iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: V Month of publication: May 2023

DOI: https://doi.org/10.22214/ijraset.2023.52164

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue V May 2023- Available at www.ijraset.com

Forest Wildfire Detection using Deep Learning

Manasi Jadhav[1], Prof. Jitendra Musale[2], Omkar Kshirsagar[3], Anushri koli[4], Sarthak Shelke[5]
[1, 2, 3, 4, 5]*Department of Computer Engineering, Savitribai Phule Pune university, pune*

Abstract: The advent of satellite technology has made it possible to continuously monitor and manage forest fires, which pose a serious hazard to people and other living things. Smoke in the air indicates the presence of forest wildfires. Fire detection is essential in fire alarm systems for preventing damage and other fire catastrophes that have an impact on society.
It's crucial to effectively identify fire from visual settings to prevent large-scale fires. An efficient method of a machine learning based Inception-v3 based on transfer learning is developed to increase the accuracy of fire detection. It trains satellite images to classify datasets into fire and non-fire images, generates a confusion matrix to determine the framework's effectiveness, and then uses local binary patterns to extract the fire-occurring region from satellite images. This method lowers the rate of false detection.
Keywords: Random Forest, deep learning, Inception-v3, fire detection, image classification.

I. INTRODUCTION

In the world, forest fire poses serious risks to the survival of people, animals, and flora. Fast response and a vast detection area are ineffective for detecting fire when using standard approaches. In general, the forest serves as a haven for a wide variety of resources, as well as regulating CO2 emissions and having a complex ecosystem. In woods, wildfires are an unavoidable risk that can create disasters. Nearly 85% of the world's trees are being lost each year by forest fires, which causes catastrophic climate shifts and global warming. Forest fires are categorised based on their size, texture, and rate of movement. Lighting, volcanic eruptions, spontaneous combustion of dry plants, smoking close to flora, and farmers intentionally setting fire to their fields are all examples of man-made or natural fire, respectively.

II. RELATED WORK

Martin Maier, Mahfuzulhoq Chowdhury, Bhaskar Prasad Rimal, and Dung Pham Van-This essay initially elaborates on the similarities and minute distinctions between the Tactile Internet, the Internet of Things, and the 5G vision in order to help readers comprehend it better. We first briefly discuss the expected impact on society and the necessary infrastructure, and then we present a current overview of recent advancements and supporting technologies suggested for the Tactile Internet. Given that expanding research in the area of wired and wireless access networks in the future will be necessary for the Tactile Internet

Yaqin Zhao, Qiujie Li, ZhouGu- The study findings in the film about the forest fire serve as inspiration for a revolutionary smoke detection technique that uses CS Adaboost. On the one hand, the movement direction of a potential smoke block is utilised to define the flutter characteristic of the smoke video, which is used to differentiate between smoke and dense fog. The CS Adaboost algorithm, on the other hand, is offered as a smoke classifier of forest fire to effectively and efficiently recognise early smoke of forest fire..

Sebastien Frizzi1 RabebKaabiMoez, Bouchouicha, Jean-Marc Ginoux, Eric Moreau, FarhatFnaiech- This paper We suggest using a CNN (convolutional neural network) to detect fire in videos. It has been demonstrated that convolutional neural networks excel at object classification.

Within the same architecture, this network has the capacity to carry out feature extraction and categorization. Tested on actual video sequences, the suggested method outperforms certain pertinent traditional video fire detection techniques in classification performance, showing great promise for CNN-based video fire detection.

