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Deep Learning Approaches for Smoke and Wildfire Detection: Yolo Model Analysis

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ABSTRACT: This project introduces forest fire detection by utilizing the YOLO (You Only Look Once) algorithm. Prior to YOLO, traditional CNN (Convolutional Neural Network) methods were employed but proved ineffective due to their limited ability to detect only the fire images present in the dataset. YOLO, being an advanced technology, better than sequential models by its capability to detect objects in any images or videos efficiently. Through effective training, YOLO can accurately identify forest fires in diverse scenarios, enabling real-time detection and response. Upon detecting a fire in the cameras, the system triggers alarms and sends messages to alert relevant stakeholders, thereby enhancing forest fire monitoring and prevention efforts. This approach offers a promising solution for early detection and mitigation of forest fires, contributing to environmental conservation and public safety.

KEYWORDS: Forest Fire Detection, Yolo algorithm, Real time detection, Stakeholder Alert, Public Safety

I. INTRODUCTION

The present invention is a cutting-edge system for efficiently detecting forest fires using the YOLO (You Only Look Once) algorithm. Leveraging the power of artificial intelligence and computer vision, this system provides real-time monitoring and early detection of forest fires, significantly enhancing fire management and response efforts.

Traditional methods of forest fire detection often rely on manual observation or stationary sensors, which can be slow and limited in coverage. In contrast, our invention utilizes YOLO, a state-of-the-art object detection algorithm known for its speed and accuracy. By analyzing high-resolution images captured by drones or satellites, the system can swiftly identify and locate potential fire incidents within vast forested areas.

The implementation of the YOLO algorithm enables the system to process images in a single pass, making it incredibly efficient for real-time monitoring. This means that forest fires can be detected and reported promptly, minimizing the risk of widespread damage and facilitating faster response by firefighting teams.

Moreover, the system is adaptable to various environmental conditions and can operate autonomously, reducing the need for human intervention. Its scalability allows for seamless integration into existing fire management infrastructure, providing a cost-effective solution for forest fire prevention and mitigation.

In summary, our invention revolutionizes forest fire detection by harnessing the power of AI and YOLO algorithm, offering a proactive approach to fire management and safeguarding our natural ecosystems and communities.

II. LITERATURE REVIEW

Literature research is the most important step in the software development process. Before creating a tool, it is important to determine the time factor, profitability, and company strengths. With these in place, the next 10 steps are to decide which operating systems and languages you can use to develop your tools. Once programmers start building tools, they need a lot of external support. This support can come from experienced programmers, books, or websites. The above evaluations will be considered in the development of the proposed system before building the system.

Edmundo Casas; Leo Ramos; Eduardo Bendek; Francklin Rivas Echeverría. "Assessing the Effectiveness of YOLO Architectures for Smoke and Wildfire Detection " 2023.

This paper presents a comprehensive evaluation of YOLO architectures for smoke and wildfire detection, including YOLOv5, YOLOv6, YOLOv7, YOLOv8, and YOLO-NAS. We aim to assess their effectiveness in early detection of

wildfires. The Foggia dataset is used for this, and performance metrics such as Recall, Precision, F1-score, and mean Average Precision are employed. Our methodology trains each architecture for 300 epochs, focusing on recall for its relevance in this area. The 'best models' are evaluated on the Foggia test set and further tested with a challenging, custom-assembled dataset from independent online sources to assess real-world performance. Results show that YOLOv5, YOLOv7, and YOLOv8 exhibit a balanced performance across all metrics in both validation and testing. YOLOv6 performs slightly lower in recall during validation but achieves a good balance on testing. YOLO-NAS variants excel in recall, making them suitable for minimizing missed detections. However, precision performance is lower for YOLO-NAS models. Visual results demonstrate that top-performing models accurately identify most instances in the test set. However, they struggle with distant scenes and poor lighting conditions, occasionally detecting false positives. In favorable conditions, the models perform well in identifying relevant instances. We conclude that no single model excels in all aspects of smoke and wildfire detection. The choice of model depends on specific application requirements, considering accuracy, recall, and inference time. This research enriches the field of computer vision for smoke and wildfire detection, laying a foundation for system enhancements and serving as a basis for future research to optimize detection effectiveness.

Muhammad Sulaiman; Fazlullah Fazal; Addisu Negash Ali; Ghaylen Laouini; Fahad Sameer Alshammari; Majdi Khalid “ A Stochastic NARX Neural Network to Investigate the Carbon Capture in the Plantations of Forests” 2023

Fast-growing forests play a vital role in decreasing global warming and have an extensive capacity for carbon capture. Three variables involved in the model are the quantity of living biomass, the intrinsic growth of biomass, and a forestry fire that has burned the area. This study explored the impact of environmental and ambient humidity parameters on the dynamics of fast-growing forest plantations. The nonlinear autoregressive network with exogenous inputs (NARX) technique is used to study the dynamics of fast-growing forest plantations. For the assessment of our soft computing technique, we use the Runge-Kutta fourth-order approach as reference solutions. The results of our simulations are compared with the reference solutions. It has been concluded that our approach is superior to the state-of-the-art. Regression, fitness, and error histogram plots are graphically displayed for further illustration of the results.

S. Fouziya Sulthana; Cross T. Asha Wise; C. V. Ravikumar; Rajesh Anbazhagan; G. Idayachandranyear “Review Study on Recent Developments in Fire Sensing Methods”2023

Scientific society has envisioned a considerable advancement in various fire detection methods. due to the development in the field of machine learning, information technology, sensors, and signal processing technology. These intelligent processing technologies help in reducing the detection time and false alerts from the sensors. Over the past few decades, there is substantial improvement in the computing power of computers and a decrease in the cost of image sensors, enabling video-based fire detection technology for real-time applications. The ability to differentiate between fire and non-fire threats is improved with the development of the Internet of Things (IoT) or Wireless Sensor Networks (WSN). Unmanned Aerial Vehicles (UAVs) are becoming a more realistic solution for monitoring and detecting fire due to their remote sensing capabilities. This paper summarizes various fire detection methods and the technologies behind them. The issues related to the present fire detection methods and future research initiatives are discussed. The primary aspects of the fire signatures like flame, smoke, ambient temperature, and surrounding gaseous levels concerning different sensors are analyzed with their benefits and drawbacks based on evaluating a range of parameters.

