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COMPARATIVE ANALYSIS IN DETECTION OF FOREST FIRES AND SMOKE FROM DRONE IMAGERY USING CNN AND RNN

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Abstract*:Our study investigates the effectiveness of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) in real-time detection of forest fires and smoke using drone-captured aerial imagery, with the CNN model achieving a 72% accuracy rate and the RNN model achieving 57%. The CNN model leverages the spatial features present in the images, while the RNN model exploits temporal dependencies over sequential data. Conducted experiments on a dataset containing annotated drone images of forested areas with varying levels of fire and smoke. The findings highlight the CNN's effectiveness in forest fire and smoke detection compared to the RNN, emphasizing the superiority of CNNs over RNNs in this specific domain. This study offers valuable insights for creating dependable systems to detect and mitigate environmental risks early, essential for protecting ecosystems and human well-being.*

Keywords: *Forest fire detection, smoke detection, drone imagery, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), comparative analysis, deep learning, spatial feature extraction, real-time monitoring,temporal dependencies, environmental hazards.*

1. INTRODUCTION:

The increasing prevalence of forest fires poses significant threats to ecosystems, wildlife, and human populations worldwide. Timely detection and mitigation of these fires are paramount to prevent catastrophic outcomes. Traditional methods of forest fire detection, such as satellite imagery and ground sensors, have limitations in terms of spatial and temporal resolution, coverage, and cost. Therefore, there is a need for alternative and efficient methods of forest fire and smoke detection using drone imagery. High resolution, flexibility, and affordability are among the advantages of drone imagery. However, drone imagery also poses challenges for fire and smoke detection, such as complex backgrounds, varying lighting conditions, and small smoke patches. To address these challenges, we propose to compare the performance of two deep learning models: Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) for forest fire and smoke detection from drone imagery. Although CNNs are commonly utilized for tasks such as image classification and object detection, they can encounter challenges such as overfitting and significant computational complexity.RNNs are suitable for sequential data analysis and can capture temporal dependencies, but they may have problems with long-term dependencies and vanishing gradients.

In this context, the utilization of deep learning methodologies, notably Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), has shown promise in automating the detection process using drone-captured imagery. CNNs excel in the extraction of spatial features from images, rendering them suitable for discerning visual patterns indicative of fire and smoke. Conversely, RNNs excel in capturing temporal relationships, essential for analysing sequences of images acquired by drones over time.

The paper offers an in-depth comparative analysis of CNNs and RNNs for forest fire and smoke detection using drone imagery. The main goal is to assess the efficacy of these deep learning architectures in discerning critical environmental conditions from aerial imagery. Specifically, we aim to evaluate their accuracy performance, robustness, and real-time detection capabilities.Each image is annotated with corresponding labels indicating the existence or non-existence of fire and smoke, facilitating supervised learning-based model training and evaluation.

Through a series of experiments conducted on a diverse dataset of drone images, we demonstrate the advantages and drawbacks of CNNs and RNNs in this context. Our findings provide important understandings regarding the suitability of these techniques for early detection and mitigation of forest fires and smoke, thereby contributing for creating more effective and dependable monitoring systems crucial for safeguarding ecosystems and human livelihoods.

2. LITERATURE REVIEW:

Using CNNs and RNNs, the literature survey reviews various approaches to improve drone-based identifying forest fires and smoke. [1] This paper investigates deep learning methods for detecting forest fires and smoke without encountering the problem of forgetting previously acquired knowledge. Accuracy depends on the specific implementation and dataset used. Results demonstrate the capability to consistently learn and adjust to evolving conditions, with reduced forgetting. Continual learning techniques in deep learning show promise for improving forest fire and smoke detection systems by maintaining adaptability over time. [2] This study utilizes a Convolutional Neural Network (CNN) to concurrently classify fire and smoke in images for fire detection, likely achieving high accuracy. Results showcase the CNN's effectiveness in accurately classifying fire and smoke, potentially aiding in early fire detection and response. Parallel classification using CNNs offers a robust approach for rapid fire and smoke detection in various scenarios, enhancing overall safety measures. [3] Detection of smoke in video sequences employing Convolutional and Recurrent Neural Networks, by combining CNNs and RNNs, this research tackles detection of smoke within video sequences. Accuracy varies derived from video complexity and model performance. Results highlight the method's effectiveness in detecting smoke over time, potentially outperforming individual CNN or RNN approaches. Integrating CNNs and RNNs proves advantageous for dynamic smoke detection in video sequences, promising enhanced surveillance capabilities in fire-prone environments.

