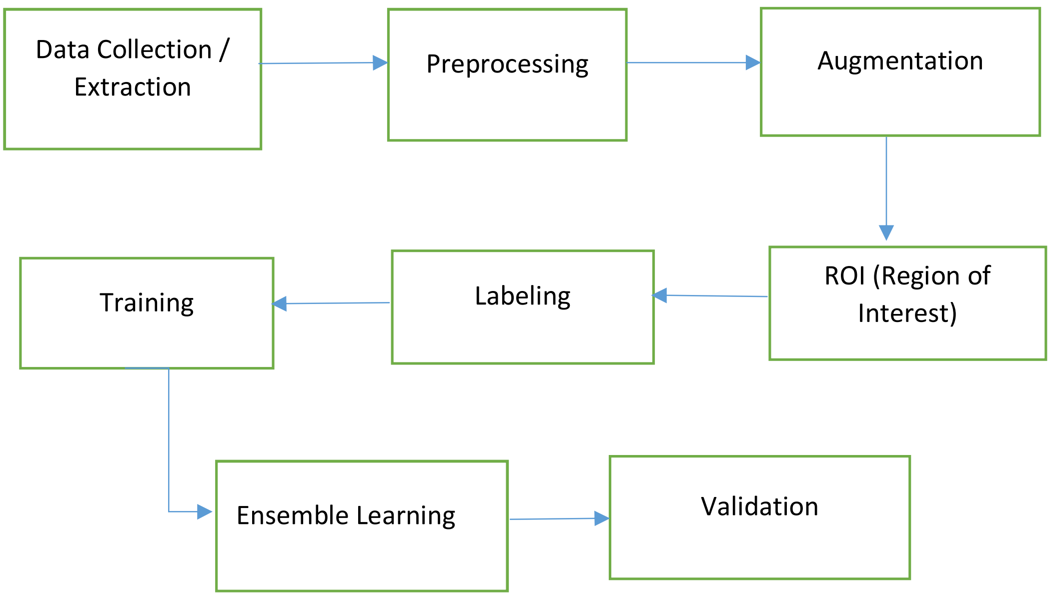
Technical Report

Introduction

This project aims to develop a system for detecting and classifying smoke intensity in images using convolutional neural networks (CNNs) and pixel segmentation. The system is designed to classify smoke into two categories: high smoke and low smoke. The dataset for this project was sourced from the Kaggle platform, and the images were annotated using the Roboflow platform. Various preprocessing, augmentation, and Deep Learning techniques were applied to achieve accurate classification.

Working Methodology



Data Collection

Source: The dataset of smoke-containing images was collected from the Kaggle platform.

Annotation Tool: Images were annotated using the Roboflow platform, with annotations in the YOLO v8 format.

Preprocessing

Bounding Box Detection: The annotated images were processed to detect bounding boxes around smoke-containing areas using the YOLO v8 model. A Python script was developed to draw rectangles around these detected areas.

```python
def draw_bounding_boxes(image, boxes):
    for (x, y, w, h) in boxes:
        cv2.rectangle(image, (x, y), (x + w, y + h), (255, 0, 0), 2)
    return image
```

Augmentation Techniques

To enhance the dataset and improve the robustness of the model, various augmentation techniques were applied:

Flipping: Images were flipped horizontally and vertically.

Rotation: Images were rotated at random angles.

Translation: Images were shifted in the x and y directions.

Blurring: Gaussian blur was applied to the images.

Region of Interest (ROI) Extraction

Process: Post augmentation, regions of interest (ROIs) were extracted from the images. Only those images where ROIs accurately detected specific annotated areas were retained for further classification.

Labeling

The labeled images were classified based on the intensity of smoke into two categories: high smoke and low smoke. The following function was used to label the images based on the average intensity of the smoke in the bounding boxes:

```python
def label_smoke_intensity(image, boxes):
    labels = []
    for (x, y, w, h) in boxes:
        roi = image[y:y+h, x:x+w]
        avg_intensity = np.mean(roi)
        if avg_intensity > 127:  # Threshold for high smoke; adjust as needed
            labels.append("High Smoke")
```

~~~
        else:

            labels.append("Low Smoke")

    return labels

```
~~~

Classification Using Convolutional Neural Networks (CNN)

For the binary classification of smoke intensity, a CNN was employed. The data was split into training (80%) and testing (20%) sets. The model was trained using the following parameters:

~~~
>>>python

 model.fit(X_train, y_train, epochs=20, batch_size=5, validation_data=(X_val, y_val))

 ```
~~~

Ensemble Learning

Three models were trained and their scores were averaged to improve the robustness of the classification. Example training output:

~~~
>>>python

 # Example of model training output

 Epoch 20/20

 818/818 [==============================] - 7s 9ms/step - loss: 0.0343 - accuracy: 0.9870 - val_loss: 0.0846 - val_accuracy: 0.9706

