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Comparison Analysis of Satellite Images for Wildfire Detection using Convolutional Neural Network (CNN)

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Abstract:
This research aims to compare the effectiveness of two datasets, the Kaggle Wildfire Prediction Dataset, and the SAT-4 dataset, in detecting wildfires using Convolutional Neural Networks (CNNs). Integrating diverse datasets from multiple sources can significantly enhance the effectiveness of disaster response efforts. The study analyzes satellite images relevant to wildfire incidents from both datasets. The Kaggle dataset, which uses satellite images to detect historical trends, has a test accuracy of 93.76%. In contrast, the SAT-4 dataset, used by Google Research, has a higher accuracy of 95.97%. Both datasets demonstrate high levels of accuracy, but the SAT-4 dataset is faster and more accurate in its implementation. Combining the historical data from Kaggle with the real-time efficiency of SAT-4 can further enhance the system's ability to detect and prevent wildfires more effectively. Integrating CNN-based image processing with remote sensing data improves the accuracy and effectiveness of wildfire identification and monitoring. The system leverages Telegram to notify users once a wildfire is detected, ensuring timely alerts and informed responses. The findings from this research have the potential to significantly improve existing approaches to wildfire management, bringing them to a new level of efficiency and accuracy.

Keywords:
Kaggle, Satellite image, SAT-4, wildfire, deep learning

1. Introduction

Wildfires are among the most devastating natural disasters, whose impact encompasses millions of hectares of forest land and endangers human and material lives. Bearing in mind that the occurrence and severity of wildfires have become increasingly observed, it is crucial to employ advanced technologies to improve its detection and response system. To elaborate on the topic of this essay, AI-dependent computer vision combined with remote sensing is a critical tool in the fight against wildfires today.

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When a fire outbreak occurs, the first step is the detection of the fire early enough, so that the response measures that will help in controlling the fire can be undertaken. However, existing systems face significant shortcomings. Traditional methods, such as human surveillance and satellite imagery, are often slow to respond and prone to delays in real-time detection. Ground-based sensors can be limited in coverage and fail to provide comprehensive data in remote or expansive areas. Additionally, many detection systems lack the integration of diverse data sources, such as meteorological information, satellite imagery, and social media reports, which could provide a more accurate and timely detection process.

Computer vision based on AI also performs well in analyzing satellite imagery and ground photos and focuses on identifying characteristic signs of smoke and fire. These technologies can help authorities quickly locate the fire and respond with the appropriate resources and evacuation procedures, thereby reducing the effects experienced by society and the repercussions on the environment.

Timely detection, monitoring, and response are crucial for minimizing the impact of wildfires. Improvements in technology have made it possible to analyze wildfire data in more efficient ways, one such method makes use of images and image analysis methods. This research aims to create Convolutional Neural Networks (CNNs) that can analyze data via images to prevent wildfires[1].

One useful and efficient method for early wildfire recognition, monitoring, and control is the use of remote sensing to take pictures of wildfires. The process of remote sensing involves collecting data from a distance[2].

1.1 Related Work

Modern approaches for forest fire prediction have been the center of contemporary research to improve the outcome of implementing early prediction and prevention measures. Some of the well-known techniques that help enhance the predictability of the model include. The paper [3] points out that, Decision Trees show choice results with regard to the used attributes Along these lines, the Random Forests give the outcomes of different trees reduced techniques to enhance accuracy. Patterns of fire are well analyzed by SVMs and non-linear classifications because these techniques are suitable when a large amount of data is used as input. KNN also uses classification based on distances to determine regions that experience frequent fires. Several aspects are used to enhance the models: integration of spatial and time data as well as images and weather data. Mobile platforms with efficient algorithms of data flow in real-time create necessary and sufficient conditions for early alerts and interventions to manage fire effectively. Challenges persist in adapting models to dynamic environmental conditions and human influences. Collaborative efforts are essential for refining these tools and deploying them effectively to mitigate wildfire impacts [3].