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[4] A thorough examination and comparison of Deep Learning Models: CNN, RNN, LSTM, GRU, while not providing accuracy or results directly, this review paper offers valuable insights into CNNs, RNNs, LSTM, and GRU models. The comprehensive analysis aids researchers in selecting appropriate models for specific tasks based on performance characteristics. Understanding the advantages and drawbacks of different deep learning models is crucial for optimizing performance across diverse applications. [5] Deep Learning, this topic serves as an introductory overview of deep learning concepts, lacking specific accuracy and results. Deep learning represents a powerful paradigm shift in artificial intelligence, revolutionizing various fields through its ability to automatically learn hierarchical representations from data. [6] Image Classification Using CNN, this paper likely achieves high accuracy in image classification tasks using CNNs. Results demonstrate the effectiveness of CNNs in accurately categorizing images into predefined classes. CNNs excel in image classification tasks, offering better performance in comparison to traditional machine learning approaches. [7] Enhancing recurrent neural networks for image classification, By enhancing RNN architectures, this study improves accuracy over baseline models. Results showcase enhanced performance in image classification tasks. RNN enhancements lead to improved accuracy and robustness, highlighting the potential for further advancements in deep learning architectures.

[8] Comparing image classification algorithms between traditional machine learning and deep learning; this research compares the accuracy of traditional ML algorithms with deep learning methods. Results provide insights into the performance differences between these approaches. Deep learning outperforms traditional ML algorithms in image classification tasks, emphasizing its superiority in handling complex data. [9] Enhancing deep learning for image classification through the implementation of data augmentation techniques, this study enhances the precision of deep learning models. Results demonstrate the effectiveness of augmentation techniques in enhancing classification performance. Data augmentation significantly improves deep learning model accuracy, offering a practical strategy for addressing data scarcity issues. [10] Simple convolutional neural network on image classification, achieving moderate to high accuracy, this study showcases the effectiveness of a simple CNN architecture in image classification tasks. Even simple CNN architectures can achieve impressive accuracy in image classification, offering a computationally efficient solution for various applications. [11] Image Recognition Using Scale Recurrent Neural Networks: This research achieves improved accuracy in recognizing objects at different scales within images. Results demonstrate the effectiveness of Scale Recurrent Neural Networks in handling scale variations. Scale Recurrent Neural Networks offer a promising approach for robust image recognition across various scales, contributing to advancements in object recognition technology.

[12] CNN-RNN: A Consolidated Framework for Multi-Label Image Classification, by unifying CNNs and RNNs, this study achieves high accuracy in tasks involving multi-label image classification. Results highlight the framework's effectiveness in labelling images with multiple labels accurately. The unified CNN-RNN framework provides a comprehensive solution for multi-label image classification, demonstrating superior performance compared to single-model approaches. [13] Evaluating the effectiveness of RNN and CNN in Image Classification, through quantitative analysis, this research evaluates the performance of RNNs and CNNs in image classification tasks. Results offer Understanding the comparative

strengths and weaknesses of each architecture. The research offers valuable perspectives on suitability of RNNs and CNNs for different types of image classification tasks, aiding researchers in selecting appropriate models based on task requirements. [14] CNN-RNN: a hierarchical framework for large-scale image classification, this paper presents a hierarchical CNN-RNN framework for large-scale classification of images tasks. Findings illustrate the scalability and efficacy of the framework with precision classifying large-scale image datasets. The hierarchical CNN-RNN framework offers a scalable solution for large-scale image classification, showing promise for real-world applications with extensive datasets.

