WildFire Forest Detection Using Deep Learning

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***Abstract*—The forests of the world are an essential and vital resource because they contain numerous kinds of flora and fauna living, such as herbs, timber, and shrubs, as well as a variety of animals. In certain ways, these renewable assets are essential to mankind. Forest fires, which are a particularly common forest danger, wreak havoc on the ecology and local environment. This abstract examines the present methods and technologies for detecting wildfires using satellite imagery, such as remote sensing methods, algorithms for machine learning, and data analytics. The use of satellite-based wildfire monitoring to improve early warning systems and guide fast response plans is also highlighted. The findings emphasize the need to use satellite images for preventative wildfire control, as well as continuous attempts to increase detection accuracy and efficiency algorithms. Initial identification and preventive measures are essential to protect forests from fires. Direct observation of people and remote video surveillance are both of the most frequent methods of conducting human surveillance to achieve early detection. To detect fires automatically, this article describes a forest fire picture recognition system based on convolutional neural networks. This approach reduces false alarms while providing precise fire detection findings.**

***Index Terms*—Wildfire, CNN, Sklearn, Transfer Learning, ResNet50.**

I. Introduction

The rising threat of wildfires recently has highlighted the crucial need for new technology in early detection and monitoring. This research aims to improve the accuracy and efficiency of wildfire detection systems by using deep learning technologies, notably convolutional neural networks (CNN) and multilayer perceptrons (MLP) [1]. CNNs, which are well-known for their image analysis abilities, and MLPs, which are adept at catching complicated patterns, are at the heart of our method. The goal of this investigation into deep learning architectures is to develop a robust model capable of properly recognizing wildfires from varied datasets. Transfer learning appears to be a critical approach among the different techniques used. We want to capitalize on learnt characteristics from large datasets by using the capabilities of CNN pre-trained models such as ResNet50, [2] fostering a greater capacity to generalize and adapt to the intricacies of wildfire detection. The pursuit of

maximal accuracy through transfer learning is a significant step in wildfire detection, with the potential to revolutionize the usefulness and dependability of early warning systems. This study exemplifies our commitment to use cutting-edge deep learning technology to address the critical difficulties posed by wildfires and contribute to the development of preventive and efficient wildfire management solutions.

II. Literature Survey

The researcher Tsalera [3] Advances in CNN-based technology, like ShuffleNet and MobileNet v2, enhance wildfire detection with high accuracy and minimal CPU usage. The system adapts to noise levels, with Gaussian causes affecting moderate scenarios and Salt and Pepper causes being more impactful in high-noise situations. This optimized CNN approach is crucial for swift wildfire detection and response. The author Chen [4] focused on Real-time fire monitoring is crucial for swift prevention and management solutions. Drones, with their 3D mobility and low flying height, excel in identifying and assessing wildfires in remote areas. A deep learning system, using RGB and thermal images, outperforms traditional video feeds in accuracy. The system incorporates a dataset with georeferenced pre-burn points cloud, RGB orthomosaic, meteorological data, and burn plan, etc. This dataset could lead to new data-driven applications for improved wildfire response. mengan, youmin [5] researcher in real-time This method enhances the deeplabv3+ fire segmentation approach by using MobileNetV3 for a faster deep convolutional neural network. While skipping atrous convolution speeds up processing, it slightly sacrifices segmentation accuracy. To compensate, this study introduces two shallow features into the decoder network, enriching it with diverse fire-related information. The experimental results show superior performance than the original method, balancing speed and accuracy for fire segmentation tasks. Jingguo and Xiaochuan focused on [6] Introducing a novel Flame Identification

