SMOKE DETECTION VIA DRONE SENSING

By

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for the degree of

MASTER OF SCIENCE IN DATA SCIENCE

Declaration

I hereby certify that this report constitutes my own work, that where the language of others is used, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions, or writings of others. I declare that this report describes the original work that has not been previously presented for the award of any other degree of any other institution.

Shalini Padapati

Date: 16 June, 2024

Signed Shalini.padapati

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ABSTRACT

Timely smoke detection and response are essential in modern fire safety systems. Conventional sensor-based methods for smoke detection often result in inaccurate readings and high false alarm rates, particularly in complex environments. This project aims to tackle these challenges by developing an advanced smoke detection system that utilizes image-processing techniques and deep-learning models

1. Development of deep learning models to accurately simulate and predict smoke behavior under various environmental conditions.

2. Implementation of innovative machine learning algorithms to effectively classify and detect smoke patterns in images and videos.

3. Creating a smoke detection system utilizing these advanced image processing, deep learning and machine learning approaches.

4. Analysis and comparison of the performance of the developed system against traditional sensor-based methods.

Through the integration of advanced image processing and deep learning techniques, this work demonstrates significant improvements in the accuracy, reliability, and responsiveness of smoke detection systems.

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1 INTRODUCTION

Fire accidents are unexpected and often devastating events that can occur in residential, commercial, or industrial areas. They pose significant risks to human life, property, and the environment. These fire accidents lead to numerous fatalities and injuries each year, highlighting the critical need for effective fire prevention and safety measures. **Error! Reference source not found.** shows the decrease of fire incidents over the years in United Kingdom,

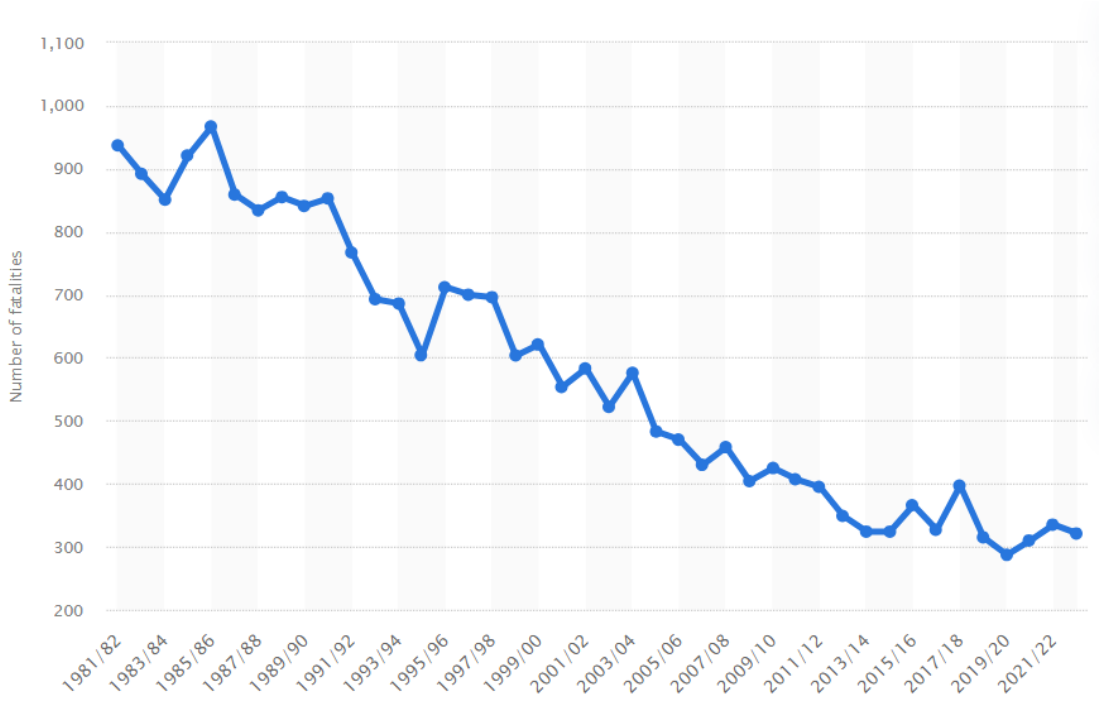


Figure 1-1 Fire incidents over years in UK

Early detection of fires is crucial for minimizing fire damage. The presence of flames and/or smoke typically serves as the initial indication of a fire accident. However, flames may not always be visible to monitoring cameras, especially if they are situated far away or obstructed by obstacles such as mountains or buildings. While smoke is a reliable indicator of a forest fire, it can be challenging to identify in images due to its lack of specific shape or color patterns. Accurate detection of smoke not only contributes to the protection of people and their property but also improves public safety. Through the use of sophisticated image processing, deep learning models and machine learning techniques the accuracy of smoke detection is improved. These Smoke images will

be pre-processed and analyzed using convolutional neural networks (CNNs) in addition to conventional machine learning algorithms Random Forests (RF), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN).