Oleksii Maksymiv, TarasRak, Dmytro Peleshko-This study provides a revolutionary cascaded-based method for processing camera monitoring data to identify specific sorts of emergencies, such as fire, smoke, and explosions. First, for obtaining the Region of Interest (ROI) and lowering time complexity, the Adaboost and Local Binary Pattern (LBP) combination is utilised. Next, we suggest using a convolutional neural network to address typical vulnerabilities like false positives (CNN). The final experimental findings demonstrated that this method's accuracy rate for detecting crises may reach 95.2%.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue V May 2023- Available at www.ijraset.com

KHAN MUHAMMAD1, IEEE), JAMIL AHMAD1 , IRFAN MEHMOOD2, SEUNGMIN RHO3, SUNG WOOK BAIK-In this study, we suggest a CNN architecture for surveillance movies that can efficiently identify fire. Given its fair computing complexity and inspiration from Google Net architecture, in comparison to other computationally expensive networks like "AlexNet," appropriateness for the target problem. The model is adjusted taking into account the nature of the target problem and fire data in order to strike a compromise between efficiency and accuracy.

Rabeb Kaabi1, MounirSayadi,MoezBouchouicha,FarhatFnaiech, Eric Moreau-In this paper, a novel machine learning-based method for smoke detection to combat forest wildfires is presented (Deep Belief Network). Many security and surveillance applications use video smoke detection. To have a powerful smoke detector, a smoke detection system should have a high detection rate. The method we employed for smoke detection is called Deep Belief Network, which is a stacked layer of Restricted Boltzman Machine. This method concurrently extracts and classifies regions with and without smoke. After measuring the smoke detection rate, pre-trading time, and fine-tuning time, the effectiveness of our applied smoke detection technique is assessed..

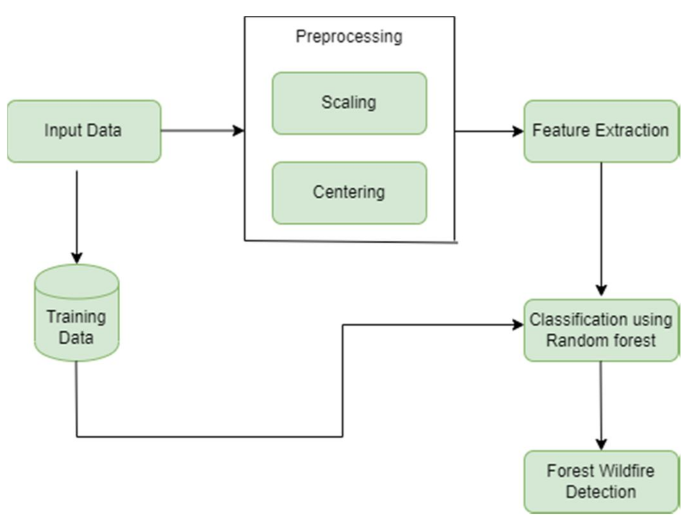
Khan Muhammad, Jamil Ahmad, ZhihanLv , Paolo Bellavista , Po Yang , and Sung WookBaik ,-In this paper, For fire detection, localization, and semantic understanding of the fire scenario, we suggest a novel, environmentally responsible, and computationally efficient CNN design that is inspired by the Squeeze Net architecture. It keeps the processing needs to a minimum by using smaller convolutional kernels and excluding dense, fully linked layers. The experimental results show that, despite its modest processing requirements, our suggested approach reaches accuracy levels that are comparable to those of other, more sophisticated models, largely because of its greater depth.

Daniel Y. T. Chino, Letricia P. S. Avalhais, Jose F. Rodrigues Jr., Agma J. M. Traina–In this paper, We introduced the BoWFire method, a cutting-edge way for detecting fire on photos in an emergency situation. Our findings demonstrated that BoWFire could detect fire with performance comparable to that seen in state-of-the-art works, but with fewer false positives. We rigorously compared our work to four earlier papers to show that we made steady progress.