According to paper [4] deploying CNNs requires a methodical approach. First, a varied dataset is gathered and annotated that includes photographs of both wildfires and non-wildfires. The next steps involve preparing the data, which includes standardizing image sizes, normalizing pixel values, and applying data augmentation methods to improve the model's flexibility. The dataset is divided into training, validation, and test sets during the training phase. Performance is continuously improved by making tweaks to the hyperparameters. Evaluation measures, such as precision and accuracy, are used in conjunction with continuous improvement tactics that are updated and monitored with fresh data. The study in [5] stated that An Artificial Neural Network (ANN) is a type of artificial intelligence that largely mimics human intellect and logical thinking. Similar to the human brain, artificial neural networks (ANNs) can recognize patterns, organize data, and learn new skills. An innovative technique that expands on previous research for identifying wildfires using a single ANN combines color and multi-color space local binary patterns of both fire and smoke features.

The paper [6] The suggested model has two layers: a data collection layer and a processing unit that employs Adaboost-MLP, Adaboost-LBP, and CNN models. Sensor data, images/videos, and datasets from the cloud and social media are gathered and stored locally, and datasets from the cloud and social media are incorporated for model training. The Adaboost-MLP model predicts the fire environment, triggering additional models for confirmation, whilst the Adaboost-LBP model supports the CNN model in creating ROIs for quicker detection. The combined models outperform typical CNN models with an accuracy of about 97.8%. The models are validated in the research using a variety of fire video and picture datasets, indicating their usefulness in categorizing distinct fire incidents. Challenges include the necessity for strong datasets, possible false alarms, and real-world deployment and scalability issues, with an emphasis on continuous research for algorithm refining and practical application.

The paper [7] focuses on convolutional neural networks (CNNs), and a novel dual-channel CNN is shown. In order to improve network efficiency and reduce overfitting, the evaluated research places a strong emphasis on the incorporation of advanced characteristics including transfer learning and attention processes. Of particular note is the dual-channel model's remarkable 98.90% fire identification accuracy. To improve model robustness, methodologies are assessed on a variety of datasets, most notably a set of 14,000 photos including disruptive variables. The research identifies persistent difficulties with dataset generation, training, and generalization. To solve these problems, a variety of realistic datasets is still required. Notwithstanding advancements, the study emphasizes the need for further research to create reliable and broadly applicable forest fire detection systems.

2. Materials and Methods

Before beginning this task, there is much planning and contention. A broad outline of the work is provided. Before the task can begin, it must be well prepared and planned to ensure that it meets the flow. It also makes sure that the process proceeds smoothly. The time management for this project is methodically planned, and the procedure is designed using a flowchart. Figure 1 shows a flowchart of the project process, whereas Figure 2 shows a block diagram.

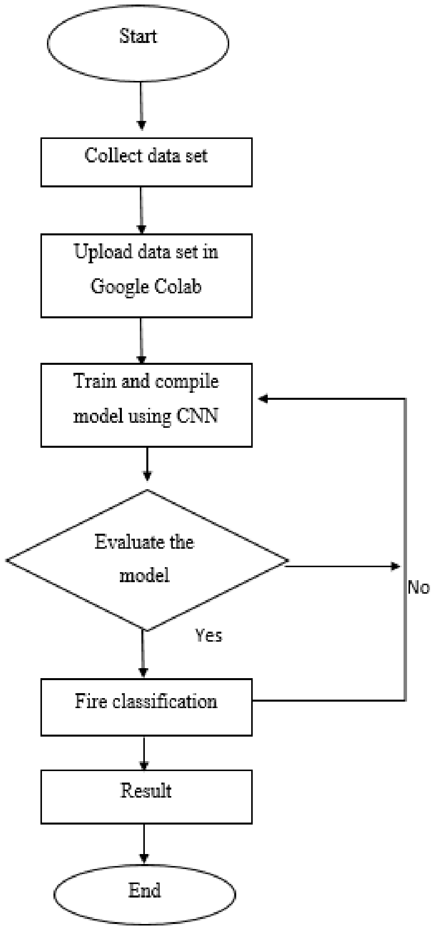

Figure 1: The process flow chart created with Google Collaboration

The flowchart in Figure 1 describes the process of using a Convolutional Neural Network for the classification of wildfire images. The flowchart below indicates the steps that are followed.