Additionally, a real-time smoke detection system will be implemented to analyze video footage, by extracting frames, and accurately identifying the presence of smoke. This approach sets a new standard in smoke detection, ensuring quicker responses to fire threats and contributing to overall safety.

By providing a reliable smoke detection solution, the current work empowers emergency response teams, improves preparedness, and reduces fire-related risks. Furthermore, it aims to address the gaps in fire safety measures by delivering scalable and accessible smoke detection solutions

1.1 Problem Statement

Today's emergency response systems have many difficulties, particularly in immediately recognizing and controlling possible fires. Existing smoke detection techniques frequently lack the accuracy and reliability needed for efficient early warning. As the conventional smoke detection methodology has always relied on basic sensor technologies it results in false alarms or missing detections. The drawbacks of the systems in place will have negative effects, such as delayed reactions to real fires and needless fear caused by false alarms.

The goal of this work is to combine advanced image processing and machine learning to develop an accurate model that reliably identifies smoke. With improved detection accuracy, it will be easier to react quickly to fire threats. It aims to enhance emergency response and prevention by enhancing detecting capabilities.

1.2 Goals and Objectives.

1.2.1 Goals:

- Building a Smoke Detection Model: Convolutional neural networks (CNNs) are used to develop an effective model that can accurately identify smoke in images.
- Comparing machine learning methods: Evaluating and analyzing the efficiency of conventional machine learning algorithms for smoke detection, including Random Forests (RF), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN).
- Real-time detection is implemented by building a system that monitors the video in real-time, extracts frames, and detects smoke precisely to allow for prompt reactions to possible fire hazards.

- Improving Emergency Response: Reducing the likelihood of fire-related incidents by offering precise and prompt smoke detection, which will improve emergency preparedness and response times.
- Evaluating System Performance: To make sure the smoke detection system is reliable and effective under a range of conditions, thorough testing and assessment must be carried out.

1.2.2 Objectives:

- By significantly improving fire safety and preventable initiatives, these objectives aim to enhance public safety and reduce the impact of fire-related risks.
- By Developing an accurate smoke detection model using advanced image processing and Deep learning techniques. Providing fast and accurate smoke detection may enhance emergency response capabilities.

1.3 Project Structure

1. Introduction: This chapter outlines the work including the gaps and the problem statement by defining the Goals, objectives and significance of undertaking the project.

2. Literature and Technology Review: This chapter provides a thorough analysis of the current research and technological solutions for smoke detection, with importance on the utilization of image processing and Deep learning.

3. Methodology: This chapter elaborates on the research methodology, project time planning, and the main tools and devices for the development of the smoke detector system.

4. Implementation: This chapter Presents step by a step-by-step guide to smoke detection systems design.

5. Results: This chapter evaluated the performance of the smoke detection system developed, the comparison of it to the other work done in this field and the implications of the conclusions.

6. Conclusion: This chapter Consolidates the main outcome of the project, makes a generalized conclusion, and indicates possible ways where the study can build on it in future.

1.4 Legal, Social, Ethical, and Professional Consideration.

While the proposed approach to solving the problem of smoke detection gains its energy to see light, several factors need keen and careful consideration. This includes but is not limited to the legal, social as well ethical and professional considerations. From a legal perspective, the project aims to comply with safety regulations as far as smoke is concerned as well as codes of conduct in the deployment sections. The implementation phase aims to follow data privacy and security regulations to govern and protect data usage and utilization as far as processing and utilization is concerned.

The project prioritizes safety to prevent false alarms and missed detection that could subject human lives and property to risk mode. This goes along to ensure the system meets all industrial standards and best practices. The project involves cooperation with relevant stakeholders the likes of safety experts building managers and regulation bodies to keep the industry's best practices and standards.