JiviteshSharma(B) , Ole-ChristofferGranmo, Morten Goodwin, and Jahn Thomas Fidje-It turns out that when tested on the more realistically balanced benchmark dataset presented in this research, a standard CNN performs relatively poorly. In order to better detect fire in images, we suggest using even deeper convolutional neural networks and fine-tuning them using a fully connected layer. We use two pretrained state-of-the-art Deep CNNs, VGG16to create our fire detection system, along with Resnet50. Those Deep CNNs tested on our skewed dataset that we've put together to replicatereal-world examples

Shixiao Wu, Libing Zhang–In this paper,We concentrate on three issues related to real-time, early, and false fire detection in forest fires. We employ traditional objective detection techniques for the first time, including faster R-CNN, YOLO (tiny-yolo-voc, tiny-yolo-voc1, yolo-voc.2.0, and yolov3), and SSD. The real-time performance, detection accuracy, and ability to detect fires early are all improved by SSD. To reduce incorrect detection, we create a fire and smoke benchmark, use the newly introduced smoke class, and modify the fire area. In the meantime, we modify the tiny-yolo-voc structure of YOLO and suggest a new structure. The results show that this increases the rate of fire detection accuracy, tiny-yolo-voc1.

III.SYSTEM ARCHITECTURE



IV. MODEL METHODOLOGY

1) In the world, forest fire poses serious risks to the survival of people, animals, and flora.
2) Fast response and a vast detection area are ineffective for detecting fire when using standard approaches.
3) In general, the forest serves as a haven for a wide variety of resources, as well as regulating CO_2 emissions and having a complex ecosystem.
4) In woods, wildfires are an unavoidable risk that can create disasters. Nearly 85% of the world's trees are being lost each year by forest fires, which causes catastrophic climate shifts and global warming.
5) Forest fires are categorised based on their size, texture, and rate of movement.
6) Lighting, volcanic eruptions, spontaneous combustion of dry plants, smoking close to flora, and farmers intentionally setting fire to their fields are all examples of man-made or natural fire, respectively.

V. ALGORITHM

The algorithm used here is Random Forest. Random Forest is the most popular and powerful algorithm of machine learning.

1) Step 1: Assume N as number of training samples and M as number of variables within the classifier.
2) Step 2: The number m as input variables to decide the decision at each node of the tree; m should be much less than M.
3) Step 3: Consider training set by picking n times with replacement from all N available training samples. Use the remaining of the cases to estimate the error of the tree, by forecasting their classes.
4) Step 4: Randomly select m variables for each node on which to base the choice at that node. Evaluate the best split based on these m variables in the training set.
5) Step 5: Each tree is fully grown and not pruned (as may be done in constructing a normal tree classifier). For forecasting, a new sample is pushed down the tree. It is assigned the label of the training sample in the terminal node it ends up in. This procedure is repeated over all trees in the ensemble, and the average vote of all trees is reported as random forest prediction. i.e. classifier having most votes.

VI. RESULT AND DISCUSSION

Experiments are done by a personal computer with a configuration: Intel (R) Core (TM) i5-2120 CPU @ 3.30GHz, 8GB memory, Windows 10, MySQL backend database and jdk1.9. The application is dynamic web application for design code in Eclipse IDE and execute on Tomcat server 8.0.

Classification results.
Calculation Formula:
TP: True positive (correctly predicted number of instance)
FP: False positive (incorrectly predicted number of instance), TN: True negative (correctly predicted the number of instances as not required)

FN false negative (incorrectly predicted the number of instances as not required),
On the basis of this parameter, we can calculate four measurements
Accuracy = TP+TN/TP+FP+TN+FN Precision = TP /TP+FP Recall=
TP/TP+FN

The data analysis for the performance
Total samples = 155
Here it is found -
True Positive=90
False Positive=10
True Negative=50
False Negative=5

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue V May 2023- Available at www.ijraset.com