i. Access the satellite wildfire image dataset [8][9], which is a set of images containing wildfire scenes and negative samples, that is, non-wildfire scenes.
ii. Google Colab is a popular cloud notebook environment that allows for program execution and access to machine learning libraries. Datasets be uploaded.
iii. Classification of the model using CNN requires the architecting of the network, the loss function, the optimizer, and the metrics..
iv. The next step is setting the parameters, which includes choosing things such as the number of epochs, batch size, learning rate, and the validation split.
v. Verify the model: this is the procedure of determining how effectively the validation dataset's characteristics are identified by the model with respect to the predetermined threshold.
vi. Plot the training model's accuracy and loss variation over the epochs on the graph if the result is good.
vii. Assuming that evaluation shows that the model is not performing optimally, the settings should be changed and the model retrained until the assessment is near perfect.
viii. Predicting new images of wildfire means applying the trained model and predicting the possibility of a new image to be containing wildfire or not.

ix. Execute the test and show the output, which is the predicted label of each image and its corresponding confidence level.

The identification of wildfire using a CNN, stated that there are three input processing and output processes. One of the earliest pieces of data that the system analyzes is satellite imagery. Some of the different kinds of land cover indicated in these photos include roads, buildings, grasslands, trees, and water bodies as in Figure 3.

CNN is utilized to process the data based on the architecture. This uses several CNN layers to extract relevant information from the satellite images seen by humans. In other words, each layer in the CNN is responsible for detecting some patterns or features within the pictures. Each convolutional layer in feature extraction takes out a part of the image; deeper layers get more complex features.

Subsequent to this process are pooling layers, whereby the spatial dimensions in the feature maps are reduced. This makes computation faster and helps the network in denoising and in general movement towards invariance to small transformations of inputs. Then layers called fully connected layers take the high-level features produced by the convolutional and pooling layers and use them to output the final results. Algorithms are trained on sets of annotated data wherein each image is classified either as wildfire or non-wildfire thereby aiding in the training of the network.

During the model training, they utilize annotated datasets that assign a 'wildfire' or 'non-wildfire' to each satellite picture as output. These annotations are then employed as ground truths by the CNN which in turn enables it to learn the distinction between photos that depict wildfires and those that do not. It does this by training on these datasets and being able to identify the relevant patterns or attributes as being linked to the presence or absence of wildfires from the photos.

3. Results and Discussion

This section focuses on how this project developed convolutional neural network (CNN) accuracy on this issue, which detects patterns of wildfires in data. Training of the algorithm was carried out on a substantial data set with annotated pictures producing good results in the classification of fire hotspots and differentiation of non-fire conditions. This study has shown that deep learning has the capability for automated wildfire detection and further work can be done to enhance the existing system and make changes to improve the system's other aspects and efficiency in order to further improve the effectiveness of the wildfire detection and prevention.

3.1 CNN Modelling

The CNN function creates a sequential model consisting of several layers: two convolutional layers and each layer includes a following max pool layer to down sample the features; a flatten layer which take the data in form of matrix and convert it into vector. A densely connected layer with dropout to avoid overfitting; and the last layer is dense layer with softmax activation function to get the classification.

```python
import numpy as np
import math
import matplotlib.pyplot as plt
import keras
import os
import tensorflow as tf
#import keras
from tensorflow import keras
from keras.models import Sequential
from keras.layers import Dense, Flatten
from keras.layers import Conv2D, MaxPooling2D, Activation, Dropout
from keras.models import model_from_json
from keras.callbacks import ModelCheckpoint
from sklearn.metrics import confusion_matrix, classification_report


def CNN(input_shape, num_classes):
    model = Sequential()

    #Convolution block 1
    model.add(Conv2D(8, (3, 3), activation='relu', input_shape=input_shape))
    model.add(MaxPooling2D((2, 2)))

    #Convolution block 2
    model.add(Conv2D(16, (3, 3), activation='relu'))
    model.add(MaxPooling2D((2, 2)))

    #Flatten layer
    model.add(Flatten())

    #Densely connected layer
    model.add(Dense(16, activation='relu'))

    model.add(Dropout(0.2))

    #Classification by softmax
    model.add(Dense(num_classes, activation='softmax'))

    model.compile(optimizer='rmsprop', loss=keras.losses.categorical_crossentropy, metrics=['accuracy'])

    return model
```