[15] Detecting smoke across various environmental conditions utilizing the approach employing Faster R-CNN based on deep neural networks, this study achieves high accuracy in smoke detection across diverse environmental conditions. Results showcase the model's effectiveness in accurately detecting smoke, even in challenging scenarios. The Approach employing Faster R-CNN based on deep neural networks provides a robust solution for smoke detection across various environmental conditions, enhancing early warning systems for fire incidents. [16] A Dual Deep Learning Approach for Smoke Detection in Image Data, by employing a dual deep learning model, this research achieves high accuracy in smoke detection tasks. Results demonstrate the model's effectiveness in accurately detecting smoke in images, potentially outperforming single-model approaches. The dual deep learning model offers a promising solution for image-based smoke detection, showing potential for improving fire detection systems' reliability.

[17] Comparison and Experimental Review of CNN and RNN for Image Classification, this paper reviews and experimentally compares Utilizing CNNs and RNNs for the classification of images tasks. Results provide understandings regarding each architecture's accuracy performance, computational effectiveness, and robustness. The study offers valuable guidance for selecting between CNNs and RNNs based on task requirements, highlighting their respective strengths and weaknesses in classification of images. [18] Employing Convolutional Neural Networks for Recognizing Images, while lacking specific accuracy and results, this topic likely discusses the general effectiveness of CNNs in image recognition tasks. CNNs serve as a potent tool for image recognition, offering cutting-edge performance throughout various recognition assignments and applications. [19] Brain Tumor Detection and Classification Using Deep Learning with CNN-LSTM Approach, through the CNN-LSTM method, this research achieves high accuracy in identifying and classifying brain tumors. Results demonstrate the method's effectiveness in accurately diagnosing brain tumors from medical images, potentially aiding in treatment planning.[20] Efficient fire detection achieved using ShuffleNet-based CNNs. High accuracy in identifying fire and smoke in images for mobiles and drones. Precision balanced with computational efficiency, promising early fire detection and mitigation. Specific dataset and accuracy details not provided.

2.1. EXISTING SYSTEM:

The existing system for comparative analysis of forest fire and smoke detection from drone imagery revolves around leveraging leveraging deep learning methodologies, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), for assess their performance in discerning critical environmental conditions. CNNs are renowned for their capacity to capture features pertaining to spatial information within images, making them well-suited for detecting visual patterns indicative of fire and smoke in drone-captured imagery. Conversely, RNNs excel in capturing time-related dependencies, an essential aspect for analyzing sequences of images over time. By conducting a comparative evaluation of these two architectures, the system seeks to offer perspectives on their respective advantages and drawbacks in the context of forest fire and smoke detection. This involves training and testing both models within a diverse dataset of drone images, annotating them with labels indicating detecting whether fire and smoke are present. Through rigorous evaluation using standard measures like accuracy, precision, recall, and F1-score, the system seeks for quantify that effectiveness from CNNs as well RNNs in real-time detection scenarios. Ultimately, the findings from this comparative analysis aid in the advancement of further robust and reliable technologies for early detection and mitigation of forest fires, crucial for preserving ecosystems and safeguarding human lives and property.

3. PROPOSED WORK:

The proposed work entails a comprehensive comparative analysis of forest fire and smoke detection from drone imagery, focusing on assessing the performance of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The research begins with the collection of a diverse dataset comprising drone-captured images depicting forested areas under varying environmental conditions, including instances of fire outbreaks and smoke emissions. These images are annotated with labels indicating detecting the occurrence of fire and smoke. Subsequently, the dataset undergoes preprocessing steps, including resizing, normalization, and augmentation, to improve the resilience and applicability of the models. For the model architecture design, both CNN and RNN architectures are tailored to the task at hand. CNNs prioritize spatial feature extraction, while RNNs are designed to capture temporal dependencies within sequences of images. Various CNN architectures, such as VGG, ResNet, or custom architectures, are explored, alongside LSTM or GRU units for the RNN architecture.