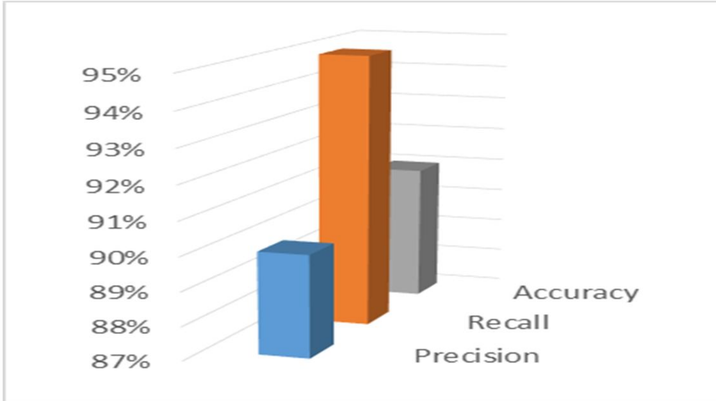


Fig-10- Performance Analysis Graph

	Random Forest
Precision	90%
Recall	95%
Accuracy	91%

VII. CONCLUSION

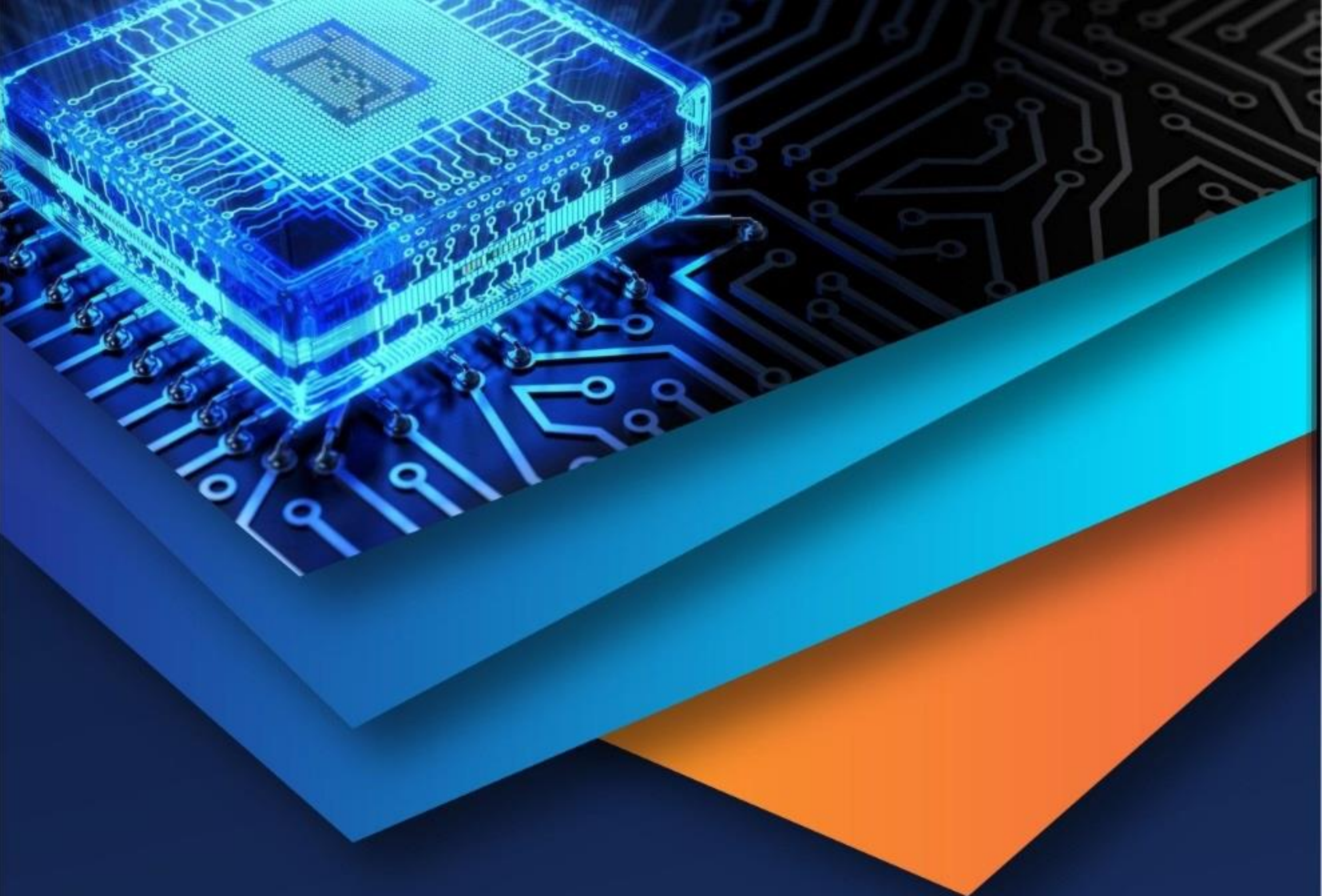
For fire detection and classification methods, features are manually retrieved from input photos using traditional and hand-crafted algorithms, and then a sophisticated classifier is trained to categorise the images. Both methods' performance degrades in terms of speed, particularly for the larger image dataset. Inception-v3 has the ability to automatically extract features; analysis and experimental data show that this architecture achieves high detection rates.