method, Fire-DETR, our approach uses an adaptive feature fusion module to effectively integrate RGB and infrared characteristics for precise flame prediction in forest settings. Integrated with DETR, our model outperforms existing counterparts such as YOLOv5 and Faster-RCNN, demonstarting its effectiveness in leveraging multimodal data. To address training time, our research focuses on parallel training strategies, and we plan to expand our dataset for iterative model optimization and broader applicability in flame detection. Richard and Jacobo [7] worked on this. This research introduces a cost-effective wildfire inspection system using a quadcopter. Achieving 19.2 FPS with 60.76% accuracy, the system aids decision-making during response operations by autonomously navigating, detecting fires, and estimating their size and position. Future enhancements include a thermal camera for improved accuracy and adaptations for varied terrains, aiming to enhance wildfire monitoring and response efficacy. Edmundo and Franklin [8] This review assesses YOLO architectures (v5, v6, v7, v8, YOLO-NAS) for smoke and wildfire detection. YOLOv5, v7, and v8 demonstrate balanced performance; YOLO-NAS excels in recall but has lower accuracy. The study highlights the importance of accuracy, recall, and inference time. S. B. Avula et al. proposed a forest fire detection system using Fuzzy Entropy Optimized Thresholding and STN-Based CNN.[9]. His work proposes a CNN-based model with fuzzy entropy optimization for accurate smoke and forest fire detection using adaptive thresholding. The architecture, incorporating STN and entropy-based thresholding, effectively reduces false alarms. S. Frizzi et al. suggested a CNN-based system for video fire and smoke detection.[10]. His study proposes a computer vision-based fire and smoke detection system using CNN. With a test set of 1427 fire photos and 1758 smoke images, it efficiently reduces processing time by only taking feature map into consideration. However, the model's limitation is its ability to detect only red fire; expanding the training sets to include other colors, like blue, is necessary for improvement. S. Wu et al. suggested a real-time forest fire warning system [11] based on Object warning Methods such as R-CNN (tiny-yolo variants and yolov3) and SSD. SSD outperformed in terms of real-time speed and detection precision. The research uses a modified tiny-yolo-voc framework to improve fire detection accuracy. While advantageous for continual forest monitoring, the problem of real-time monitoring is a disadvantage. Rahul et al. [12] presented a deep learning approach for early forest fire detection, utilizing transfer learning anet al. [t50. The model preprocesses image data, employs augmentation methods, and distinguishes between fire and non-fire in training and test sets. A limitation is that not all images are classified. B. Arteaga et al. published "Deep Learning Applied to Forest Fire Detection"[13] to assess CNN models using pre-trained forest fire pictures with low-cost devices such as the Raspberry Pi. They demonstrated two pre-trained CNN models, ResNet, and two additional families, totaling eight models and five kinds. The ResNet152 model was used on a Raspberry Pi 3 Model B, using a small library of 1800 pictures for analysis.

III. Methodology

The main objective of our work is to predict wildfire. Depending on the fire and smoke with different combinations as fire, non-fire and smoke that are needed for testing and training to predict the wildfire. For predicting we used the best method, i.e. The process is performed by using the following methods:

- Data set description
- Exploratory data analysis
- Validation accuracy metrics

A. Data set description

This dataset, specifically curated for fire and smoke detection, comprises a total of 42,900 images distributed across three distinct categories:" fire,"" smoke," and" non-fire." The balanced data distribution includes designated training and testing set folders, each serving a unique purpose in model development and assessment. The substantial training set of 10,800 samples for each category aims to expose the model to diverse instances for effective learning and generalization. In addition, a separate testing set of 3,500 samples (shown in Fig. 1) for each category ensures fair evaluation. Evaluation criteria, including precision (PREC), recall (REC), and accuracy (ACC), were used to measure the system's effectiveness in distinguishing between fire, smoke, and non-fire instances. Ultimately, the primary purpose of this dataset is to provide the development and evaluation of machine learning models for fire and smoke detection, which are significant in applications such as surveillance and early warning systems for fire incidents.