Figure 2: CNN Modelling Coding in Google Colab

Because of its shown ability to handle complicated, high-dimensional data, we chose a deep CNN architecture for this investigation. This allowed the network to learn hierarchical features that are pertinent to wildfire detection automatically. To capture a range of spatial and temporal patterns found in both historical and real-time data, the architecture combines several convolutional layers, pooling layers, and fully connected layers. A ResNet-like architecture was used to tackle the problem of finding tiny or weak wildfire signs in big, noisy datasets. The model can maintain a deeper network without experiencing the vanishing gradient problem thanks to the usage of residual connections, which is essential for identifying early-stage wildfires that might not be immediately apparent. The simplicity and efficacy of the VGG-inspired architecture were also taken into account.

Because of its ease of use and efficiency in feature extraction with fewer parameters—which guarantees quicker training and lessens overfitting—the VGG-inspired architecture was also taken into consideration. Additionally, we used data augmentation techniques like random rotations, shifts, and flips—which mimic real-world fluctuations in satellite images and sensor data—to increase the model's robustness and generalization capabilities. Given that conditions can differ greatly between regions, this is especially crucial for detecting wildfires. Finally, because the dataset could be unbalanced in terms of wildfire occurrences, the architecture incorporates Dropout layers to avoid overfitting. We think the model will offer excellent accuracy and resilience for real-time wildfire identification and early warning systems by combining these tactics and carefully selecting the CNN layers.

3.2 Load the Dataset

The chosen dataset from Figure 3 is loaded, and the training and test data, along with their corresponding labels, are extracted. The data format is then converted to match TensorFlow's default channel-last ordering. A random selection of images from the dataset is visualized, showcasing different channels such as color, red, green, blue, and near-infrared.