Wei Li; Jinbao Sun; Zijian Chen; Kunjian Liu; Zhe Zhang; “Smoke and Flame Identification Method for the Entire Process of Grassland Fire Based on YOLOv5m-D and Static and Dynamic Characteristics”2023

The current detection methods for grassland fires mainly rely on manual means, which are costly, inefficient, and difficult to achieve real-time and full coverage detection. Therefore, the YOLOv5m-D model and its static and dynamic characteristics are proposed to detect and identify smoke and flame throughout the entire process of grassland fires, and its effectiveness is verified. The experimental results showed that in smoke recognition and detection, YOLOv5m-D model showed slow local convergence under the condition of low Learning rate, and the mAP value of YOLOv5m-D was 86.4% when the batch size was 16. In the comparison of mAP values under the optimal hyperparameters, the Faster RCNN value was 72.34%, SSD value was 75.90%, YOLOv5m value was 86.75%, and YOLOv5m-D value was 89.28%, which was higher than the comparison model. In flame recognition detection, in the Hul moment, the ordinary image sequence and infrared thermal imaging sequence, except for a few that were around 0.8, were mostly maintained at around 0.3-0.7, while the color tent was both below 0.1. After combining infrared images with flame static and dynamic feature recognition, the flames are basically recognized. In the comparison of single feature recognition time, the current frame recognition time of different images under the vast majority of features is lower than the reference frame. Overall, the YOLOv5m-D model proposed in the study and its static and dynamic characteristics are effective in detecting and identifying smoke and flame throughout the entire process of grassland fires, and have high practical effects for practical grassland fire detection.

Lidong Wang; Huixi Zhang; Yin Zhang; Keyong Hu; Kang An; “ A Deep Learning-Based Experiment on Forest Wildfire Detection in Machine Vision Course” 2023

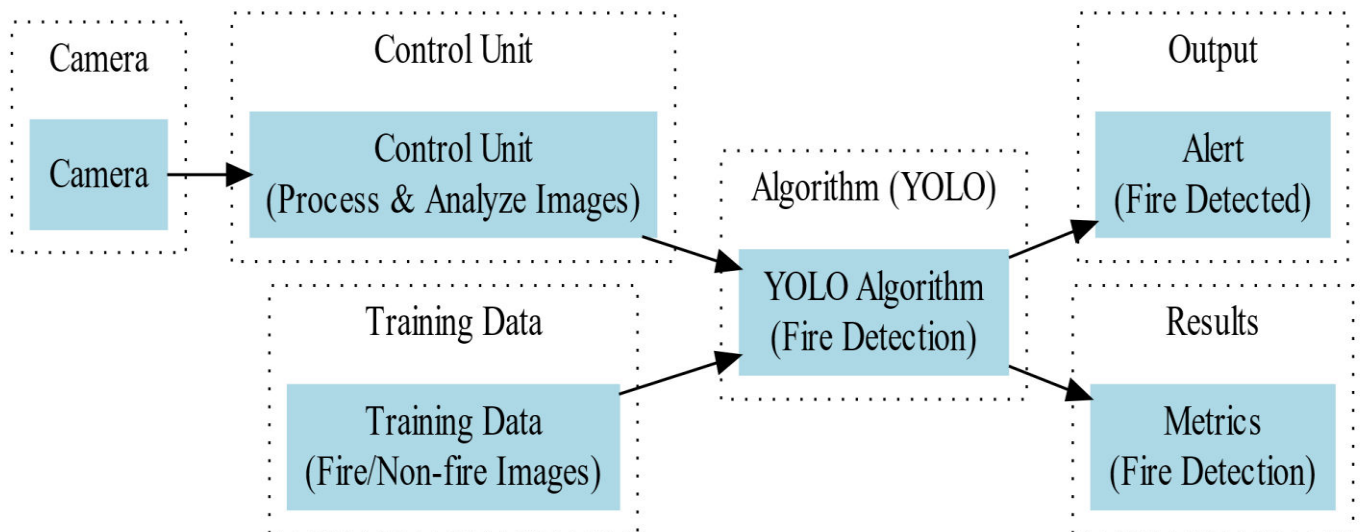
As an interdisciplinary course, Machine Vision combines AI and digital image processing methods. This paper develops a comprehensive experiment on forest wildfire detection that organically integrates digital image processing, machine learning and deep learning technologies. Although the research on wildfire detection has made great progress, many experiments are not suitable for students to operate. Also, the detection with high accuracy is still a big challenge. In this paper, we divide the task of forest wildfire detection into two modules, which are wildfire image classification and wildfire region detection. We propose a novel wildfire image classification algorithm based on Reduce-VGGnet, and a wildfire region detection algorithm based on the optimized CNN with the combination of spatial and temporal features. The experimental results show that the proposed Reduce-VGGNet model can reach 91.20% in accuracy, and the optimized CNN model with the combination of spatial and temporal features can reach 97.35% in accuracy. Our framework is a novel way to combine research and teaching. It can achieve good detection performance and can be used as a comprehensive experiment for Machine Vision course, which can provide the support for talent cultivation in machine vision area.

III. METHODOLOGY

Camera is the input source, for capturing images of the environment, specifically focusing on areas where fire detection is crucial. Control Unit is responsible for processing and analyzing the images captured by the camera. It uses a set of algorithms and machine learning models for this purpose. Before deploying the system, a dataset of images containing both fire and non-fire scenarios is required. This data is used to train the machine learning model for accurate fire detection. YOLO (You Only Look Once) is a real-time object detection algorithm. It's employed here to detect the presence of fire in the images processed by the control unit. YOLO can efficiently detect multiple objects in an image simultaneously. YOLO Algorithm for fire detection is a specific implementation of YOLO is tuned to detect fire instances within the processed images. It uses the training data to learn the features and characteristics of fire, enabling accurate detection.