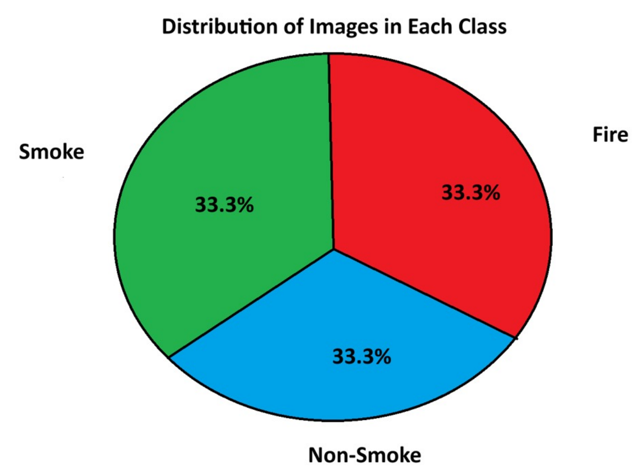

Fig. 1: Data Set

B. Exploratory Data Analysis

The exploratory data analysis focuses on a wildfire dataset comprising images of fire, non-fire, and smoke. This involves examining the distribution of images across these categories, assessing image quality and dimensions, and exploring potential features for analysis. Visualizations will be used to present the class distribution, sample images, and image quality metrics. The analysis aims to gain insights into the dataset's characteristics and identify potential applications in wildfire detection and related fields.

C. Model Architecture

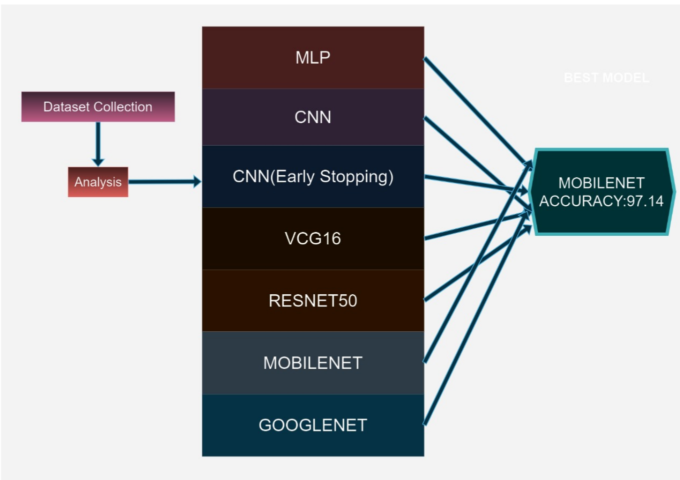

Fig. 2: Architectural Diagram

D. Validation Accuracy Metrics

Metrics for validation accuracy are critical for evaluating the performance of machine learning models. We may determine how effectively the model generalizes to new, unknown data by comparing the prediction accuracy of a validation dataset with that of a training dataset. The use of a line plot to visualize training and validation accuracy over epochs provides insight into the model's learning process and directs future model optimization.

E. Models

- MultiLayer Perceptron
  A Multilayer Perceptron (MLP) is a type of feedforward artificial neural network characterized by its architecture, which consists of multiple layers of nodes (neurons) arranged in a sequence. It has three components: Input Layer, Hidden Layer and Output Layer. In our model there are a total of three trainable layers: two hidden layers and one output layer. Flatten layer serves as the input layer, reshaping the data into a format suitable for processing but doesn't learn any parameters. We trained our data for 20 epochs. The dense layers with ReLU activation (256 neurons, 128 neurons) are considered hidden layers. They perform computations and apply activation functions to the input data, transforming it before passing it to the next layer.The final dense layer with softmax activation (3 units) is the output layer.
- Convolutional Neural Networks
  A Convolutional Neural Network (CNN) is a type of deep neural network specifically designed for processing structured grid-like data, such as images. In our model, there are three convolutional layers with ReLu as activation function.We trained our data for 20 epochs. Following each convolutional layer, there is a max pooling layer. Therefore, there are three max pooling layers. After the last max pooling layer, there's a single flatten layer. There are two dense layers in the code snippet: First dense layer with 128 neurons uses ReLu activation function and the final dense layer uses softmax as its activation function. label=•

  1) VCG-16: The VCG is a CNN model. VCG16 is one of the variants, consisting of 16 layers, with 13 convolutional layers stacked on top of each other, followed by three fully connected layers at the end. In our model the layers used are the VGG16 convolutional base followed by three dense layers: two with 4096 units each and ReLU activation, and a final output layer with 3 units and softmax activation. These fully connected layers are often used for classification tasks in neural networks.We trained our data for 20 epochs.