 ```
~~~

Ensemble Score: 0.99

Cross-Validation

Cross-validation was performed to assess the model's performance.

Mean Cross-Validated Accuracy: 0.9890

Mean Cross-Validated Entropy Loss: 0.0406

Experiment

In this project, I developed a comprehensive system for detecting and classifying smoke intensity in images using advanced machine learning techniques. The dataset, sourced from the Kaggle platform, consisted of smoke-containing images which were annotated using the Roboflow platform, following the YOLO V8 annotation format. The preprocessing phase involved detecting and drawing bounding boxes around smoke regions using the YOLO V8 model, followed by applying various augmentation techniques such as flipping, rotation, translation, and blurring to enhance the dataset. Regions of interest (ROIs) were then extracted from the augmented images, retaining only those that accurately detected specific annotated areas. For classification, the system labeled the images as either "High Smoke" or "Low Smoke" based on the pixel intensity within the bounding boxes, using a function that calculated the average intensity. A Convolutional Neural Network (CNN) was employed for the binary classification task, with the dataset split into 80% for training and 20% for testing. The model was trained with specific parameters, and ensemble learning was implemented by training three separate CNN models to improve robustness. The ensemble model achieved an impressive accuracy score of 0.99 after 20 epochs. Cross-validation and entropy loss tests were conducted, resulting in a mean cross-validated accuracy of 0.9890 and a mean entropy loss of 0.0406. This rigorous approach ensured the development of a highly accurate and reliable model, suitable for practical applications such as environmental monitoring and fire detection.

Purpose

The purpose of this experiment was to develop an efficient method to classify smoke intensity in images using pixel segmentation and CNN-based binary classification.

Detailed Experimentation and Hypothesis

1. Aim

The primary aim of this project is to perform pixel segmentation on specific portions of images where smoke is present, utilizing Region of Interest (ROI) and pixel intensity within those areas. The goal is to accurately classify smoke intensity using a robust machine learning approach.

2. Dataset Selection

A dataset containing images with smoke was selected from the Kaggle platform. This dataset was chosen to focus on pixel segmentation in areas where smoke is present.

3. Data Annotation

The smoke-containing areas were annotated using the Roboflow open-source platform, which is designed for object detection. Roboflow's capabilities were leveraged to detect smoke in the images and export the annotated model in the YOLO V8 format. This format was then utilized to perform accurate annotations.

4. Data Augmentation

To enhance the dataset and improve the robustness of the model, various data augmentation techniques were applied, including flipping, rotation, translation, and blurring.

5. Labeling

Labeling was carried out with a focus on ROIs and pixel segmentation. The smoke intensity within the pixels was analyzed, and areas with high pixel intensity were labeled as "High Smoke," while areas with lower intensity were labeled as "Low Smoke."

6. Classification

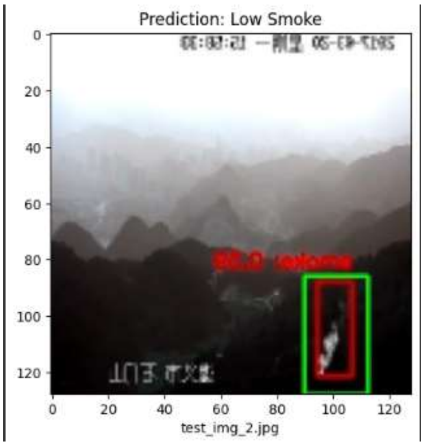
For the classification task, a Convolutional Neural Network (CNN) was employed. Ensemble learning was used to train three separate models, which were then combined to improve accuracy. The ensemble learning process resulted in an impressive score of 0.99.

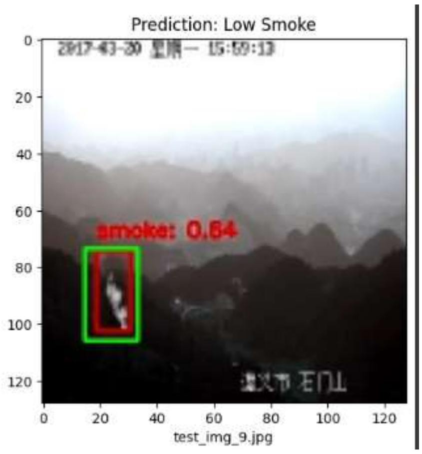
7. Validation and Testing

The models were validated using cross-validation and entropy loss detection. The results showed a cross-validated accuracy of 0.9890 and a mean entropy loss of 0.0406, indicating the model's high performance and reliability.

8. Prediction

The trained ensemble model was then used to perform predictions on unseen data. The model successfully predicted smoke intensity accurately, demonstrating its effectiveness in real-world applications.





9. KPI

The crack of this experimentation is that by using a combination of ROI-based pixel segmentation, data augmentation, and ensemble learning, we can achieve a highly accurate classification of smoke intensity in images. The high cross-validated accuracy and low entropy loss support this hypothesis, proving that the proposed approach is effective for smoke detection and classification tasks.

Results

- **Training Parameters**:

  - Epochs: 20

  - Batch Size: 5

  - Validation Data Split: 20%

- **Ensemble Score**: 0.99

- **Cross-Validation**:

  - Mean Accuracy: 0.9890

  - Mean Entropy Loss: 0.0406

Conclusion

The experiment demonstrated that using a combination of data augmentation, ROI extraction, and ensemble learning significantly improved the accuracy of smoke intensity classification. The high cross-validated accuracy and low entropy loss validate the effectiveness of the approach. The developed model can be reliably used for identifying high and low smoke intensity areas in images, aiding in various practical applications such as environmental monitoring and fire detection.