2 LITERARY REVIEW

Most smoke detection technologies rely on sensing methods such as photoelectric and ionization. However, there is growing interest in advanced management approaches, including image processing modelling and machine learning, to enhance the reliability of smoke detection systems. Researchers are focusing on incorporating more sophisticated techniques, such as machine learning and statistical analysis, to achieve higher accuracy and reliability in smoke detection systems.

2.1 Smoke detection models

2.1.1 The statistical modelling of smoke behaviour

A substantial amount of work has been carried out to explore the use of statistical models in simulating and predicting the behaviour of smoke in various environmental conditions. These models are often built on theories from the fields of fluid dynamics, thermodynamics, and combustion chemistry to understand the intricate relationship between smoke and air flows around physical objects. For example, Quintiere et al. (2009) developed a statistical model that considers factors like smoke density, velocity, and temperature, which are critical in detecting smoke in complex buildings. This model has proven to be valuable in enhancing smoke detection in such environments.

Another thing that researchers have studied is the use of data-driven techniques, which are based on CFD simulations to generate synthetic smoke data for training and validating detection algorithms (Wang et al., 2018). The use of these approaches has been a massive boost in the development of smoke detection systems in poor conditions where obtaining real-world data is complicated.

2.1.2 Machine Learning for Smoke Detection

The development of machine learning has given us a new way of looking at algorithms and techniques for better smoke detection. Researchers are studying how different supervised learning methods (SVMs and Artificial Neural Networks) can be applied to classify smoke patterns based on only sensor data to save time and enhance efficiency (Barczentewicz & Dorohinicki, 2017). They have done Extensive performance tests and established that the new approaches could improve the accuracy and robustness of previous rule-based detection systems.

Unsupervised learning methods, such as clustering and anomaly detection, have been utilized to identify unusual smoke patterns that could indicate a fire or other hazardous conditions (Fenza et al., 2019). By combining statistical modelling and machine learning, the smoke detection network can become more sophisticated and adaptable. This will enable it to intuitively adjust to variations in environmental conditions and identify various smoke patterns.

2.2 Technology Review

To build the proposed smoke detection system, there is a need to assemble technological components such as sensors, data processing units, and machine learning algorithms. This technology review will explore the available options and provide the reasons for selecting the chosen approaches.

2.2.1 Smoke Sensing Techniques.

The utilization of a mixture of optical, thermal, and gas sensors will allow for the collection of comprehensive and highly accurate information about the amount of smoke. These sensors will be strategically placed within the designated location in the chosen environment to monitor changes in smoke behaviour. The sensor data will be processed through image processing and deep learning algorithms as part of the input approach.

2.2.2 Data Processing and Computational Infrastructure

The smoke detection system will operate on a distributed computing infrastructure, incorporating both edge devices and cloud-based resources. This will involve using open-source and commercially available frameworks for image processing modeling and deep learning, with TensorFlow and PyTorch being utilized to implement various neural network architectures. These tools will be used for developing, training, and deploying the Smoke Detection Models.

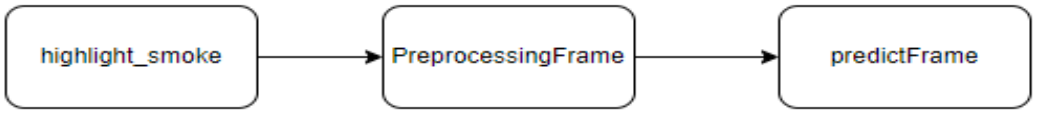


Figure 2-1 Data Processing Workflow

Following a scientific review, the most suitable variables have been identified, including sensors, computational modules, and the analytical framework for use in the smoke detection system. The system will be developed by combining these technological elements, aiming to address the shortcomings of traditional smoke detection methods by leveraging the strengths of statistical modeling and machine learning.

2.3 Integrated Approaches

The integration of image processing and deep learning techniques is a very promising way of improving the performance of smoke detection systems. As opposed to getting into a competition, there is a high level of balance between these technology approaches, therefore, researchers developed an approach that demonstrates high performance and diverse applicability in the smoke detection scenarios that happen in the real world.

2.3.1 Statistical Modeling Approaches

The CFD simulation serves as a vital tool for combining image processing, statistical modeling, and machine learning to detect smoke. CFD-based models are utilized to model and capture various features of smoke, including density, temperature, specific velocity, and patterns. These statistical models provide structure to the chaotic world of smoke propagation and distribution. They help in understanding the interactions and relationships between different environmental factors, establishing a physical basis for their influence.

