

Forest Wildfire Detection from Satellite Images using Deep Learning

Prajith A M¹ and Prashant Ankalkoti²

PG Student, Department of MCA, Jawaharlal Nehru New College of Engineering, Shivamogga, India¹
Assistant Professor, Department of MCA, Jawaharlal Nehru New College of Engineering, Shivamogga, India²
prajithgowda23@gmail.com and prashantsa@jnnce.ac.in

Abstract: Forest wildfires pose a significant threat to ecosystems, human lives, and infrastructure, and this project presents a deep learning-based approach for the early detection of forest wildfires from satellite images, employing data preprocessing, model training, and inference steps, where satellite images are pre-processed to enhance features and reduce noise, a deep learning model is trained using convolutional neural networks on a large dataset of labelled images, and the trained model is applied to new images in a sliding window manner to detect potential wildfire regions and generate a heatmap for visualization, resulting in a high accuracy detection system that surpasses traditional methods and aids in early warning and decision-making for fire management authorities

Keywords: Machine learning, deep learning, convolutional neural network, forest fire detection

I. INTRODUCTION

Early detection of wildfires is critical to the safety and security of environmental spaces and is one of the important and most large challenges in the government sector and forest fire managers. Forest fire is the important one is decreasing the space of the forest area. This fire detection technique also reduces human protocols and helps to monitor and protect the areas that are hard to protect. The new technique is used to facilitate the implementation of systems that allow monitoring is efficient in detailed areas, regardless of the state of the atmosphere or daytime. Satellite images also gave a fire monitoring tool, management, and finding the damaged tool for compliance with burn areas to understand a favourable fire range. The principle of classifying this fire, such as materials from the original fire, is to check the colour consistency.

The parameters that were adopted in our proposed system operation to analyse the forest fire, threshold value, the detection of matrix value, and the differential matrix value of the system. The forests as a whole have been greatly endangered by human activities. Area due to inaccessibility, lack of necessary equipment and shortage of manpower. Also, the constant monitoring of these forests is very tedious and nearly impossible. This module senses human and animal activity using infrared thermal imaging cameras. The IR sensor is used to monitor the entry and exit of humans or animals. Early forest fire detection is of great importance to avoid the huge damage of forests caused by fires. Early fire detection focuses on smoke detection. The forest area is gradually decreased because of increasing forest fire and human activities. The satellite sensor is used to collect the forest thermal image in different places and analyse the data in these images to detect the fire region if they occur. Image processing technique can effectively predict the fire in the forest. The input image is pre-processed to enhance the image quality, because the input image has the noise, so the pre-processing technique is used to eliminate the noise in this system and enhance the image quality.

The pre-processed image is taking to the segmentation process; it processes the image to adjacent the forest sub-area. In this system, the affected area is separately detected, and it gives the accurate forest fire in this system because the output image intensity is better to stabilize the average value of the image. In our proposed system we propose a deep learning method that uses a Convolutional Neural Network (CNN) to predict the forest fire detection. The convolutional layer is the main building block of the convolutional neural network. Usually, the layers of the network are fully connected in which a neuron in the next layer is connected to all the neurons in the previous layer. We are going to detect the fire in the forest result based on the accuracy which we get in train and test of the dataset-based CNN algorithm using that we show the graph result.

1.1 Problem statement

The detection of forest wildfires from satellite images is crucial for early intervention and effective mitigation of the damages caused by these disasters. However, traditional methods for wildfire detection often lack accuracy and timeliness, hindering prompt response and decision-making by fire management authorities. Therefore, there is a need for an advanced and efficient approach that utilizes deep learning techniques to detect forest wildfires accurately and in a timely manner, leveraging the wealth of information available in satellite imagery. The objective of this project is to develop a deep learning-based wildfire detection system that can analyse satellite images, classify fire and non-fire regions accurately, and generate timely alerts to support early warning systems and decision-making processes for fire management authorities.

II. RELATED WORK

Aditi Kansal, et al., 2015 [1], have proposed a system where different machine-learning techniques such as regression, SVM, neural networks, decision trees, etc. are compared. Wireless Sensor Networks. In WSNs, sensors are used to monitor specific environmental factors and transmit the resulting data to a ground station for analysis. The perfect sensor node uses little power, can collect data quickly, is reliable, inexpensive, and requires little maintenance. It also detects events, allowing for adequate and effective physical world sensing. By dividing the dataset into months, the method suggested in this research demonstrates how regression performs best for accurately identifying forest fires. This algorithm generates the result without processing the complete dataset and yields a low mean square error and large R-squared.

Medi Rahul, et al., 2020 [2], have proposed a convolutional neural network-based picture identification technique for early forest fire detection. Fire detection methods based on image processing systems have reached their peak and have replaced many conventional methods. In this study, a technique based on transfer learning is proposed for the early detection of forest fire. Two categories may be employed to appropriately classify the majority of photos using the suggested model: fire and no fire. ResNet50 is demonstrated to be a trustworthy model from DenseNet121, ResNet50 and VGG16. ResNet50 accurately classifies majority of these photos with a high training and testing accuracy of 92 and identifies the model's input image type.

Preeti T, et al., 2021 [3], have proposed Random Forest regression and hyperparameter tuning with the Randomized SearchCV algorithm which uses different subsamples of datasets that fit multiple decision trees and uses averaging to enhance control overfitting and prediction accuracy. The forest fire incidents are portrayed based on the study of the models using meteorological parameters. Various forest fire prediction methods (regression techniques) such as random forest, decision tree, artificial neural network (ANN) and support vector machine algorithm are compared in this paper. These models were implemented on the Python platform. By squaring the distances between the points and the regression curve to exclude any negative signs, mean square error calculates how near a regression curve is to a set of points. Experiments are conducted to obtain a various number of training and evaluation occurrences for wildfire prediction

A. Sheryl Oliver et al., 2020 [4], have proposed an approach for recognizing forest fires built on Convolution Neural Network (CNN). Numerous classification strategies have been put forth, however the models that have been suggested suffer from drawbacks that make them ineffective and unable to deliver accurate results. When compared to supervised machine learning techniques, which involve human data-training, a revolutionary convolution neural network algorithm offers great efficiency, accuracy, and relative reduced data-training stress. The approach primarily reshapes the raw dataset to meet the requirements before training the CNN model. When the trained model is given the visuals to predict, it outputs whether or not the image contains a forest fire. With a 94.3% accuracy rate, the algorithm performs well.

Rafik Ghali et al., 2021 [5], have proposed an approach for segmenting wildfire pixels and detecting fire areas developed on U2-Net, EfficientSeg and U-Net (deep convolutional networks). The loss functions (Binary Cross Entropy Dice loss and Dice loss) and also the data augmentation methods (rotation and horizontal flip) were utilized to train these models. The three models exhibit outstanding F1-score results and accuracy, demonstrating their dependability to partition pixels of fire and identify the specific contours of wildfire zones. EfficientSeg, U-Net, and U2-Net performed well on the CorsicanFire dataset, with F1-scores of 0.95, 0.94, and 0.92, and accuracy of 0.96, 0.98,

and 0.97, respectively. According to the F1-score, which measures the effectiveness of per-pixel segmentation, EfficientSeg is the method that performs the best.

R. Shanmugapriya et al.,2019[6], have proposed classification and detection of forest fire in satellite images. For improving the performance of feature extraction using traditional and hand-crafted algorithms which are not suited for large datasets, the use of an efficient approach of Inception-V3, CNN based, is proposed by the system for training the satellite images and for improving the accuracy in classifying the images dataset into ‘non-fire’ and ‘fire’ images. Inception-V3 framework is implemented for extracting features of datasets containing fire, also Local Binary pattern is applied to mark the locations showing the presence of fire and apply bounding box in the fire occurred region.

João Alves et al.,2019 [7], have proposed a system for automatic detection of forest fire in early stages. This system works by processing or classifying the images of the forest environment for having the presence of smoke or flame using Deep Convolutional Neural Network Inception-V3 which extracts the descriptors. A Machine-Learning Classifier is trained with the use of descriptors obtained which are also applied to the supervised learning model LR. Computational Vision technique applications are also used by the proposed system to spot the area under ignition to give information about the size of the area affected. The system aims for detection of forest fire during both night and day and also in various different scenarios of the forest. M. Shreya et al.,2022

III. METHODOLOGY

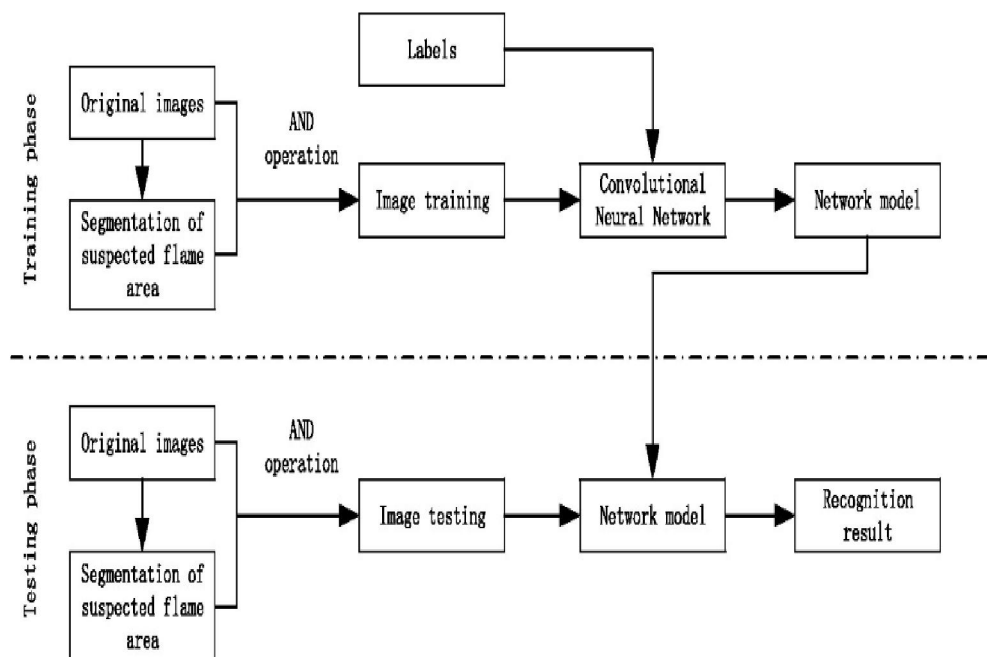


Figure 1: Flow of algorithm

This project involves several key steps, including image collection, image preprocessing, image segmentation, feature selection and extraction, training, and classification. Deep learning techniques are utilized for the detection and identification of forest wildfires. The following provides an overview of each step in the methodology:

- **Image Collection:** The first step is to gather satellite images of forested areas from reliable sources. These images should cover a wide range of regions and capture different seasons and weather conditions to ensure robustness in the wildfire detection system.
- **Image preposing:** In this step, the collected satellite images undergo preprocessing to enhance their quality and suitability for analysis. Preprocessing techniques may include noise removal, contrast adjustment, image resizing, and normalization to ensure consistency and optimize the performance of subsequent steps.
- **Image Segmentation:** Image segmentation is performed to partition the satellite images into meaningful regions or objects. This step aims to differentiate between various land cover types and identify potential areas

of interest for wildfire detection. Segmentation algorithms, such as thresholding, clustering, or advanced techniques like U-Net, can be applied to accomplish this task.

- **Feature Selection and Extraction:** The relevant features are selected and extracted from the segmented images. Features could include colour histograms, texture descriptors, shape information, or spectral characteristics. The goal is to capture distinctive patterns and characteristics associated with potential wildfire occurrences
- **Training:** Here, a deep learning model is trained using the extracted features from the satellite images. Convolutional Neural Networks (CNNs) are commonly employed due to their effectiveness in image analysis tasks. The training process involves feeding the labelled data (wildfire and non-wildfire examples) to the model, optimizing its parameters through techniques like backpropagation, and iteratively refining the model's ability to classify wildfire instances accurately.
- **Classification:** Once the deep learning model is trained, it can be deployed for real-time classification of satellite images to identify the presence of wildfires. Unseen or newly acquired images are fed into the trained model, and the model predicts whether a given image contains a wildfire or not based on the learned patterns and features. The classification output can be visualized or further integrated into a broader wildfire monitoring system for timely intervention and mitigation.

IV. RESULTS AND ANALYSIS

The performance of CNN is affected by some hyperparameters, including initial learning rate, batch size, pooling, and so on. The performance of CNN from the above aspects is analysed

Training samples	Testing Samples	Accuracy (%)
Original image	Original image	84.2
Original image	Segmented fire area	81.6
Segmented fire area	Original image	80.4
Segmented fire area	Segmented fire area	90.7

Figure 2: Result Table

It is evident from Table 5 that the recognition rate is 84.2% and 81.6% when training the algorithm on the original image. However, when using the segmented fire area image as the training sample and the original image as the testing sample, the accuracy drops significantly to 80.4%. This decrease in accuracy can be attributed to the fact that the segmented fire area image only contains the features of fire without the background information. On the other hand, when both the training and testing samples are the segmented fire area images, the accuracy improves significantly to 90.7%. This result further confirms that the combination of the CNN fire recognition algorithm with color features yields higher accuracy. Therefore, it can be concluded that incorporating color features into the CNN fire recognition algorithm improves the accuracy of fire detection. By using the segmented fire area images for both training and testing, a higher recognition rate can be achieved. This research provides valuable insights into enhancing fire recognition algorithms and underscores the importance of considering color features in such systems

4.1 Screenshots

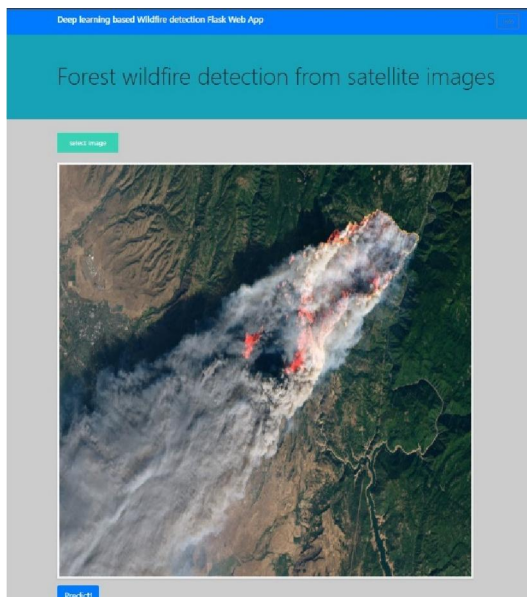


Figure 3: Data Uploading

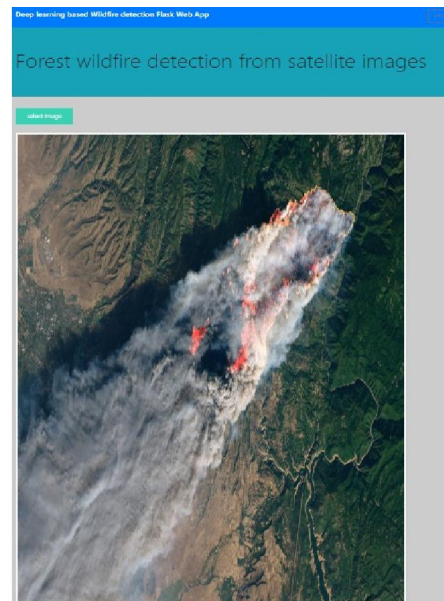


Figure 4: Result

V. CONCLUSION

In this project, we present a forest fire image recognition algorithm based on CNN. The algorithm utilizes flame images for both training and testing purposes. We introduce the Alex Net model and propose an adaptive pooling method combined with colour features to address the issue of traditional pooling methods in CNN weakening image features in certain cases. We conduct experiments to analyse the effects of learning rate, batch size, and other parameters on the performance of the CNN. Through these experiments, we determine the optimal parameters for our algorithm. To extract the candidate flame area, we utilize colour features. This approach reduces the image feature of the non-flame area in the hidden layer while enhancing features such as shape and texture. By adopting adaptive pooling, we avoid information loss in the images. We compare the recognition rates of the segmented fire area images and the original images without segmentation. The results demonstrate that our proposed algorithm achieves a high recognition rate and is feasible for forest fire image recognition. In future work, we plan to further develop the modified pooling technique applied in CNN for forest image recognition. We aim to deepen our analysis by comparing recognition rates and consuming time with other existing algorithms. By conducting these comparisons, we can assess the effectiveness and efficiency of our algorithm against alternative approaches

REFERENCES

- [1]. Kansal, A., Sharma, A., & Taneja, G. (2015). Forest fire detection using machine learning techniques. *Procedia Computer Science*, 48, 647-653.
- [2]. Rahul, M., Ramesh, S., Karthikeyan, P., & Saravanan, M. (2020). Convolutional neural network-based forest fire detection using transfer learning. *2020 IEEE International Conference on Recent Trends in Electrical, Control and Communication (RTECC)*, 1-6.
- [3]. Preeti, T., Nirmal, V., & Lajish, V. L. (2021). Forest fire prediction using machine learning algorithms. *2021 IEEE International Conference on Inventive Computation Technologies (ICICT)*, 1569-1574.
- [4]. Sheryl Oliver, A., Gandhi, S., & Radha, S. (2020). Forest fire detection using convolutional neural network. *2020 7th International Conference on Computing for Sustainable Global Development (INDIACom)*, 201-206.
- [5]. Ghali, R., Fandi, K., & Kherfi, M. L. (2021). Deep learning-based wildfire pixel segmentation. *2021 International Conference on Advanced Communication Technologies and Networking (CommNet)*, 1-7.

- [6]. Shanmugapriya, R., & Lakshmi, S. (2019). Classification and detection of forest fire in satellite images using CNN based efficient approach. 2019 International Conference on Intelligent Sustainable Systems (ICISS), 1005-1010.
- [7]. Alves, J., Ribeiro, A., Ferreira, L., & Botelho, S. (2019). Automatic detection of forest fires in early stages. 2019 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), 1-6.
- [8]. Shreya, M., Raghavendra, A., Meghana, R. M., & Raju, P. (2022). A comprehensive review of forest fire detection techniques. 2022 Fourth International Conference on Computing Methodologies and Communication (ICCMC), 1297-1304.