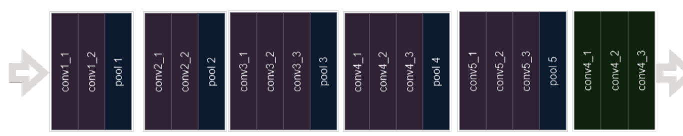

Fig. 3: Architecture of VCG-16

  2) ResNet-50: It is celebrated for its introduction of skip connections that mitigate the vanishing gradient issue in deep neural networks, presents a formidable architecture. Our implementation leverages a pre-trained ResNet50 model, featuring 50 layers, as the foundational architecture for transfer learning. The code incorporates this model, excluding its classification layers, into a Sequential model. Our setup extends this transfer learning architecture with a global average pooling layer, succeeded by two dense layers utilizing ReLU activation functions. We used 20 epochs for training.
  3) GoogleNet: Our model uses an Inception-v3 model, which is an improved version of GoogleNet. Inception-v3 has 48 layers. It incorporates various modules called Inception modules that use multiple convolutional filters of different sizes within the same layer. Majority of the layers within the Inception-v3 architecture utilize the ReLU activation function, while the output layer employs the softmax function for multi-class classification.The

model is compiled using the Adam optimizer and categorical cross-entropy loss for multi-class classification. It's then trained on the specified data for 20 epochs.

4) MobileNet: Our model utilizes MobileNetV2 as a pre-trained base model. MobileNetV2 is a lightweight Convolutional Neural Network (CNN) architecture optimized for mobile and embedded vision applications. It has 53 layers. We used 20 epochs for our training. Uses ReLU (Rectified Linear Unit) activation functions in its convolutional layers. The output layer uses the softmax activation function for multi-class classification.

IV. Result

Our wildfire detection research made use of sophisticated neural network architectures, yielding impressive accuracy results. Using Transfer Learning with ResNet50 resulted in an astounding 98.01 accuracy, highlighting the model's capacity to generalize to new data by using information from large-scale datasets. Furthermore, adopting a Convolutional Neural Network (CNN) with Early Stopping for wildfire detection yielded an impressive 96.64 accuracy. This comprises three Conv2D layers utilizing 32, 64, and 128 filters individually, each followed by ReLU activation, alongside corresponding 3x3 filter sizes. Sequentially, MaxPooling2D layers with a 2x2 pooling window follow each Conv2D layer, reducing spatial dimensions. After the convolutional stack, a Flatten layer reshapes the output for dense layers. Two Dense layers ensue: a hidden layer with 128 neurons using ReLU activation, and an output layer featuring 3 units with softmax activation, catering to a presumed 3-class classification. The model is compiled employing the Adam optimizer, employing sparse categorical cross-entropy loss for multi-class classification, with accuracy as the designated evaluation metric. When validation set performance reaches a plateau, this strategy halts training, confirming the model's robustness and usefulness in detecting wildfires. Furthermore, the inclusion of VGG-16 in our CNN model yielded a 90.000 accuracy, with its deep architecture boosting the extraction of detailed attributes for strong wildfire pattern detection. These findings together highlight the efficiency of sophisticated neural network approaches in improving wildfire detection accuracy, opening the path for significant real-world applications in wildfire tracking and response systems.In our model selection, MobileNet, despite its slightly lower accuracy of 97.14% compared to ResNet's 98.01%, emerges as the preferred choice due to its inherent speed and computational efficiency. While ResNet boasts a marginally higher accuracy, MobileNet's swiftness compensates for this difference, making it a superior option in contexts prioritizing real-time inference or environments with limited computational resources. The sacrifice of a mere less than 1% accuracy is considerably outweighed by MobileNet's agility, ensuring rapid predictions and efficient deployment, a critical advantage especially in scenarios where speed and resource constraints take precedence over marginal gains in accuracy. Hence, MobileNet stands as the optimal model for our specific application, harmonizing commendable accuracy with unparalleled efficiency to deliver swift and reliable performance.