By using CFD-based statistical models in combination with smoke detection algorithms, important statistical features, such as the number of smoke regions, average smoke area, means, medians, modes, and standard deviations, can be significantly extracted. These features serve as inputs for the machine models, resulting in a comprehensive representation of smoke history and improving the efficiency of classification.

2.3.2 Machine learning techniques.

Computer program-based algorithms have also helped in the development of integrated smoke detection systems. Several software applications have been built upon supervised learning using algorithms like Support Vector Machines (SVM), Random Forests, and Gradient Boosting that detect smoke in image and video data.

Machine learning algorithms are trained to understand the features associated with fire such as the visuals of smoke and the motion cues from the thermal imaging. This has, in turn, resulted in a substantial

improvement in the accuracy and reliability of smoke detection systems, as the models can adjust to the varied characteristics and environmental conditions of smoke.

2.3.3 Integrated Machine Learning.

Through the use of the predictive power of CFD-based models and the adaptability and learning capacity of machine learning algorithms, researchers have created smoke detection systems that show improved performance in real-world conditions.

The adoption of this approach yields encouraging findings in enhancing the resolution, precision, and credibility of smoke alarm systems. The statistical models working here lay the foundation theory of smoke behaviour and the machine learning algorithms, which use information from the models of the predicted smoke behavior as well as their ability to figure out if the smoke patterns are changing, work together.

The relation between statistical modelling and deep learning is working well and has created new opportunities for improvements in smoke detection technology. Through the application of the strengths, they have managed to outplay the weak points of the sensor-based approaches and they are proceeding on their way to create new technologies that give a better response to the smoke detection problems in the tricky world where sensors could not function properly.

2.4 Gaps and Opportunities

From the previous research done by other researchers, it is clear that this field deserves attention as far as accuracy and precision are concerned. All the approaches reviewed have provided a solution, even though this has not been optimal for the problem in question, the quest for reliability has always risen in the conversation. As such, this work has worked its best to bring a more optimal solution with a high breed of Image processing techniques in conjunction with Deep learning techniques. It is expected that the results will be more convincing and more reliable as far as fire detection and rescue is concerned. Scalability remains the key concern as the growth of data demands growth in computational capabilities. The utilization of the latest technologies paves the road for the revolution of fire safety capabilities as well as emergency response competencies. As this is a growing field, this work acknowledges the work previously done and welcomes possible growth to enhance the results.

3 METHODOLOGY

3.1 Introduction

The methodology for this work involves a systematic approach to developing an effective smoke detection system. The process is divided into several key components: data collection, image preprocessing, model development and evaluation. Each step is designed to ensure the creation of a reliable and accurate system capable of detecting smoke in various environments, thus enhancing fire safety measures

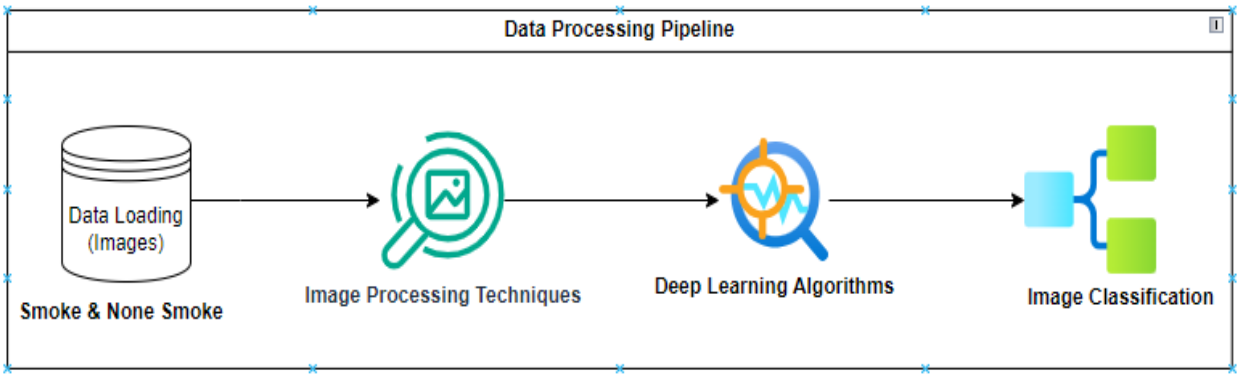


Figure 3-1 Project Workflow Image

3.2 Implementation Architecture

The smoke detection system architecture begins with Image Loading, where images are gathered for analysis. Next, Image Processing is performed to enhance and isolate smoke-relevant features, which are then saved in Processed Data Storage. After this, Exploratory Data Analysis is carried out to identify patterns and gain insights from the processed data. The data then undergoes Feature Engineering and is split into training and testing sets during the Train Test Split phase. Following this, the model is trained and evaluated in the Model Training and

Evaluation phase, where performance metrics are assessed. Finally, Performance Reports and Forecasts are generated to provide insights for continuous improvement.

