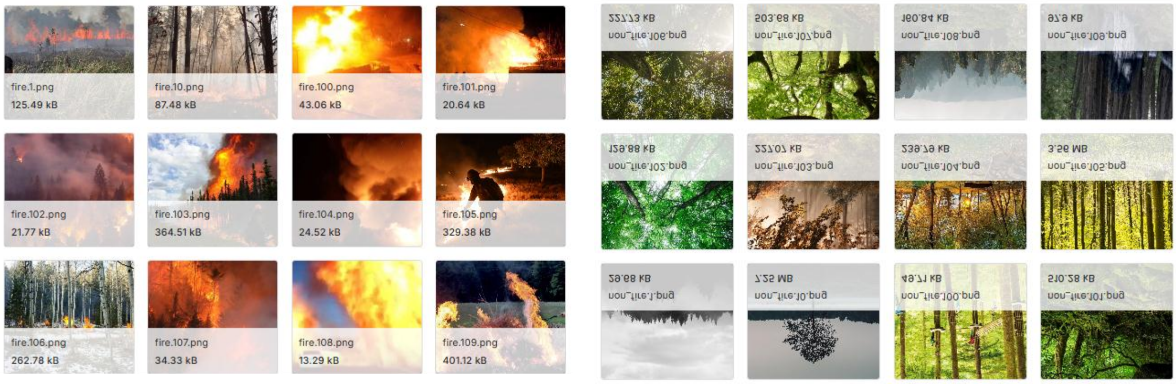


Figure 1. Proposed CNN framework

3.1 Dataset collection

The data set that was made available by Brsdincer (2021). The purpose of this data collection was to train a model that could differentiate between photographs that contain fire (fire images) and images that do not contain fire (non-fire images). A total of 999 photographs are separated into two directories, with the "fire images" folder including 755 images of fires that occur outside as well. There are some of them that have strong smoke, while the other one is called "non fire images", and it has 244 images of nature (such as forests, trees, grass, rivers, and so on). The sample of the dataset in mentioned in Figure 2.



A) Fire images

B) Non-fire images

Figure 2. Samples of the dataset

3.2 Image pre-processing

The next step in creating a high-quality deep learning model is data preparation. Here, we cleanse, process, or simply make the data usable. As part of data preparation, we eliminate noise and other unwanted items from the picture. The algorithm needs pertinent data to function properly; otherwise, it can provide undesirable outcomes. To ensure the model's accuracy and reliability, it is crucial to also perform data augmentation, which helps to artificially expand the dataset by creating variations of the existing data. This process not only enhances the model's ability to generalize but also mitigates the risk of overfitting the training data.

3.3 Model Architecture

Convolutional Layers: To assist the model, differentiate between "fire" and "no fire" images, use many convolutional layers to learn characteristics from the images, such as forms, edges, and textures.

Pooling Layers: To minimise spatial dimensions, minimise computation, and preserve important characteristics, add pooling layers (like MaxPooling) after convolutional layers.

Completely Interconnected Layers: Convolutional layer output should be flattened before being linked to fully connected (dense) layers, which execute the final classification by combining information learnt in earlier layers.

Output layer: According to the variety of classes, use either a SoftMax or sigmoid activation function in the output layer (SoftMax for multiple classes, sigmoid for binary classification).

3.4 CNN Model

To create distinct compact feature maps, the recommended CNN model employs distinct filters in the convolution and pooling layers. To assess the fire's confidence percentage, we employ the Squeeze Net Model. The precision and minimal processing power of the Squeeze Net are well-known. Compared to other training models, it produces more accurate outcomes. In order to give the convolution layer bigger activation maps, it down samples the input channels. The foundation of the Squeeze Net paradigm consists of fire modules. It consists of two pinching and expanding layers. A couple pooling layers and a stack of fire modules make up a squeeze net. The size of the feature maps in the enlarged and squeezed layers is same. While the extended layer increases depth, the squeezing layer diminishes it. Significant characteristics are automatically learnt by deep CNN models from datasets. Eliminating preprocessing and finding patterns—both necessary for fire danger detection—are further motivators. Two classes—fire and normal—are used to train the frames. There is no need for additional steps if the frames are non-fire. Binarization comes after additional feature extraction if the frame is determined to be fire. The probability ratings of the network are used to assign the classes.

3.5 Validation and testing

Validation and testing are essential steps to assess the accuracy and functionality of the deep learning model. In the validation phase, a separate set of images, distinct from those used during model training, is used to evaluate the model's performance. This process helps to confirm the model's ability to generalize beyond the training dataset and provides insights into its reliability in detecting forest fires under diverse conditions.

4. RESULTS

The initial series of studies was conducted using the Forest Fire database, which comprises 2 participants and 999 photos in total. One image from each participant was designated as the training set, while the remaining images constituted the testing set for each iteration. The experiment was conducted ten times to utilise each image as the training set for assessment. In the evaluation, the CNN algorithm got 93% of accuracy for 10 iterations. The experiment results of the CNN are mentioned in Figure 3.