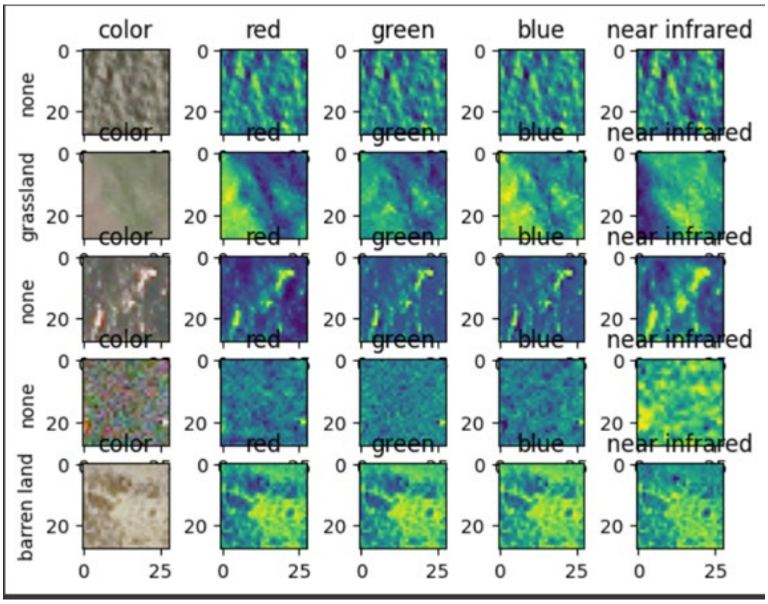

Figure 3: Dataset extracted

3.3 Comparison of SAT Datasets with Kaggle Datasets

The Kaggle Wildfire Prediction Dataset and the SAT-4 data set are both valuable resources for wildfire detection and prediction, each with unique strengths. The Kaggle dataset includes satellite photos of locations that have already experienced wildfires, making it useful for training machine learning algorithms to recognize wildfire patterns. This dataset contains a total of 42,850 images, divided into two categories: 22,710 photos labeled "Wildfire," which represents active fire occurrences, and 20,140 photos labeled "No wildfire," showing landscapes unaffected by flames. In contrast, Google Research's SAT-4 dataset allows for real-time surveillance of wildfire boundaries and comprises 500,000 picture patches that represent four main land cover classifications: barren ground, trees, grassland, and a class that includes all other land cover types. Of these, 400,000 patches were selected for training, with the remaining 100,000 chosen as the testing dataset. The Kaggle dataset, which is similar to the dataset depicted in Figure 4, originates from Canada's Open Government Portal's Forest Fires section. By utilizing the historical data from the Kaggle dataset and the real-time capabilities of the SAT-4 dataset, it is possible to develop a comprehensive system for wildfire detection and prevention that leverages the strengths of both datasets.

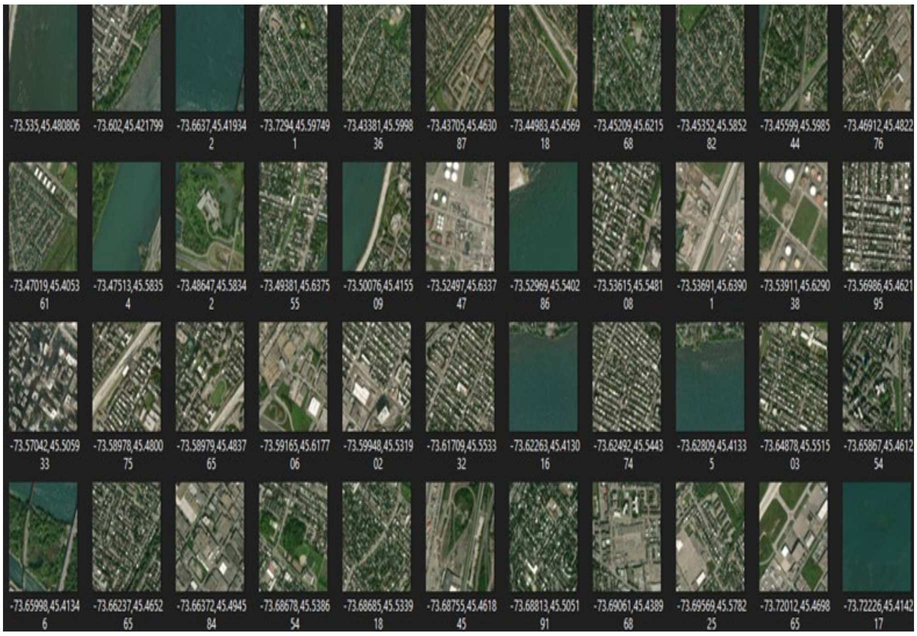

Figure 4 (a): Data sets from Kaggle from the Forest Fires section of Canada's Open Government Portal

Figure 4 (b): Satellite image data set from SAT-4

3.4 Evaluation Model from Sat 4 Data Set