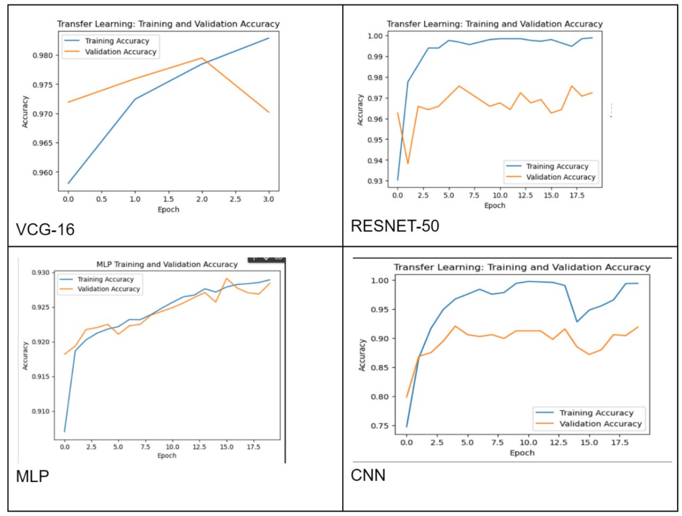

Fig. 4: Validation Accuracies.

The validation accuracy for the ResNet50 model (shown in Fig. 3) outperforms competing models such as CNN, VGG, and MLP. This highlights the effectiveness of ResNet50 in accurately validating data compared to its counterparts. With its advanced architecture and feature extraction capabilities, ResNet50 demonstrates superior performance in this evaluation, showcasing its potential for robust and reliable results in practical applications. This notable achievement underscores the significance of leveraging ResNet50 for tasks that demand high validation accuracy, solidifying its position as a leading model in the realm of deep learning and image recognition.
This is the validation loss of (shown in Fig.3) The validation loss plot of ResNet-50 shows the model's performance on unseen data during training. A smooth decrease in validation loss indicates effective learning, while erratic behavior may suggest overfitting or underfitting. Understanding the validation loss plot helps in assessing the model's generalization ability and identifying the optimal training point. For ResNet-50, monitoring the validation loss over epochs provides crucial insights into the model's convergence and potential issues, guiding adjustments to improve its performance on real-world data. In wildfire prediction, the heat map created by ResNet50 gives vital insights into the model's decision-making process. The heat map offers an interpretability of the neural network's attention by visualizing (shown in Fig. 5) the portions of the picture that significantly contribute to the model's categorization. The heat map may highlight places that the model deems suggestive of fire occurrence in the context of wildfire detection, offering a visible picture of the underlying factors impacting the prediction. This interpretability not only improves the model's dependability, but it also assists in its refinement by putting light on crucial picture components