Fire is Detected When the YOLO algorithm identifies fire in an image, it triggers an alert to notify relevant personnel or systems about the detected fire. Metrics (Fire Detection): This component tracks and records metrics related to fire detection performance. Metrics such as accuracy, precision, recall, and F1 score are commonly used to evaluate the effectiveness of the fire detection system

Fig1. The architecture of the proposed system



YOLO (You Only Look Once) algorithm, which is like a smart advanced technology. This algorithm helps us find potential wildfires much faster and more accurately than before. Where YOLO algorithm analyze the data to detect signs of a fire .the system can alert authorities and provide real time updates on the fire location and it enabling prompt response and mitigation efforts .Create a specialized module enabling the system to capture and analyze live video feeds from sources like surveillance cameras for real-time forest fire detection. Implement the YOLO (You Only Look Once) algorithm, specifically YOLO, on the live video frames to swiftly and accurately identify potential forest fire

regions. This module ensures the system's ability to respond in real-time to emerging fire threats, allowing for timely intervention and mitigation efforts.

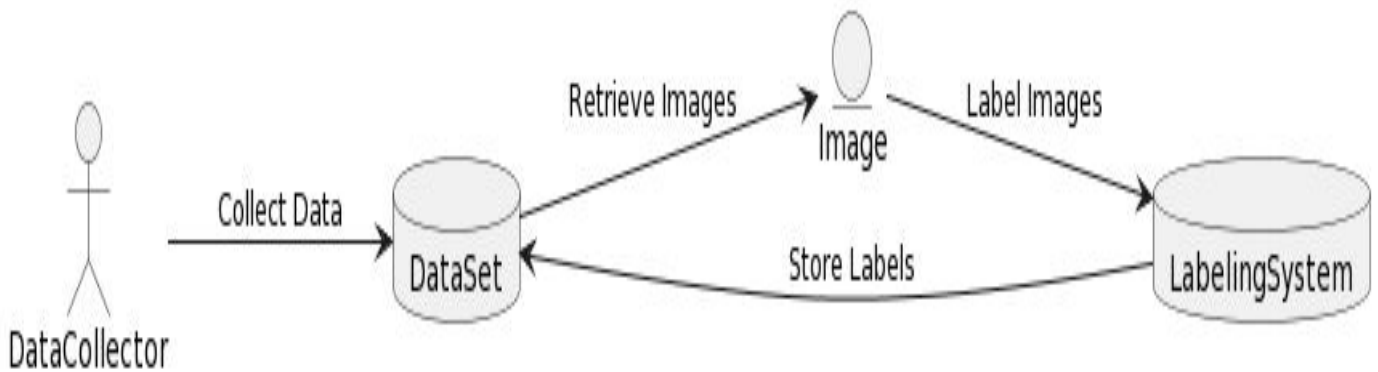
YOLO is known for its real-time object detection capabilities. It processes images in a single forward pass, enabling fast detection and response times. This is crucial for applications where quick identification of fires is essential. YOLO is designed to be computationally efficient, making it suitable for deployment on resource-constrained devices or in scenarios where computational resources are limited.

YOLO is capable of detecting multiple objects in a single frame. This is beneficial in fire detection scenarios where there might be multiple instances of fires or other relevant objects in the environment.

IV. RESULTS AND DISCUSSION

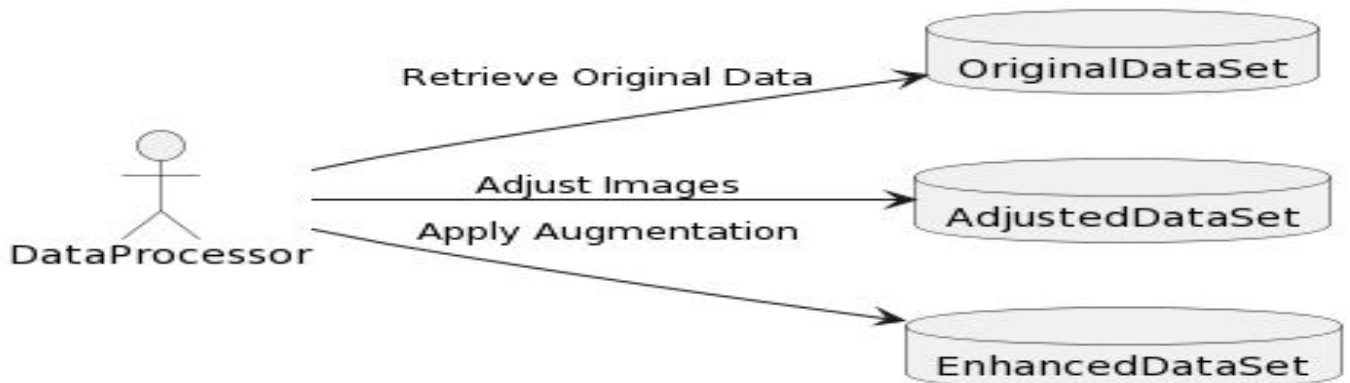
1. Data Collection:

Gather a diverse set of images featuring various forest fire scenarios, ensuring the inclusion of different environments and conditions. Associate each image with relevant information on the severity of the fire. Organize and clean the dataset to ensure consistent labeling and image quality, addressing any missing or inaccurate data.