The models are then trained on the annotated dataset using appropriate loss functions and optimization algorithms, followed by evaluation employing common metrics like accuracy, precision, recall, and F1-score. Cross-validation trials are conducted to evaluate resilience and generalization. Fine-tuning hyperparameters and optimizing computational efficiency are integral steps, considering real-time processing requirements for drone-based applications. A comprehensive comparative analysis is performed, interpreting the results to pinpoint the advantages and disadvantages of each model architecture, with spatial and temporal aspects of the problem domain considered. Finally, potential future research directions, including the integration of multiple modalities and ensemble methods, are discussed to advance automated monitoring systems for environmental hazard detection. Through this proposed work, the study aims to offer valuable perspectives on the efficiency of CNNs as well RNNs for detection of wildfires and smoke from drone imagery, contributing to advancing further reliable and effective detection mechanisms.

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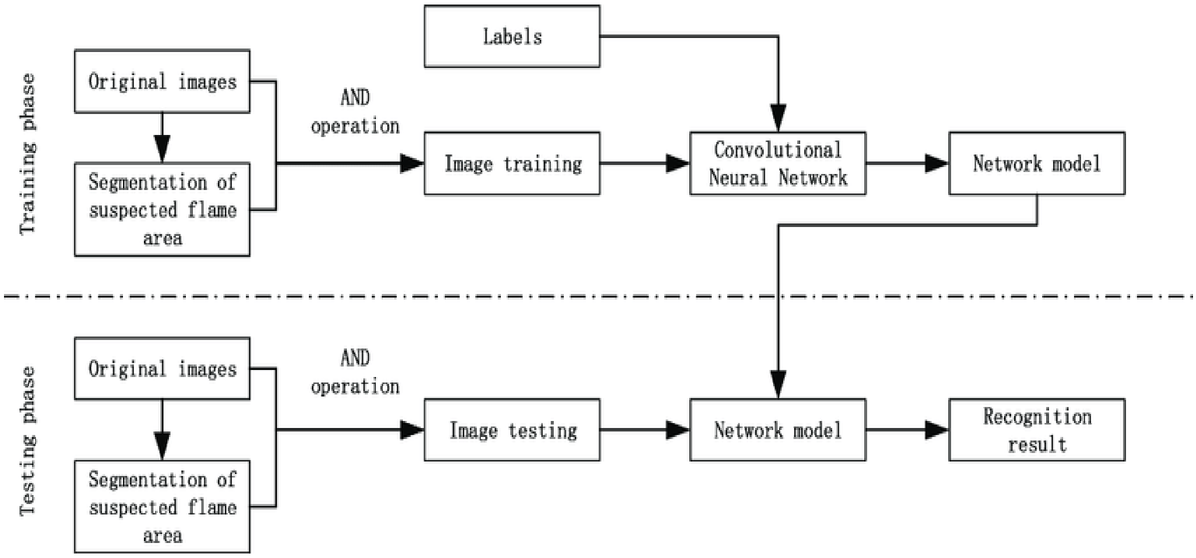
Fig.1 The flow chart describes how to use a CNN to train and test images for flame detection.

Fig.1 CNN Architecture



3.1. Train Phase:

1). Original Images AND Operation:
The process begins with gathering "original images," likely photos of forests or landscapes. The "AND operation" likely indicates a combination of the original image with other data to aid the training process. This additional data might be:

- Manually labelled images where suspected flame areas are highlighted.
- Data from other sensors (e.g., thermal imaging) superimposed on the original image.

2). Segmentation of Suspected Flame Area:
An algorithm segments the image (combined with any additional data) to isolate regions that potentially contain flames. This segmentation might use colour, texture, fire, non-fire, fire and smoke
and smoke for identification.

3). Image Training:
The segmented images of potential flames are used as input to train the core of the system.