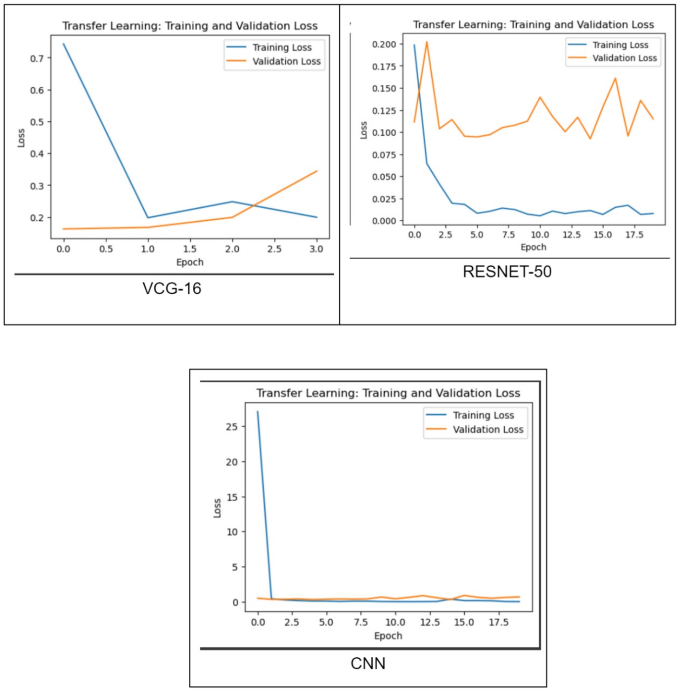

Fig. 5: Validation Loss

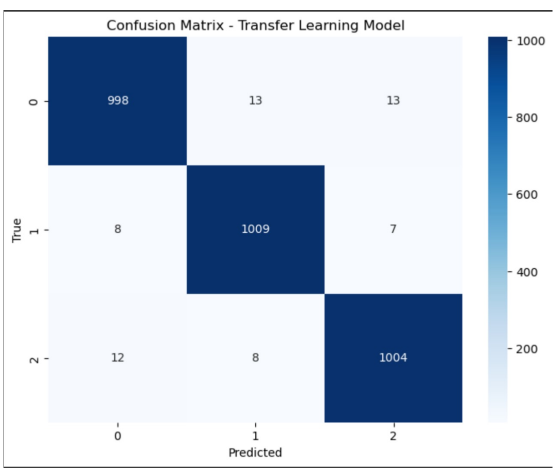

Fig. 6: Heat Map of Resnet-50

that lead to accurate wildfire detection. The heat map created by ResNet50 serves as a significant tool for studying and optimizing the model's decision-making in this case.

V. Conclusion

According to research on wildfire detection, ResNet50 outperformed six other models with different topologies. This emphasizes the significance of carefully choosing models in effective wildfire detection applications. The various models gave useful insights into the complexity of wildfire detection, with ResNet50 appearing as the best option. But MobileNet, despite its slightly lower accuracy of 97.14% compared to ResNet's 98.01%, emerges as the preferred choice due to its inherent speed and computational efficiency. While ResNet

Model	Accuracy	Recall	F1-Score	Precision	Support
MLP	92.71	93	93	93	14947
CNN	85.77	85	85	83	3072
RNN	66.25	66	66	79	10500
ResNet50	98.01	98	98	98	3072
VCG-16	97.57	97	97	96	3072
CNN(Early Stopping)	81.41	81	81	81	3072
MobileNet	97.14	97	98	97	10500
GoogleNet	96.51	97	97	97	10500

Fig. 7: Accuracy Table

boasts a marginally higher accuracy. This accomplishment emphasizes the need of employing advanced model architectures adapted to certain applications.This study lays the groundwork for future improvement of detection approaches, emphasizing the necessity for tactical model selection in achieving increased efficacy and precision in the ever-changing context of wildfire monitoring. In our wildfire detection study,

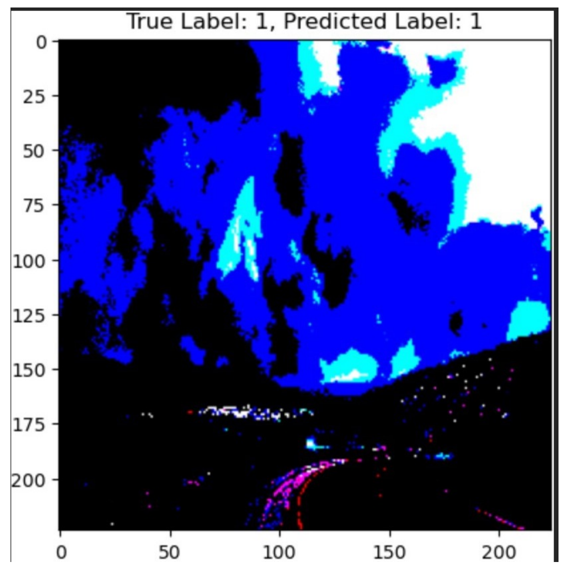

Fig. 7: Predicted Output

the anticipated output from the ResNet50 model additionally exhibits great accuracy(shown in Fig.5.) but also acts as a trustworthy indication, providing real-time insights into future wildfire occurrences.

VI. Future Work

VGG-16's performance can be due to its deep convolutional layers, which allow the model to successfully interpret complicated visual characteristics. This level of precision is especially useful for activities like wildfire detection, where recognising minute characteristics in photos is critical.Further investigation might go into why VGG-16 thrives in this particular application. Examining the parameters of the wildfire dataset and determining how effectively VGG-16 generalizes to the particular variables associated with fire patterns may be required. Insights into the trade-offs between model complexity and computing efficiency may also be obtained.

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