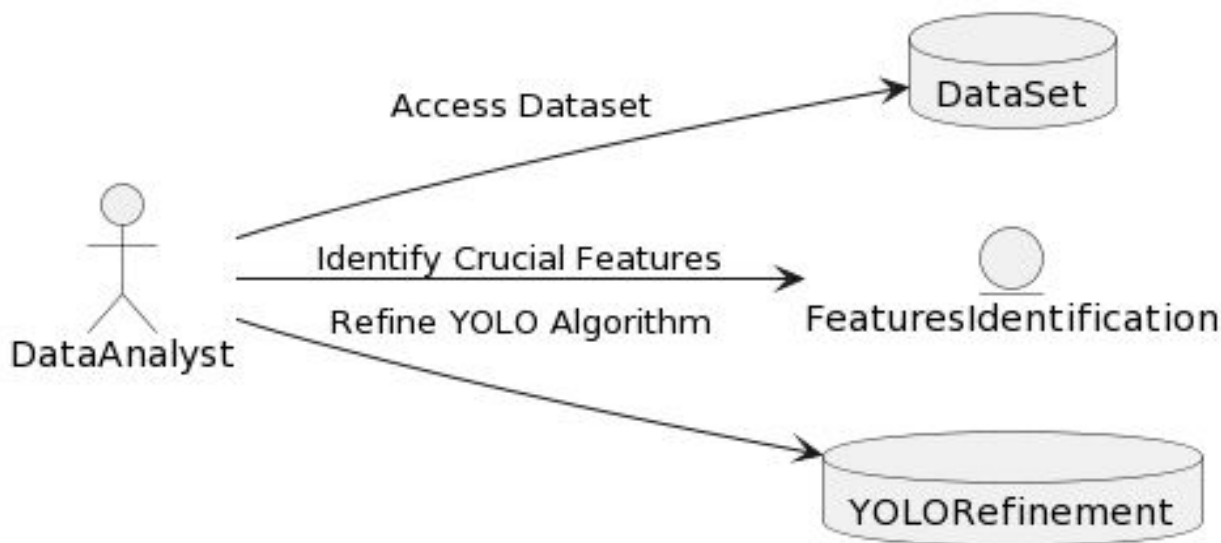
2. Preprocessing:

Adjust the images to a standardized format suitable for the YOLO algorithm used in our efficient forest fire detection system. Ensure uniformity in pixel values for cohesive image data. If needed, enhance the dataset through augmentation techniques to provide a more diverse set of examples, aiding the model in better understanding different aspects of forest fires.



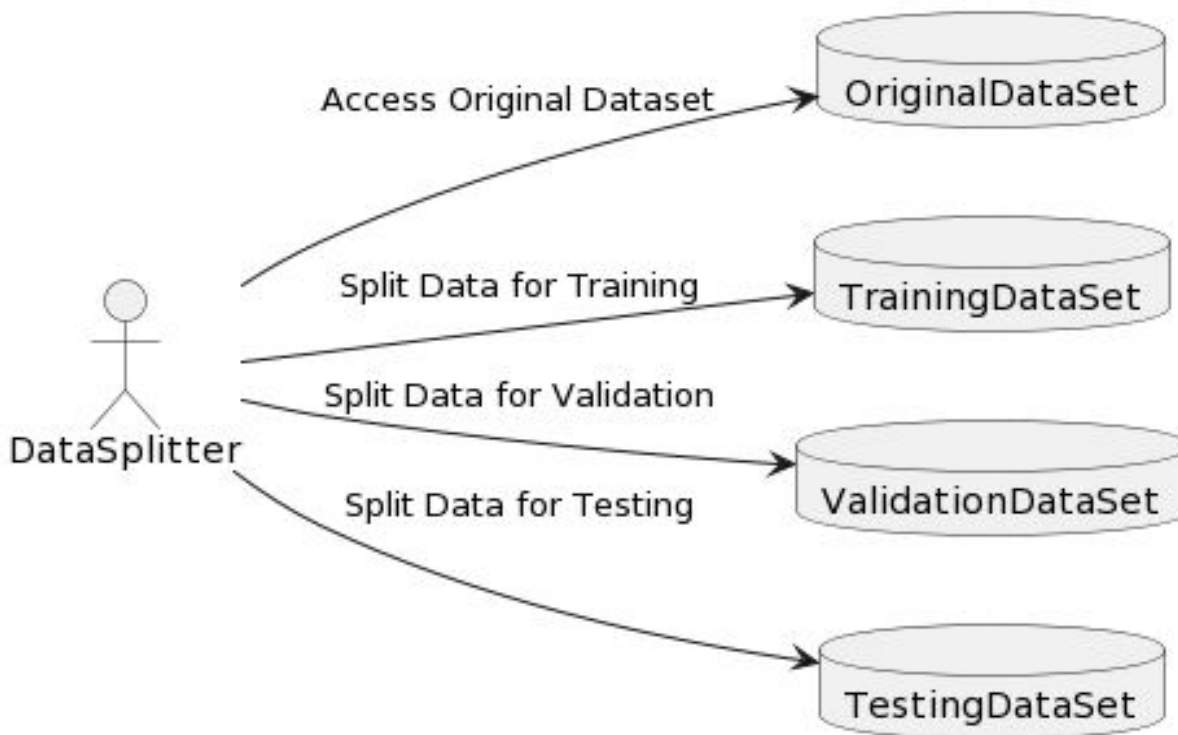
3. Feature Importance:

Identify crucial features within the dataset that contribute significantly to the accurate detection of forest fires. Analyze the importance of different attributes related to forest fires, such as flame size, smoke density, and environmental conditions, in determining the severity and location of the fire. This step is crucial for refining the YOLO algorithm and improving its ability to precisely detect forest fires based on key features.



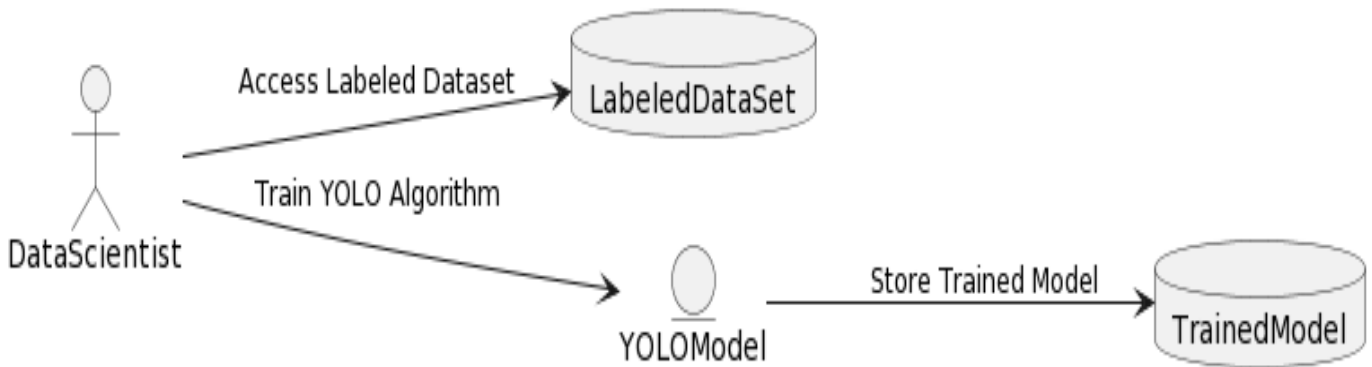
4. Data Splitting:

Divide the forest fire dataset into three sets – training, validation, and testing – to help the YOLO algorithm learn and assess its performance accurately. Ensure an even distribution of different forest fire scenarios in each set, allowing the algorithm to understand a broad range of situations.