4). CNN Model:
A Convolutional Neural Network is a specialized a form of deep learning architecture excellent at image analysis. During training, the CNN learns:

- To identify patterns within the segmented images that correspond to real flames.

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- To distinguish between flames and other objects that might visually resemble them.

3.2. Test Phase:

1. Original Images AND Operation:

New, unseen "original images" are presented to the system. Again, an "AND operation" might combine the new images with additional data, but it's unclear precisely what type.

2. Segmentation of Suspected Flame Area:

The same segmentation algorithm used in the training phase is applied to the new images, isolating areas with potential flames.

3. Image Testing:

The segmented images are inputted into the CNN model that has been trained.

4. Network Model Recognition Result

The CNN analyses the segmented images from the test phase. Derived from its training experience, it determines whether those areas contain genuine flames. The final output is a "recognition result" indicating whether a fire is detected, and potentially highlighting the flame regions in the image.

3.3 Dataset for Evaluation:

The training and testing dataset were sourced from the Wildland Fire Detection and Monitoring video dataset, accessed through IEEE Xplore, utilizing coding techniques to extract a series of images. These images were consolidated into a single folder for further analysis. The study centered on a prescribed burn conducted in Kaibab National Forest, Arizona, USA, near Grand Canyon National Park, with the objective of reducing surface fuel, maintaining logs/snags, and minimizing fire-related mortality.

Data collection involved the use of a DJI Mavic 2 drone for capturing 4K RGB and thermal infrared imagery, complemented by a DJI Matrice 200 drone for pre-burn photogrammetry. Challenges arose due to helicopter ignitions, which limited unmanned aerial systems (UAS) operations to the last ignited perimeter. Dual imagery at 60 meters provided a focused view, addressing challenges and improving the understanding of fire characteristics. The dataset features include 'Data_Name', 'Data_Type', 'camera', 'File_Type', 'Resolution(p*p)', 'Duration', 'FPS', 'File_Size', and 'Labeled', offering valuable insights into the characteristics and metadata associated with each image in the dataset. This diverse and meticulously curated dataset enables comprehensive evaluation and validation of algorithms for detecting forest fires and smoke, facilitating advancing the creation of reliable and precise detection systems for environmental monitoring and disaster management.

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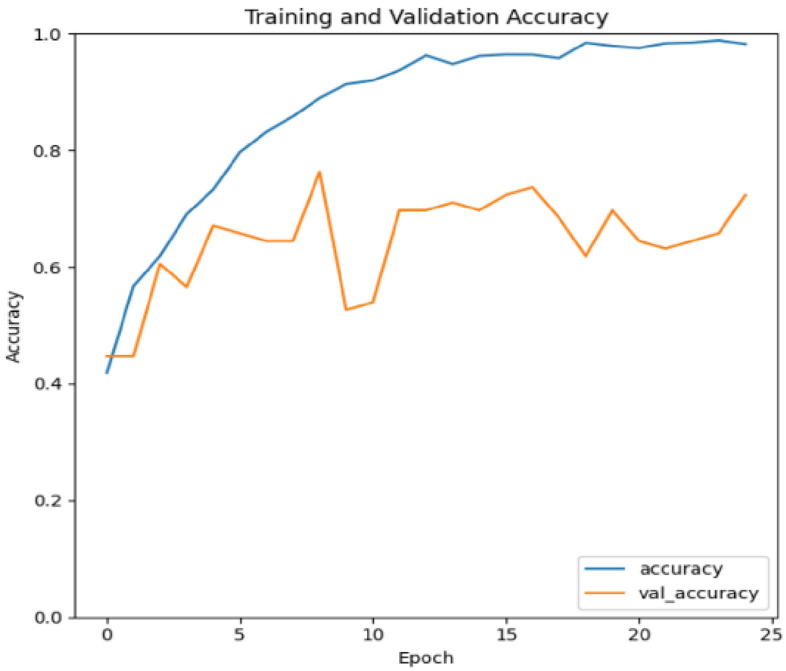
4. RESULT:

The foundation of CNNs, this layer performs convolution operations. The kernel (or filter) within this layer executes the convolution operation, adjusting horizontally and vertically based on a specified stride rate. The kernel is smaller than the input image but has more depth. It scans the entire image, extracting relevant features. Pooling Layer (POOL) is referred to as subsampling or downscaling, this layer reduces the spatial size of the feature map. Typical pooling methods comprise max pooling (choosing the highest value within each region) and average pooling (calculating the mean value).Fully Connected Layer (FC) arelayers link each neuron to every other neuron within adjacent layers. They are responsible for generating predictions using the extracted features.

RNNs are a category of neural networks. specifically intended for modelling sequential data. They excel in tasks where the order of data matters, such as time-series data, natural language processing, and speech recognition. Unlike traditional feedforward neural networks, recurrent neural networks (RNNs) possess an internal memory state, enabling them to capture



temporal dependencies across successive time steps.

Fig.2. CNN ALGORITHM ACCURACY CURVE GRAPH

The Fig.2.CNN algorithm accuracy curve depicts how well the CNN performs on both the training and validation data over successive training epochs. Initially, both training and validation accuracies increase, indicating effective learning. However, as training continues, the validation accuracy plateaus or even decreases slightly.

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This divergence suggests potential overfitting occurs when the model excessively tailors itself to the training data, resulting in poor generalization performance on unseen examples.

Fig.3. CNN ALGORITHM LOSS CURVE GRAPH

The Fig.3. CNN algorithm loss curve represents the variance between predicted values and actual outcomes (loss function). Training loss decreases consistently, while validation loss initially drops but then starts increasing. This divergence aligns with the accuracy trend and further highlights overfitting. To strike a balance, consider early stopping or regularization techniques to prevent overfitting and improve generalization.

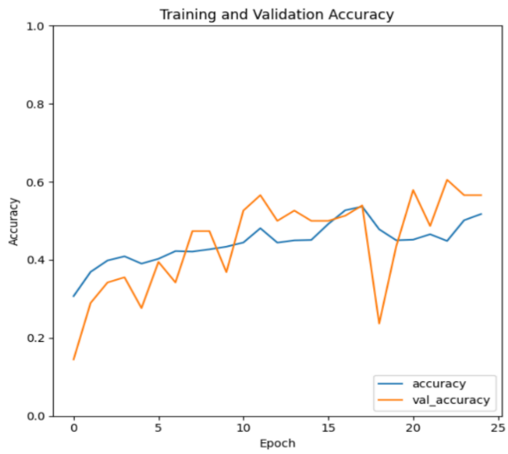

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Fig.4. RNN ALGORITHM ACCURACY CURVE GRAPH

The Fig.4. the accuracy curve of the RNN algorithm illustrates its performance on both training and validation data across consecutive training epochs. Initially, both training and validation accuracies increase, indicating effective learning. However, as training continues, the validation accuracy plateaus or even decreases slightly. This divergence suggests potential overfitting refers to a scenario in which the model becomes excessively tailored to the training data, resulting in poor generalization to unseen examples.

Fig.5. RNN ALGORITHM LOSS CURVE GRAPH

The Fig.5. RNN algorithm loss curve represents the variance between predicted values and observed outcomes (loss function). Training loss decreases consistently, while validation loss initially drops but then starts increasing. This divergence aligns with the accuracy trend and further highlights overfitting. To strike a balance, consider early stopping or regularization techniques to prevent overfitting and improve generalization.