Performance is shown in Figure 5, where accuracy is attained on the validation (test) dataset. The model generalizes well to new data, as demonstrated by the training accuracy increasing across epochs and the validation accuracy remaining high over time. The low test loss and high test accuracy indicate that CNN is using the provided SAT dataset to learn and make accurate predictions.

```
Start learning...
Epoch 1/10
600/600 [============================] - 28s 44ms/step - loss: 0.7804 - accuracy: 0.6759 - val_loss: 0.5382 - val_accuracy: 0.8091
Epoch 2/10
600/600 [============================] - 23s 38ms/step - loss: 0.4691 - accuracy: 0.8254 - val_loss: 0.3966 - val_accuracy: 0.8418
Epoch 3/10
600/600 [============================] - 29s 48ms/step - loss: 0.3600 - accuracy: 0.8685 - val_loss: 0.2105 - val_accuracy: 0.9263
Epoch 4/10
600/600 [============================] - 23s 38ms/step - loss: 0.2951 - accuracy: 0.8921 - val_loss: 0.1900 - val_accuracy: 0.9273
Epoch 5/10
600/600 [============================] - 26s 43ms/step - loss: 0.2581 - accuracy: 0.9083 - val_loss: 0.2934 - val_accuracy: 0.8851
Epoch 6/10
600/600 [============================] - 27s 45ms/step - loss: 0.2301 - accuracy: 0.9201 - val_loss: 0.1465 - val_accuracy: 0.9496
Epoch 7/10
600/600 [============================] - 27s 44ms/step - loss: 0.2036 - accuracy: 0.9304 - val_loss: 0.1210 - val_accuracy: 0.9590
Epoch 8/10
600/600 [============================] - 23s 38ms/step - loss: 0.1856 - accuracy: 0.9379 - val_loss: 0.1314 - val_accuracy: 0.9549
Epoch 9/10
600/600 [============================] - 26s 43ms/step - loss: 0.1740 - accuracy: 0.9409 - val_loss: 0.1103 - val_accuracy: 0.9635
Epoch 10/10
600/600 [============================] - 24s 40ms/step - loss: 0.1659 - accuracy: 0.9448 - val_loss: 0.1059 - val_accuracy: 0.9625
Start evaluation...
```