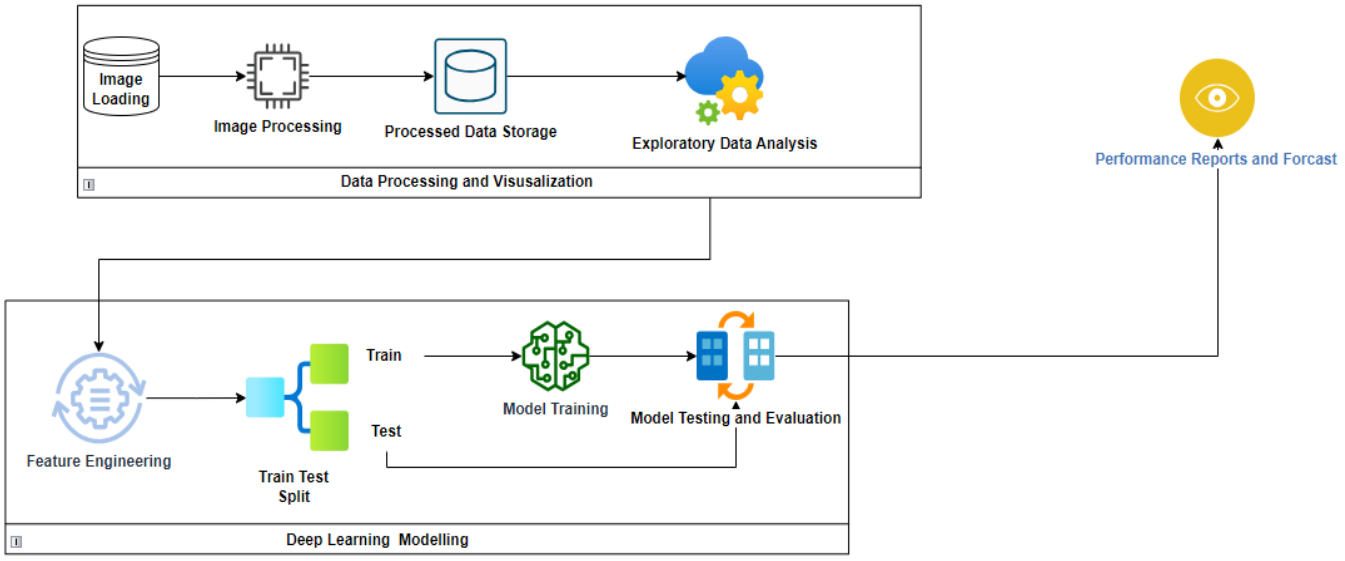


Figure 3-2 implementation Diagram

3.3 Data Collection

The data utilized for this work comes from existing repositories of images containing both smoke and no-smoke scenarios. These images are collected from different environments to make sure that the model is trained on a wide range of data, which helps it accurately detect smoke in various situations. The images were collected from the kaggle where 57% of images being Non-smoke and the rest being smoke images.

3.4 Methods and Technologies

3.4.1 Image pre-processing

The images collected from data collection undergo image preprocessing by following steps

- Converting to HSV Color Space: The image is converted from BGR to HSV (Hue, Saturation, and Value) color space. This transformation is beneficial as it separates intensity from color information, which can help effectively isolate smoke colors.

- Applying Color Thresholding: In the HSV color space, a threshold is applied to create a binary mask that isolates colors associated with smoke. This process involves defining a range of HSV values (lower_smoke and upper_smoke) that correspond to typical smoke colors.
- Creating Smoke Mask: Using the defined HSV range, a mask is generated where pixels within the specified range are set to white (255) and others to black (0). This mask highlights areas in the image that likely contain smoke.
- Bitwise-AND Operation: Finally, a bitwise AND operation is applied between the original image and the mask. This operation retains only those pixels from the original image where the corresponding mask pixel is non-zero, effectively highlighting smoke regions while suppressing non-smoke areas.