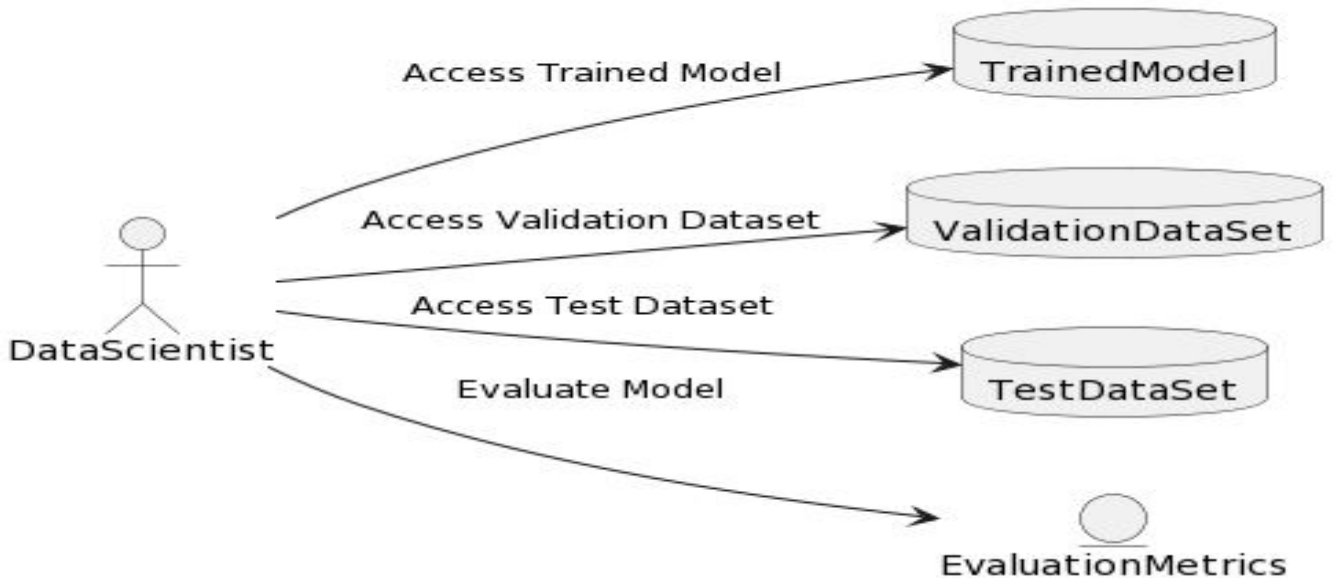
5. YOLO Algorithm Model Training:

Implement the YOLO (You Only Look Once) algorithm for efficient forest fire detection. Train the algorithm using the labeled dataset, teaching it to recognize and classify different aspects of forest fires, such as fire size and location. Fine-tune the model to enhance its accuracy and effectiveness in identifying potential fire regions



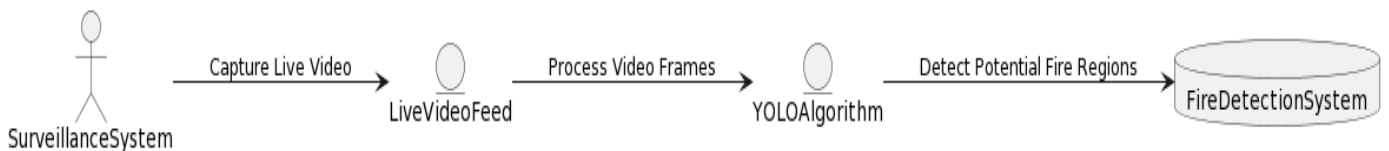
6. Model Evaluation:

Evaluate the trained YOLO algorithm on both the validation and test sets to gauge its accuracy and overall performance in detecting forest fires. Employ metrics like precision, recall, and F1 score to quantitatively measure the algorithm's success in identifying and classifying fire regions accurately. This evaluation process ensures that the YOLO algorithm is reliable and effective in real-world scenarios



7. Fire Detection:

Create a specialized module enabling the system to capture and analyze live video feeds from sources like surveillance cameras for real-time forest fire detection. Implement the YOLO (You Only Look Once) algorithm, specifically YOLO, on the live video frames to swiftly and accurately identify potential forest fire regions. This module ensures the system's ability to respond in real-time to emerging fire threats, allowing for timely intervention and mitigation efforts.



ALGORITHM

Why CNN and YOLO for Forest Fire Detection?

Efficient Forest Fire Detection relies on the combined power of Convolutional Neural Networks (CNNs) and the YOLO (You Only Look Once) algorithm. Unlike traditional methods, CNNs excel in extracting meaningful features from images, crucial for identifying fire-related patterns. YOLO's real-time object detection capabilities enhance the speed and accuracy of pinpointing fires within forest landscapes, ensuring timely responses to potential threats.

Steps:

Step 1: Dataset Collection from Kaggle

For this project, we sourced our dataset from Kaggle ([kaggle.com](https://www.kaggle.com)), a popular platform for datasets and competitions. We chose an image dataset containing various scenes of forests and wildfires, ensuring a diverse and comprehensive set of images for training our model.

Step 2: Preprocessing Steps:

Color Image to Grayscale Conversion:

Convert color images to grayscale to simplify processing and reduce computational load.

Image Resizing:

Resize images to a standard size suitable for input into our CNN and YOLO models (e.g., 224x224 pixels).