The comparative analysis of forest fire and smoke detection from drone imagery using CNN and RNN, confusion matrices are used to evaluate the performance of these models.

$$\text{Accuracy (A)} = \frac{TP+TN}{TP+TN+FP+FN} \qquad - (1)$$

Precision evaluates the correctness of positive predictions generated by the model, computed as the ratio of true positives to the sum of true positives and false positives. In the context of forest fire and smoke detection, precision indicates how accurately the model identifies actual instances of fire and smoke among all the predicted instances.

$$\text{Precision (P)} = \frac{TP}{TP+FP} \qquad - (2)$$

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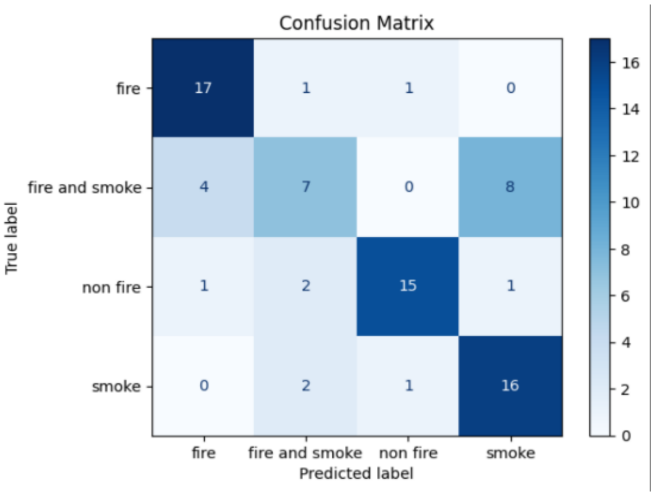
Recall, alternatively termed sensitivity or true positive rate, assesses the model's capacity to accurately detect positive instances among all actual positive instances. It is computed as the ratio of true positives to the sum of true positives and false negatives. In the context of fire and smoke detection, recall indicates how effectively the model captures all instances of fire and smoke in the dataset.

$$\text{Recall ®} = \frac{TP}{TP+FN} \qquad \text{- (3)}$$

The F1 score represents the harmonic mean of precision and recall, offering a balanced evaluation of both metrics with equal importance. It proves valuable, especially in scenarios where there's an unequal distribution between positive and negative instances within the dataset. A high F1 score indicates both high precision and high recall, signifying a robust performance of the model.

$$\text{F1 Score} = \frac{2*(P*R)}{(P+R)} \qquad \text{-(4)}$$

Accuracy quantifies the overall accuracy of the model's predictions, computed as the ratio of the combined true positives and true negatives to the total dataset size. In the context of fire and smoke detection, accuracy indicates how well the model classifies both fire and non-fire



instances

Fig.6. CNN CONFUSION MATRIX

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The Fig.6. confusion matrix illustrates the performance of the CNN model across individual classes. It highlights both correct predictions (diagonal cells) and misclassifications (off-diagonal cells). In each row, the true class is represented, while each column corresponds to the predicted class. The confusion matrix helps us identify where the model struggles. For example, if the CNN consistently misclassifies a specific class (e.g., “fire and smoke”), we can focus on improving its performance in that area.

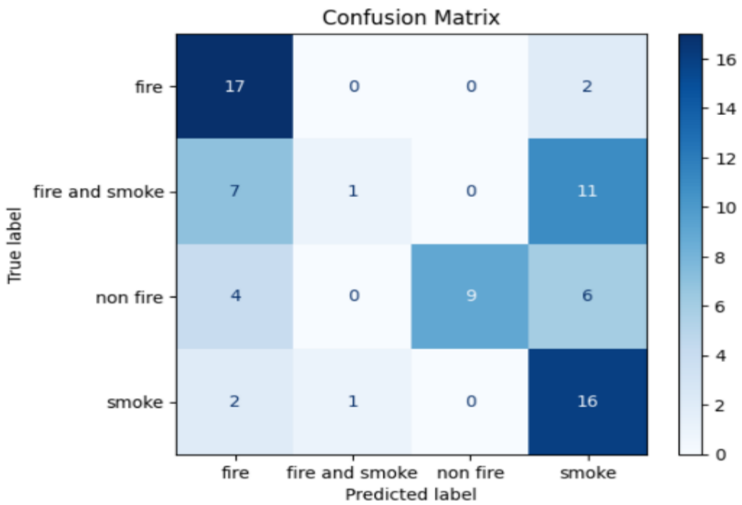

Fig.7. RNN CONFUSION MATRIX

The Fig.7. confusion matrix provides an in-depth perspective on how well the RNN model performs for every class, it indicates both the count of accurate predictions (found on the diagonal) and misclassifications (found off the diagonal) for different categories. Each row corresponds to the true class is depicted in each row, while every column denotes the predicted class. The confusion matrix helps us identify where the model gets confused. For instance, if the RNN consistently misclassifies a specific class (e.g., “fire and smoke”), we can focus on improving its performance in that area.