Figure 5: Ten Epochs test from Sat-4 data set

3.5 Accuracy and Loss of Fire Classification

From Figure 6. (a) accuracy quantifies the percentage of correctly predicted instances out of the total number of instances evaluated. It is a straightforward measure of how well the model performs in terms of making correct classifications. For example, an accuracy of 96% indicates that the model correctly predicts 95 out of every 100 instances. High accuracy is desirable as it reflects the model's ability to generalize well to new, unseen data and make accurate decisions across different classes or categories.

Meanwhile in Figure 6. (b) model loss represents the error between the model's predictions and the actual ground truth during training. It quantifies how far off the model's predictions are from the true values. The goal during training is to minimize this loss function, typically using optimization algorithms like gradient descent. By minimizing loss, the model learns to adjust its parameters to improve its predictions and reduce errors. A lower loss indicates that the model's predictions are more accurate with time since they are closer to the real values.

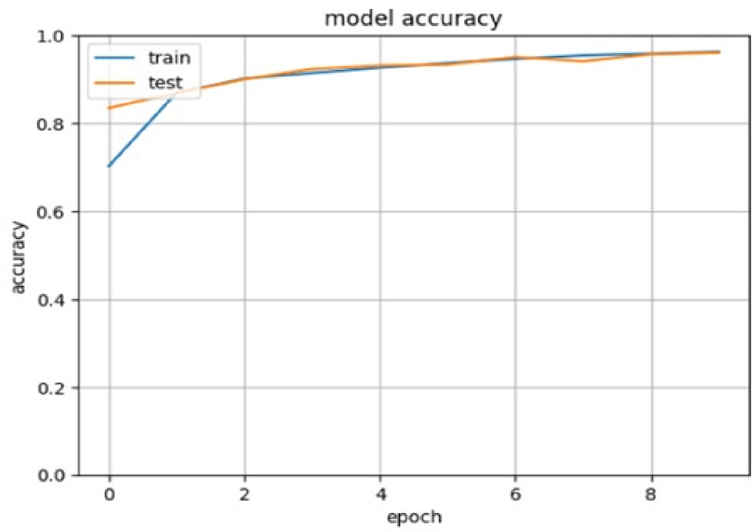

Figure 6 (a): Values of accuracy for the test and training sets

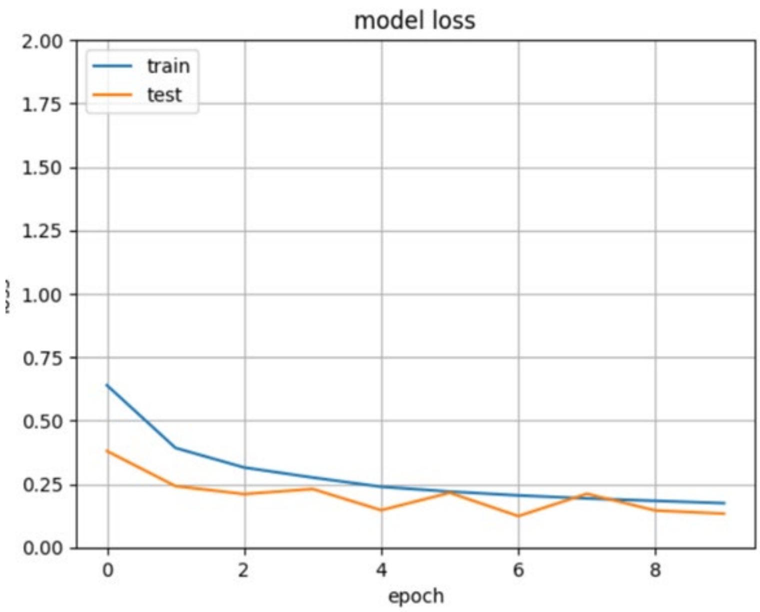

Figure 6 (b): Loss values for training and test sets

3.6 Results of the SAT 4 and Kaggle

Table 1: Result of testing comparison between SAT 4 and Kaggle dataset

Dataset	Epochs	Average Epoch Time (seconds)	Final test accuracy
SAT-4	10	3-5	95.97%
Kaggle	10	152-170	93.76%

From Table 1, the effective learning for both datasets is indicated by the training logs, which show a consistent pattern of decreasing loss and increasing accuracy throughout the training period. But SAT-4 shows better overall accuracy, with a final test score of 95.97%, compared to 93.76% for Kaggle, as Table 1 illustrates. This implies that either the model architecture was better adapted to the features of SAT-4, or SAT-4 was more favorable to the neural network's learning process. Regarding training duration, Kaggle necessitates significantly lengthier epochs compared to SAT-4. Each Kaggle epoch spans 152-170 seconds, while SAT-4's epochs last only 3-5 seconds. This difference may arise from variations in dataset size or complexity, with Kaggle potentially being larger or more intricate.

In conclusion, both datasets show excellent training results, attaining high test-data accuracy. However, SAT-4 outperforms Kaggle in terms of training efficiency and accuracy, suggesting potential advantages in terms of dataset features or learning ease.

3.7 Discussion of Limitations:

While the proposed wildfire detection system demonstrates strong performance in terms of accuracy and real-time detection capabilities, several limitations must be acknowledged.

1. **Data Quality and Availability:** In regions where satellite coverage is limited or data collection infrastructure is sparse, the system's detection capabilities may be compromised. Additionally, incomplete or noisy data can introduce inaccuracies in the model's predictions, especially in the early stages of wildfire events.
2. **Generalization to Diverse Environments:** Localized environmental factors, such as smoke or humidity levels, might also impact the model's sensitivity and accuracy in detecting wildfires.
3. **Real-Time Processing Constraints:** In resource-constrained environments or when working with limited hardware, processing delays may arise, affecting the timeliness of the wildfire detection and response.
4. **Interpretability of Model Decisions:** This lack of interpretability can pose challenges in operational settings, where stakeholders may require a clear explanation of the model's decisions to trust its outputs fully.

4. Conclusion

In conclusion, convolutional neural networks (CNNs), in particular, are integrated with deep learning models. into the project has proven to be a transformative advancement in wildfire detection. The high accuracy achieved across various data sources, including satellite imagery, aerial images, and real-time video feeds, reflects the capability of these models to autonomously learn complex patterns from raw data. The project's results have the potential to completely transform approaches to managing and preventing wildfires. The early identification that these models provide allows for efficient response effort coordination, the deployment of firefighting resources, and the execution of evacuation plans. By using this preventative measure, wildfire-related fatalities, property losses, and ecological effects can be significantly reduced. The project's overall impactful synergy between deep learning, advanced technology, and wildfire control is demonstrated, opening the door to improved safety and resilience in the face of natural disasters. As advancements in technology continue to drive improvements in wildfire detection, this research highlights the importance of integrating diverse datasets and optimizing deep learning models like CNNs to enhance accuracy and efficiency. The promising results from this study suggest that future wildfire management can benefit significantly from the continuous development of AI-driven solutions.

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