YOLO Preprocessing Using Makesense AI for Annotation:

Annotation Process:

Utilize Makesense AI or similar tools for annotating images to label regions of interest, such as fire or nofire, within the forest scenes.

Step 3: Data Representation

Organize the dataset into training arrays containing image pixel values and corresponding category indices for model training.

Step 4: Shuffle the Dataset

Randomly shuffle the dataset to ensure unbiased training and validation sets.

Step 5: Feature Extraction

Implement Convolutional Neural Networks (CNNs) to extract relevant features from forest fire images, capturing spatial dependencies crucial for accurate detection.

Step 6: Integration of YOLO Algorithm

Incorporate the YOLO algorithm to enable real-time object detection within forest landscapes, enhancing the model's ability to swiftly identify and locate fires.

Step 7: Model Training

Define, compile, and train the combined CNN-YOLO model using the prepared dataset, optimizing parameters to achieve optimal performance.

Step 8: Evaluation

Assess the accuracy and performance of the trained model using evaluation metrics, ensuring its effectiveness in forest fire detection scenarios.

Step 9: Model Prediction and Evaluation:

Real-Time Prediction:

Deploy the trained model for real-time forest fire detection, analyzing new images or video streams to identify and localize fire incidents.

Accuracy Assessment:

Evaluate the model's performance based on metrics like precision, recall, and F1-score to assess its effectiveness in detecting forest fires.

```
# Import necessary libraries
```

```
import tensorflow as tf
```

```
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
```

```
from tensorflow.keras.models import Sequential
```

```
# Define CNN model architecture
```

```
model = Sequential([
```



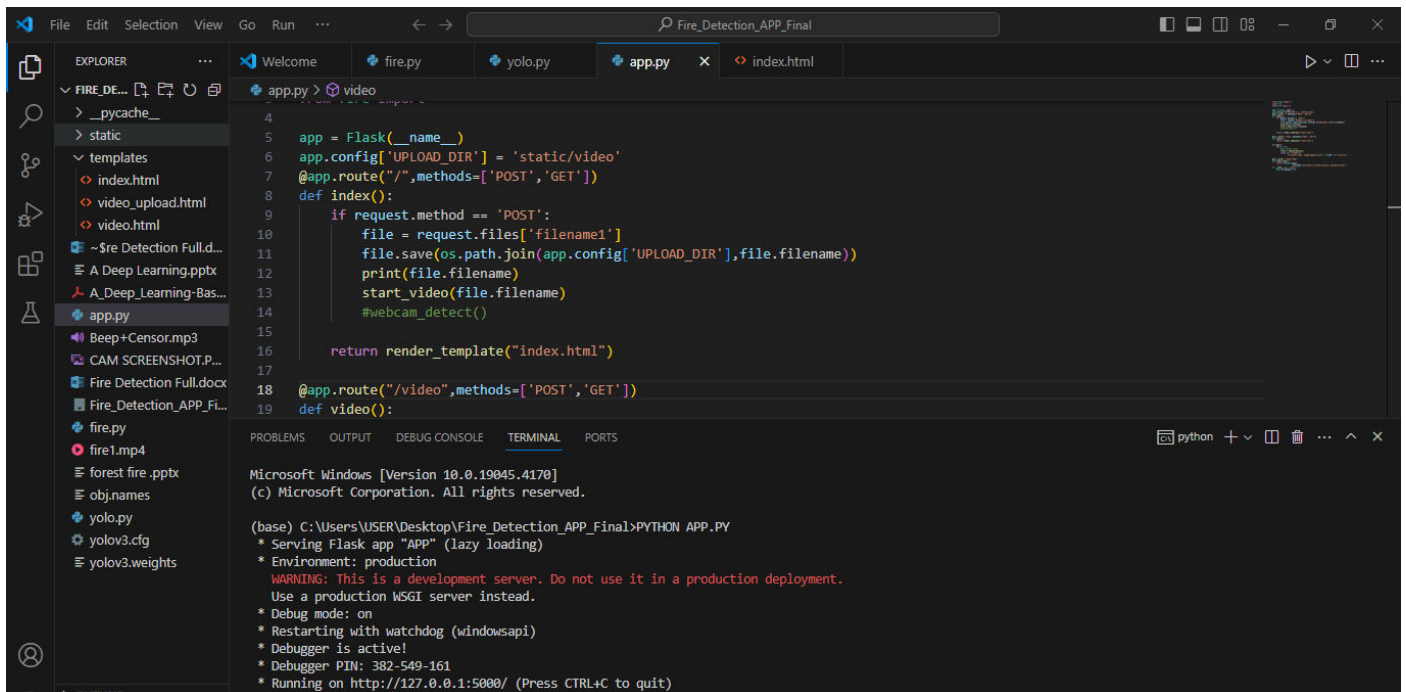
```

Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)),
MaxPooling2D((2, 2)),
Conv2D(64, (3, 3), activation='relu'),
MaxPooling2D((2, 2)),
Flatten(),
Dense(128, activation='relu'),
Dense(1, activation='sigmoid')
)

# Compile and train the CNN model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10, validation_data=(X_val, y_val))

# Integrate YOLO for object detection
# Implementation of YOLO algorithm for real-time fire detection

```

OUTPUT:


```

4
5 app = Flask(__name__)
6 app.config['UPLOAD_DIR'] = 'static/video'
7 @app.route("/", methods=['POST', 'GET'])
8 def index():
9     if request.method == 'POST':
10         file = request.files['filename1']
11         file.save(os.path.join(app.config['UPLOAD_DIR'], file.filename))
12         print(file.filename)
13         start_video(file.filename)
14         #webcam_detect()
15
16     return render_template("index.html")
17
18 @app.route("/video", methods=['POST', 'GET'])
19 def video():

```

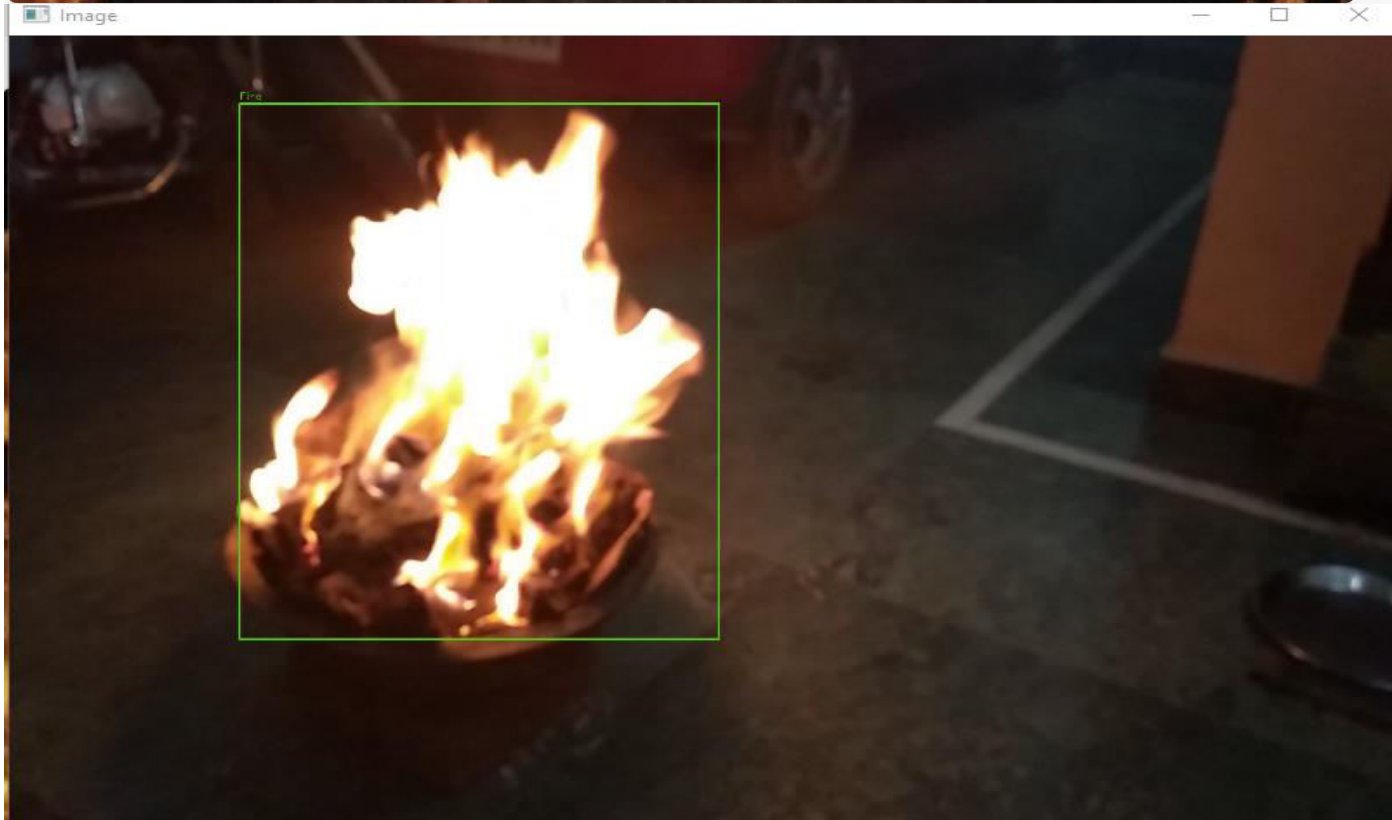
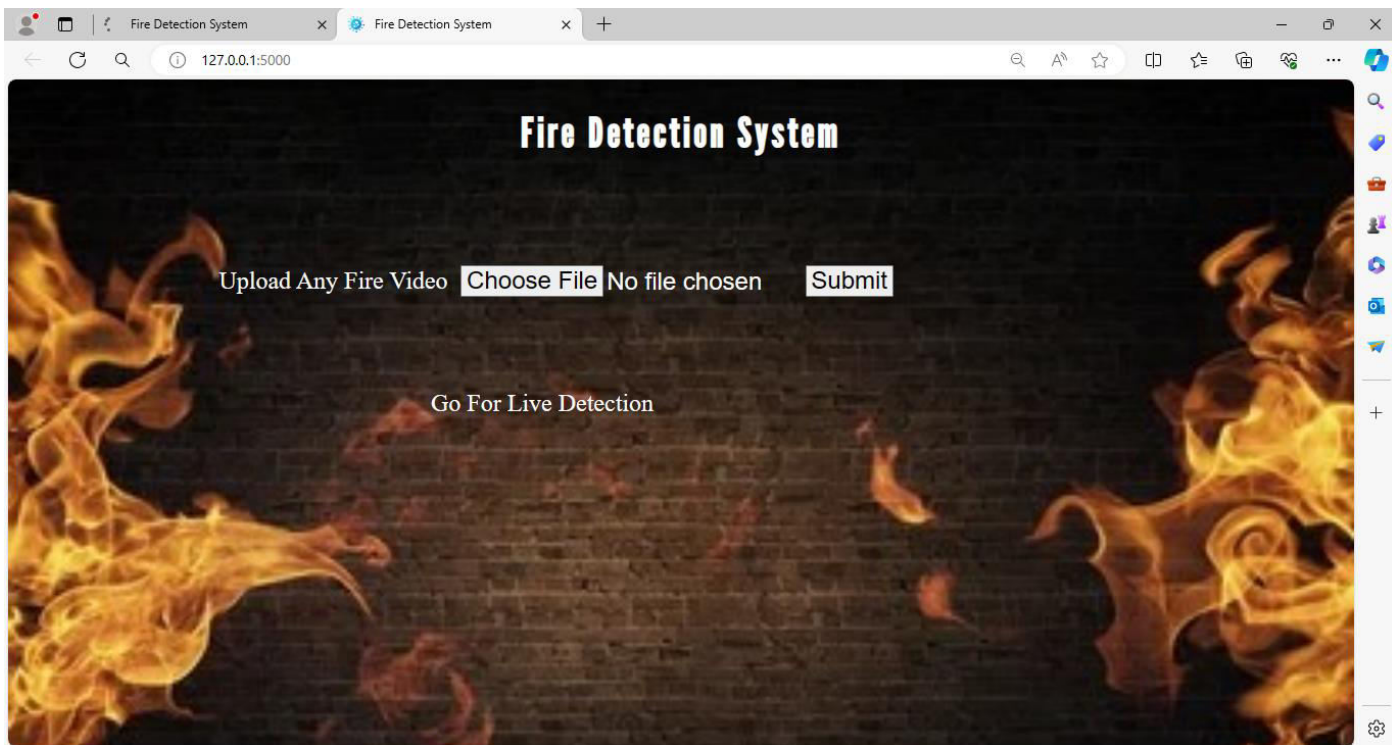
Microsoft Windows [Version 10.0.19045.4170]
(c) Microsoft Corporation. All rights reserved.