In the table batch size, image resolution and accuracy are listed.

- **Batch Size:** Specifies the number of training examples utilized in a single training iteration, including forward and backward passes. Larger batch sizes can speed up training but may require more memory.
- **Image Resolution**: The dimensions of the input images (e.g., 256x256 pixels).
- **Accuracy**: The performance metric indicating how well the model predicts the correct class labels. Higher accuracy values are desirable.

TABLE I.CNN ALGORITHM ACCURACYRESULTS

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CNN	16	(256, 256)	71%
	32	(128,128)	63%
		(256, 256)	72%
	64	(128,128)	63%
		(256, 256)	68%

From the Table I, find that the configuration with a batch size of 32 and an image resolution of (256, 256) achieved the highest accuracy of 72%**.** Here’s why this configuration might be optimal:

- **Batch Size**: A batch size of 32 achieves a compromise between computational efficiency and model convergence. While larger batch sizes may accelerate convergence, smaller batch sizes can enhance generalization.
- **Image Resolution**: Higher-resolution images contain more details, but they also require more computational resources. The (256, 256) resolution likely captures relevant features without overwhelming the model.
- **Accuracy**: The 72% accuracy indicates how well the model performs on the test data. It’s essential to consider both training and validation accuracy to avoid overfitting.

TABLE II. RNN ALGORITHM ACCURACY RESULTS

Algorithm	Batch Size	Image (Height,Width)	Accuracy
RNN	16	(128,128)	51%
		(256, 256)	46%
	32	(128,128)	25%
		(256, 256)	25%
	64	(128,128)	57%
		(256, 256)	37%

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In Table II, the configuration featuring a batch size of 64 and an image resolution of (128,128) attained the highest accuracy of 57%. This configuration is potentially optimal due to the following reasons: Larger batch sizes can expedite convergence, whereas smaller ones may offer improved generalization.

- **Batch Size:**A batch size of 64 achieves a middle ground between computational efficiency and model convergence. While larger batches may expedite convergence, smaller ones can enhance generalization.
- **Image Resolution:**Higher-resolution images contain more details but also require more computational resources.The (128,128) resolution likely captures relevant features without overwhelming the model.
- **Accuracy:**The 57% accuracy indicates how well the model performs on the test data.It's essential to consider both training and validation accuracy to avoid overfitting.

The CNN outperforms the RNN in terms of accuracy, achieving 72% compared to RNN's 57%. Additionally, CNN operates with a slightly smaller image resolution while maintaining higher accuracy, indicating better utilization of computational resources. Therefore, the CNN model appears to be the better choice for the detection of forest fires and smoke. from drone imagery in this comparative analysis.

5. CONCLUSION:

In comparing the CNN and RNN detection models for forest fires and smoke. from drone imagery, CNN demonstrates superior performance. With a batch size of 32 and an image resolution of (256, 256), CNN achieves an accuracy of 72%. This indicates its effectiveness in capturing relevant features while balancing computational resources. On the other hand, RNN, with a batch size of 64 and a resolution of (128, 128), achieves a lower accuracy of 57%. While RNN also strikes a balance between efficiency and convergence, its performance lags CNN. The CNN model's higher accuracy suggests better generalization and performance on test data, crucial for real-world applications. Therefore, for forest fire and smoke detection from drone imagery, CNN proves to be the preferred choice due to its superior accuracy and efficient use of computational resources, ensuring reliable detection and mitigation of forest fire incidents.

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