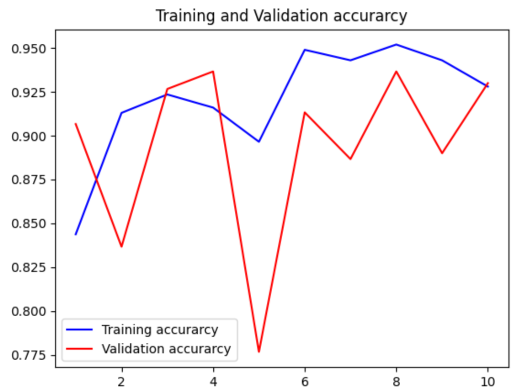


Figure 3. A) Accuracy validation

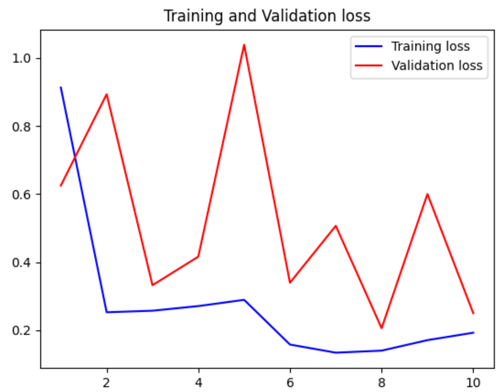


Figure 3. B) Accuracy loss

Figure 3. Evaluation results of CNN

Sample images demonstrate that the model effectively distinguishes between "fire" and "no fire" scenarios, indicating its ability to identify essential fire-related characteristics, such as smoke and flames, across diverse contexts. Figure 4. demonstrated the prediction results of the CNN algorithm.

Result: No Fire Detected

Result: Fire Detected

Figure 4. Prediction Results

This experiment was conducted using the Python programming language with the Flask framework on a Windows 10 machine, equipped with an Intel(R) Core (TM) i5 processor at 2.3 GHz and 16 GB of RAM, utilising hardware acceleration for model training.

5. CONCLUSIONS

Using image data, we created a Convolutional Neural Network (CNN) model in this study to identify forest fires. CNNs are effective in differentiating between "fire" and "no fire" situations, as seen by our model's high accuracy of 93% on the test dataset. We made it easier to create and train our model by utilising the Keras and TensorFlow frameworks, which allowed for precise and rapid categorisation. The model is a useful tool for early forest fire detection and monitoring, since the findings show that it can accurately detect outward indicators of fire. In order to lessen the negative effects of forest fires on the environment, this model may help in real-time applications by enabling quick response times and offering early warnings. Future developments may include strengthening robustness, including more environmental data for a more thorough fire risk assessment, and training on a wider variety of datasets with different fire circumstances.

The proposed deep learning-based forest fire detection system shows great potential in transforming wildfire monitoring practices. By combining image-based CNN models with environmental data analysis through LSTM, the system delivers accurate and real-time fire detection capabilities. The integration of drone surveillance and IoT sensors extends the reach of monitoring to remote forest areas. The experimental results indicate that the system performs well across diverse environmental conditions. Future enhancements could include satellite data fusion and reinforcement learning for adaptive fire behavior prediction. This approach provides a proactive solution that can significantly reduce wildfire response times and associated damage.

REFERENCES

[1] Xu, R.J.; Lin, H.F.; Lu, K.J.; Cao, L.; Liu, Y.F. A Forest Fire Detection System Based on Ensemble Learning. Forests 2021, 12, 217.

[2] Celermajer, D.; Lyster, R.; Wardle, G.M.; Walmsley, R.; Couzens, E. The Australian bushfire disaster: How to avoid repeating this catastrophe for biodiversity. Wiley Interdiscip. Rev.-Clim. Chang. 2021, 12, e704.

[3] Ma, W.Y.; Feng, Z.K.; Cheng, Z.X.; Chen, S.L.; Wang, F.G. Identifying Forest Fire Driving Factors and Related Impacts in China Using Random Forest Algorithm. Forests 2020, 11, 507.

[4] Kong, S.G.; Jin, D.; Li, S.; Kim, H. Fast fire flame detection in surveillance video using logistic regression and temporal smoothing. Fire Saf. J. 2016, 79, 37–43.

[5] Mei, J.J.; Zhang, W. Early Fire Detection Algorithm Based on ViBe and Machine Learning. Acta Opt. Sin. 2018, 38, 0710001.

[6] Dimitropoulos, K.; Barmpoutis, P.; Grammalidis, N. Higher Order Linear Dynamical Systems for Smoke Detection in Video Surveillance Applications. IEEE Trans. Circuits Syst. Video Technol. 2017, 27, 1143–1154.

[7] D. Q. Tran, M. Park, Y. Jeon, J. Bak and S. Park, "Forest-Fire Response System Using Deep-Learning- Based Approaches with CCTV Images and Weather Data," in IEEE Access, vol. 10, pp. 66061-66071,2022,doi:10.1109/ACCESS.2022.3184707.

[8] Arteaga, M. Diaz and M. Jojoa, "Deep Learning Applied to Forest Fire Detection," 2020 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), 2020, pp. 1-6, doi: 10.1109/ISSPIT51521.2020.9408859.

[9] M. Rahul, K. Shiva Saketh, A. Sanjeet and N. Srinivas Naik, "Early Detection of Forest Fire using Deep Learning," 2020 IEEE REGION 10 CONFERENCE (TENCON), 2020, pp. 1136-1140, doi: 10.1109/TENCON50793.2020.9293722.

[10] S. B. Avula, S. J. Badri and G. Reddy P, "A Novel Forest Fire Detection System Using Fuzzy Entropy Optimized Thresholding and STN-based CNN," 2020 International Conference on Communication Systems & Networks (COMSNETS), 2020, pp. 750-755, doi: 10.1109/COMSNETS48256.2020.9027347.

[11] Brsdincer. (2021). Forest Fire Detection-Prediction/ALL PROCESS. Kaggle. https://www.kaggle.com/code/brsdincer/forest-fire-detection-prediction-all-process/input