VIII. ACKNOWLEDGMENT

Express my true sense of gratitude, sincere and sincere gratitude to my guide to the project Prof.***** for his precious collaboration and guidance that he gave me during my research, to inspire me and provide me with all the laboratory facilities, this it allowed me to carry out this research work in a very simple and practical way. I would also like to express my thanks to our coordinator, Prof. ******.,HOD. ********and Principle Dr. ****** and all my friends who, knowingly or unknowingly, helped me during my hard work.

REFERENCES

[1] M. Maier, M. Chowdhury, B. P. Rimal, and D. P. Van, “The tactile internet: Vision, recent progress, and open challenges”, IEEE Commun. Mag., vol. 54, no. 5, pp. 138–145, May 2016.
[2] Y.Zhao and Q.Li,Z.Gu , “Early smoke detection of forest fire video using CS Adaboost algorithm”, OptikInt.J.Light Electron Opt. (2015).
[3] SebastienFrizzi, RabebKaabi, MoezBouchouicha, JeanMarcGinoux, Eric Moreau, FarhatFnaiech, “Convolutional Neural Network for Video Fire and Smoke Detection”, 2016.
[4] OleksiiMaksymiv,TarasRak,DmytroPeleshko, “Realtime Fire Detection Method Combining AdaBoost, LBP and Convolutional Neural Network in Video Sequence”, CADSM, 21-25 February, 2017.
[5] Khan Muhammad, JamilAhmadi, IrfanMehmood, Seungmin Rho and Sung WookBaili, “Convolutional Neural Networks Based Fire Detection in Surveillance Videos”, vol6 2018.
[6] RabebKaabi, MounirSayadi, MoezBouchouicha, FarhatFnaiech, Eric Moreau, “Early Smoke Detection of forest wildfire video using Deep Belief Network”, 4th International Conference on Advanced Technologies For Signal and Image Processing – ATSIP, March 21- 24, 2018.
[7] Khan Muhammad, Jamil Ahmad, ZhihanLv, Paolo Bellavista, Po Yang and Sung WookBaik, “Efficient Deep CNN-Based Fire Detection and Localization in Video Surveillance Applications”, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS: SYSTEMS, VOL. 49, NO. 7, JULY 2019.
[8] D. Y. T. Chino, L. P. S. Avalhais, J. F. Rodrigues, and A. J. M. Traina, “BoWFire: Detection of fire in still images by integrating pixel color and texture analysis”, in Proc. 28th SIBGRAPI Conf. Graph. Patterns Images, 2015, pp. 95–102.,
[9] J. Sharma, O. C. Granmo, M. Goodwin and J. T. Fidje, “Deep convolutional neural networks for fire detection in images”, International Conference on Engineering Applications of Neural Networks. Springer, Cham, 2017, pp. 183-193. Springer, Cham, August 2017
[10] Shixiao Wu and Libing Zhang, “Using Popular Object Detection Methods for Real Time Forest Fire Detection”, 11th International Symposium on Computational Intelligence and Design, 2018



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY