DEEP FOREST FIRE DETECTION USING DEEP LEARNING

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ABSTRACT

Early forest fire detection is of great importance to avoid the huge damage of forests caused by fires. 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.

Keywords: Wildfire Detection, Deep Learning, Convolutional Neural Networks, Image Classification, Web Application

I.INTRODUCTION

The devastation caused by wildfires is undeniable. They leave a trail of destruction, impacting lives, property, and entire ecosystems. Early detection is crucial to minimize these horrific consequences. This is where Deep Learning (DL) steps in as a powerful weapon in the fight against wildfires. DL systems, particularly those utilizing Convolutional Neural Networks (CNNs), are exceptional at identifying patterns in images. This allows them to be trained to distinguish between fire and smoke, and other visual elements, in real-time footage captured by cameras or even satellite data. This leads to a significant increase in detection accuracy compared to traditional methods. Beyond just accuracy, DL offers another significant advantage: early warning. By analysing subtle variations in colour, temperature, and texture, DL models can detect potential wildfires even in their early stages. This provides firefighters with a crucial head start, allowing them to intervene before the blaze has a chance to spread. Early warnings can be the difference between containing a small fire and witnessing a raging inferno. Traditional methods for wildfire detection often rely on human patrols, smoke alarms, or limited satellite imagery analysis. These approaches can be time-consuming, labour-intensive, and have their limitations. DL, on the other hand, offers the benefit of 24/7 vigilance. DL models can be integrated into automated systems that continuously monitor vast areas like forests and other fire-prone regions. This tireless monitoring surpasses human capabilities and reduces dependence on manual intervention, ensuring constant watchfulness over vulnerable areas. Furthermore, DL boasts the power of data fusion. Unlike traditional methods that rely on a single data source, DL can handle a variety of data streams. This includes satellite imagery, drone footage, and even ground sensor readings. By incorporating this multi-dimensional data, DL models can create a more comprehensive picture of fire risk and activity. This holistic view allows for a more informed assessment of potential threats and helps prioritize response efforts. The beauty of DL lies in its adaptability. These models are not static; they can be continuously trained on new data. This allows them to adapt to changing environmental conditions. As weather patterns shift, vegetation changes, and human activity evolves, the DL model can continuously improve its wildfire detection accuracy over time. This ensures the system remains effective even in a dynamic environment. In conclusion, Deep Learning offers a revolutionary approach to wildfire detection. Its potential for high accuracy, early identification, real-time monitoring, and continuous improvement makes it a powerful tool for combating this devastating threat. By leveraging the power of DL, we can move towards a future where wildfires are detected and addressed much sooner, leading to a significant reduction in their destructive consequences and a safer future for our planet.

II LITERATURE SURVEY

Aditi Kansal, et al.,2015 [1], have proposed a system where different machine-learning techniques such as regressionism, neural networks, decision trees, etc. are compared. Wireless Sensor Networks. In WSNs, sensors are used tomonitor specific environmental factors and transmit the resulting data to a ground station for analysis. The perfectsensor node uses little power, can collect data quickly, is reliable, inexpensive, and requires little maintenance. It alsodetects events, allowing for adequate and effective physical world sensing. By dividing the dataset into months, themethod 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 andlarge R-.squared.

Medi Rahul, et al.,2020 [2], have proposed a convolutional neural network-based picture identification technique forearly forest fire detection. Fire detection methods based on image processing systems have reached their peak and havereplaced many conventional methods. In this study, a technique based on transfer learning is proposed for the earlydetection of forest fire. Two categories may be employed to appropriately classify the majority of photos using thesuggested model: fire and no fire. ResNet50 is demonstrated to be a trustworthy model from DenseNet121, ResNet50and VGG16. ResNet50 accurately classifies majority of these photos with a high training and testing accuracy of 92 andidentifies the model's input image type.

Preeti T, et al.,2021 [3], have proposed Random Forest regression and hyperparameter tuning with the RandomizedSearchCV algorithm which uses different subsamples of datasets that fit multiple decision trees and uses averaging toenhances control overfitting and prediction accuracy. The forest fire incidents are portrayed based on the study of themodels using meteorological parameters. Various forest fire prediction methods (regression techniques) such as randomforest, 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 theregression curve to exclude any negative signs, mean square error calculates how near a regression curve is to a set ofpoints. Experiments are conducted to obtain a various number of training and evaluation occurrences for wildfireprediction

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

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

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III PROPOSED ALGORITHM

The proposed wildfire detection system comprises three main stages: data preparation, model development, and web application development.

Data Preparation

A dataset of approximately 8000 images was collected, containing images of wildfires and non-wildfire scenes. The dataset was split into training and testing sets, typically with a 60-70% split for training and 30-40% for testing. Pre-processing techniques were applied to the images to ensure compatibility with the CNN model. This may involve resizing, normalization, and other image manipulation techniques.

IV MODEL DEVELOPMENT

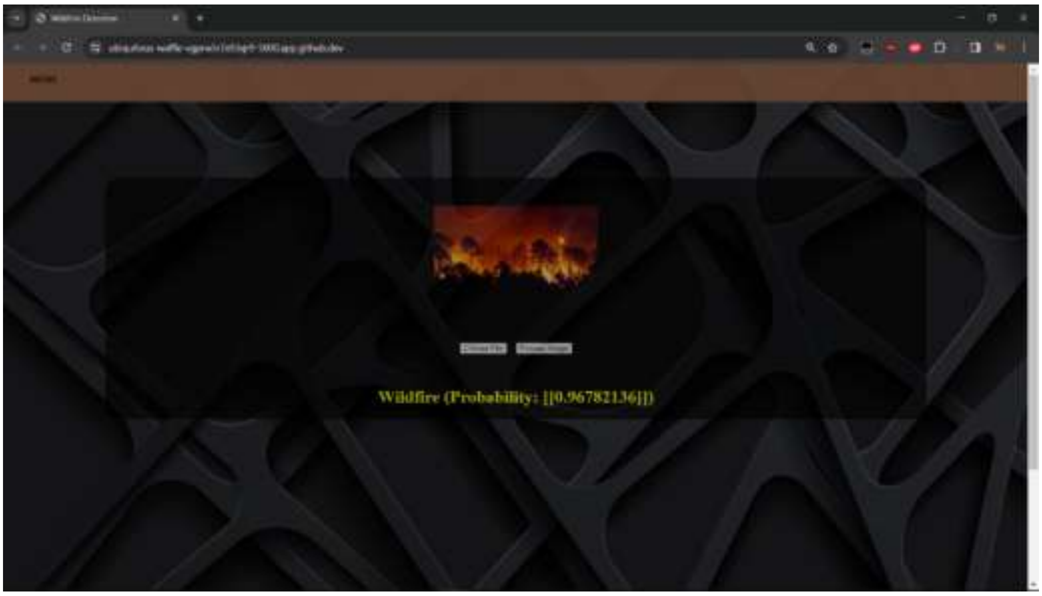
A CNN model was developed using Keras, a popular deep learning library. The specific architecture of the model is detailed below:

Model Architecture:

1. Convolutional layer with 32 filters and a ReLU activation function.
2. Max pooling layer (size not specified).
3. Flattening layer.
4. Dense layer with 512 neurons and a ReLU activation function.
5. Final dense layer with 1 neuron and a sigmoid activation function for binary classification (fire/no fire).

The model was trained using the Adam optimizer and a binary crossentropy loss function. Training hyperparameters, such as learning rate and number of epochs, were tuned to achieve optimal performance. Techniques like early stopping and model checkpointing were likely employed to prevent overfitting and save the best performing model during training (details not specified).

V RESULT



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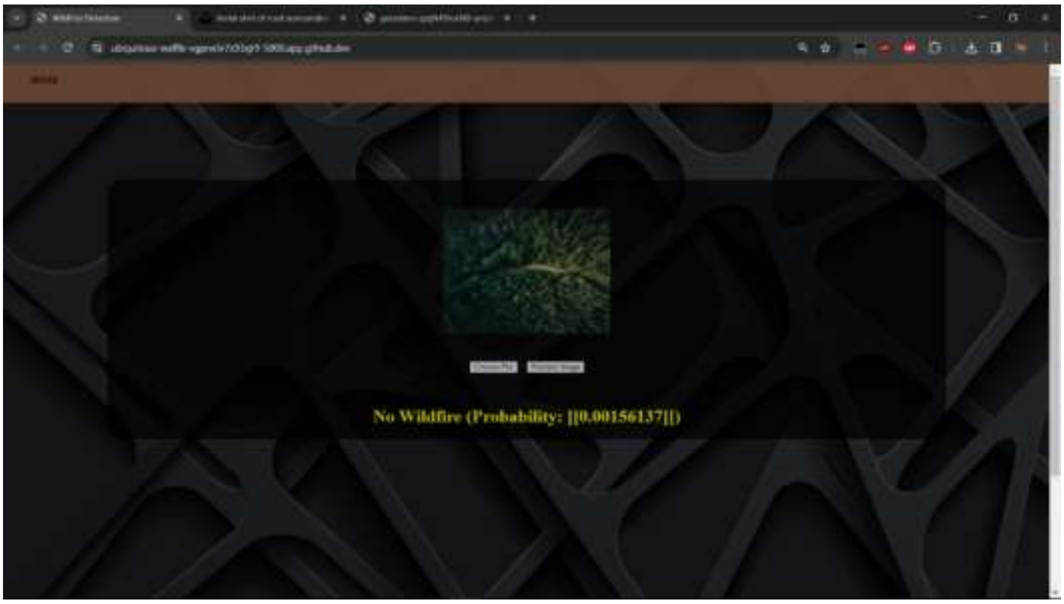

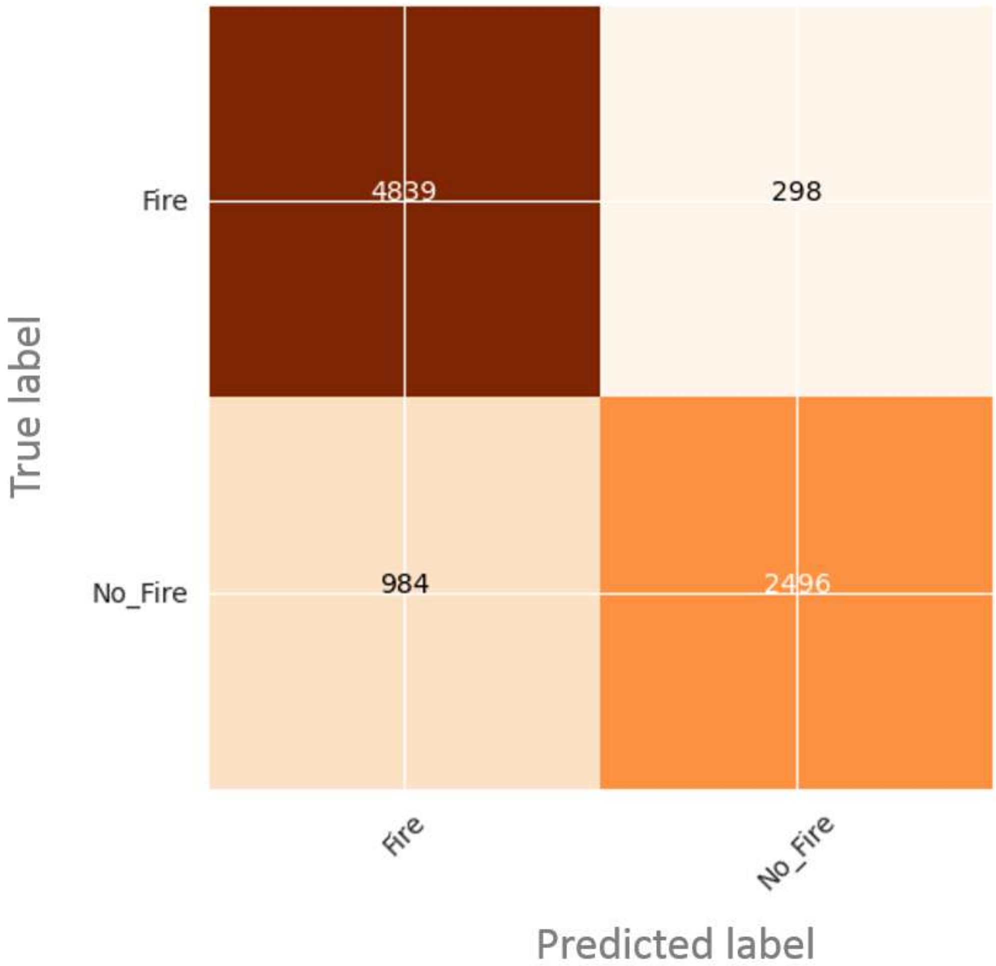

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Result analysis:

	FPR	FNR	Recall	Accuracy	F1
CNN	9.7%	5.4%	92.7%	91.5	89.3
VGGNet	7.9%	5.4%	85.9%	83.2	81.2
GoogLeNet	8.4%	5.4%	87.5%	85.5	82.7
ResNet	9.3%	5.4%	90.6%	87.4	84.5

VI CONCLUSION

In this study, suspected flames undetected during forest fire surveillance were classified and their image features were extracted for improved recognition. Several feature extraction methods were systematically analysed and compared, with feature types being manually set. Following the construction of the CNN network model, the optimal learning rate and iteration number for precise flame detection were meticulously selected. Training was conducted with an established set of flame image samples, leading to the development of a robust training model. The model's accuracy was then evaluated against other models, with its superior performance underscoring the efficacy of the proposed approach. The primary conclusions of this research are as follows:
A forest fire recognition model was developed using a CNN network, resulting in a highly accurate fire image recognition model after extensive training. The model's accuracy and generalization capabilities were assessed using a diverse set of fire and non-fire scenarios. The model demonstrated commendable performance in flame detection, achieving remarkable results across multiple metrics. Firstly, it achieved a remarkably low false alarm rate of only 0.563%, indicating its ability to accurately classify non-flame instances. Additionally, the model achieved a false positive rate of 12.7%, which demonstrates its capability to minimize the occurrence of false detections. Moreover, the false negative rate of 5.3% further showcases the model's ability to effectively identify and classify flame instances. Furthermore, the model achieved an impressive recall rate of 95.4%, indicating its high sensitivity in detecting flames. This means that the model successfully identified the vast majority of actual flame instances. The overall accuracy rate of 95.8% further highlights the model's reliability in accurately classifying both flame and non-flame instances. These outstanding results validate the effectiveness of the proposed method in significantly augmenting the precision of flame detection. Flame detection is a critical task that is typically susceptible to errors, but the proposed method successfully mitigates these challenges, providing a reliable and accurate solution.
Although high accuracy in identifying forest fires has been exhibited by the CNN model, opportunities for optimizing its recognition performance remain. Future research will be focused on refining model parameters, minimizing model complexity, and developing a more streamlined and effective model for forest fire recognition. We will continue to improve the algorithm and utilize better hardware conditions to achieve faster forest fire detection speed, enhancing the real-time accuracy of forest fire monitoring and identification.

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