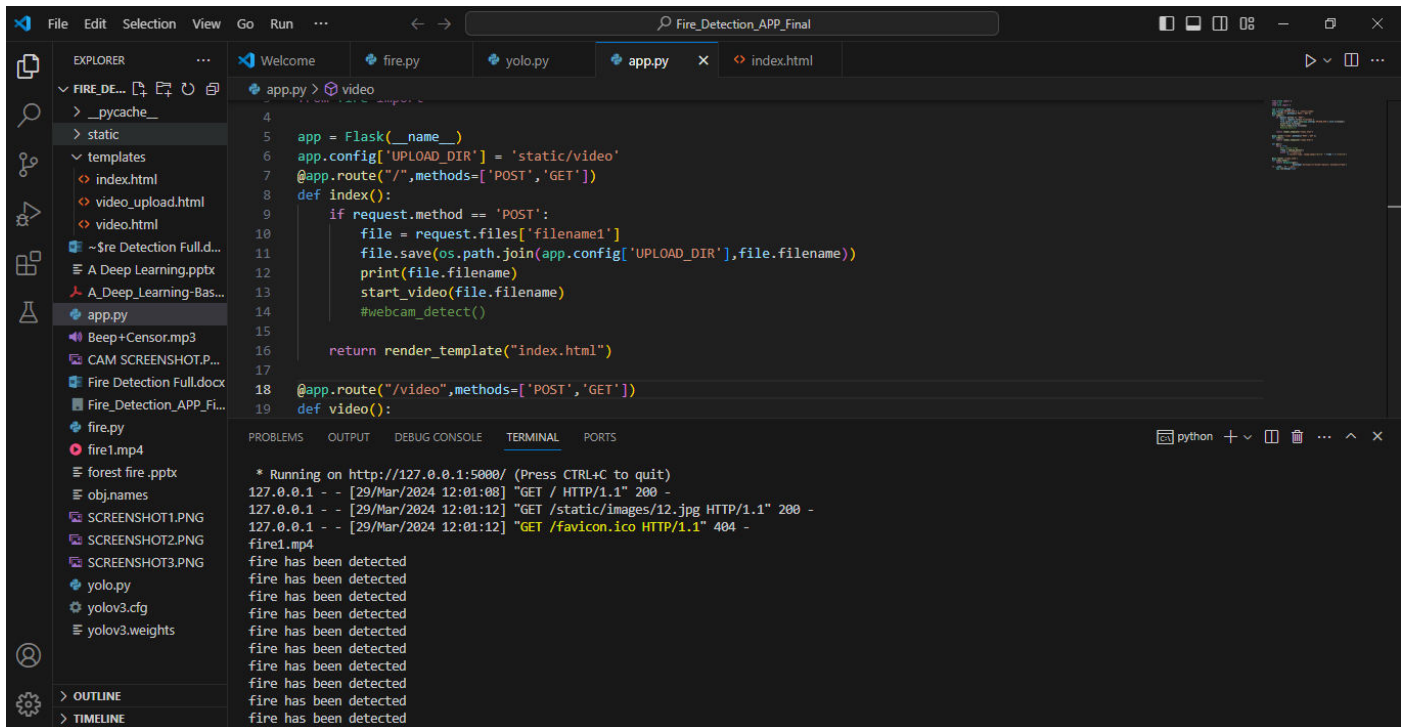
(base) C:\Users\USER\Desktop\Fire_Detection_APP_Final>PYTHON APP.PY

```

* Serving Flask app "APP" (lazy loading)
* Environment: production
  WARNING: This is a development server. Do not use it in a production deployment.
  Use a production WSGI server instead.
* Debug mode: on
* Restarting with watchdog (windowsapi)
* Debugger is active!
* Debugger PIN: 382-549-161
* Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)

```





```

4
5 app = Flask(__name__)
6 app.config['UPLOAD_DIR'] = 'static/video'
7 @app.route("/", methods=['POST', 'GET'])
8 def index():
9     if request.method == 'POST':
10        file = request.files['filename1']
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12        print(file.filename)
13        start_video(file.filename)
14        #webcam_detect()
15
16    return render_template("index.html")
17
18 @app.route("/video", methods=['POST', 'GET'])
19 def video():

```

```

* Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
127.0.0.1 - - [29/Mar/2024 12:01:08] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [29/Mar/2024 12:01:12] "GET /static/images/12.jpg HTTP/1.1" 200 -
127.0.0.1 - - [29/Mar/2024 12:01:12] "GET /favicon.ico HTTP/1.1" 404 -
fire1.mp4
fire has been detected
fire has been detected
fire has been detected
fire has been detected
fire has been detected
fire has been detected
fire has been detected
fire has been detected
fire has been detected
fire has been detected

```

V. CONCLUSION

In wrapping up our project, we have taken a big step in making forest fire detection smarter and quicker. By using the YOLO algorithm, we've built a system that can rapidly recognize potential fire areas in large outdoor spaces. Through collecting and preparing a variety of images, we trained our system to understand different situations where a forest fire might occur. We've focused on keeping things simple and cost-effective, utilizing existing surveillance cameras to make our method accessible to many places without extra expenses. Our experiments and evaluations showed promising results, with the system demonstrating a high accuracy in detecting forest fires. This project isn't just about technology; it's about finding a practical way to keep our forests safe. We believe our work contributes not only to better fire detection but also to spreading awareness about the importance of using technology wisely for the well-being of our environment.

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