3.4.2 Deep learning model

- Creating the CNN Model: The Convolutional Neural Network (CNN) model was built using TensorFlow/Keras. The model consists of multiple convolutional layers with ReLU activation, followed by max-pooling layers for down sampling. Dropout layers were added for regularization to reduce over fitting. The final layers included fully connected layers leading to a binary classification output using sigmoid activation.
- Compiling the Model: The model was compiled using the Adam optimizer with a learning rate of 0.001, Loss function and performance metrics.
- Training the Model: The CNN model was trained using a training dataset with specified batch sizes over multiple epochs. The validation dataset was used to monitor the model's performance during training. Early stopping with a patience of 10 epochs was implemented to prevent over fitting and to restore the best weights.
- Evaluating the Model: After training, the model was evaluated using an independent test dataset to assess its generalization performance. The evaluation computed metrics such as test loss and accuracy to measure the model's effectiveness in smoke detection.

3.4.3 Machine learning models

- Support Vector Machine (SVM): SVM is skilled at managing high-dimensional data and identifying complex decision boundaries. In smoke detection, SVM can accurately classify smoke patterns in images by recognizing nonlinear relationships between pixel values. This is essential for precise smoke detection under different lighting and environmental conditions.

- Random Forest (RF): Random Forest (RF) is reliable in avoiding overfitting and excels in high-dimensional feature spaces. In smoke detection, Random Forest can combine multiple decision trees to effectively identify intricate smoke patterns and differentiate them from background noise or similar-looking features in images. This collective approach contributes to achieving high accuracy and dependability in smoke detection tasks.
- K-Nearest Neighbors (KNN): KNN uses proximity-based classification, which makes it well-suited for smoke detection tasks that rely on the spatial relationships between image pixels as crucial indicators of the presence of smoke. By analyzing neighboring pixels, KNN can effectively classify smoke patterns based on their similarity to previously observed smoke instances in the dataset, making it a powerful tool for real-time smoke detection applications.

3.4.4 Evaluation metrics

The performance of the smoke detection models is evaluated using essential metrics such as accuracy, precision, recall, and F1-score. Cross-validation techniques are employed to assess the models' ability to generalize to new data and to prevent overfitting. Furthermore, practical implementation tests and input from emergency response professionals are integrated into the evaluation process to ensure the usability and effectiveness of the smoke detection system. This comprehensive evaluation approach helps validate the robustness and reliability of the models in real-world scenarios.

Classification Report:

	precision	recall	f1-score	support
0	0.99	0.97	0.98	165
1	0.96	0.99	0.98	123
accuracy			0.98	288
macro avg	0.98	0.98	0.98	288
weighted avg	0.98	0.98	0.98	288

Figure 3.4.4.1: Evaluation Metrics.

3.5 Video as an input:

3.5.1 Feature extraction from video:

To analyze video inputs for smoke detection, the initial step involves extracting individual frames from the video file. This task is carried out by the extract_frames_from_video function, which involves the following steps:

1. Video Loading: OpenCV's VideoCapture is used to open the video file.

2. Frame Extraction: The function iterates through the video, capturing each frame and storing them in a list.

3. Completion Check: Upon extracting all frames, the video capture object is released.

3.5.2 Preprocessing Frames

Each extracted frame undergoes preprocessing to ensure compatibility with the trained model. The "PreprocessingFrame" function manages this step:

- Resizing: The frame is resized to 250x250 pixels.

- Normalization: Pixel values are normalized by dividing by 255.0.

3.5.3 Prediction on Frames

The predictFrame function is used to predict the presence of smoke in a preprocessed frame:

- Preprocessing: The frame is preprocessed and converted into a batch format.

- Prediction: The frame is fed through the trained model to predict the presence of smoke.

- Display Result: The original frame is displayed along with the prediction result ('SMOKE' or 'NO SMOKE') using Matplotlib.

3.5.4 Random Frame Selection for Prediction

A random frame is chosen from the extracted frames for smoke prediction. This random selection ensures testing the model's performance on various frames from the video

3.5.5 Program Execution:

The main function coordinates the entire process, performing the following steps:

- Input Paths: Specify paths for the video file and the trained model.

- Frame Extraction: Extract frames from the video.

- Random Frame Prediction: Select a random frame, preprocess it, and pass it through the model for prediction

3.6 Project Management

The smoke detection project utilizes agile project management, specifically the Scrum framework, to ensure efficient and flexible development. By dividing the project into sprints, can deliver results incrementally and adapt to feedback quickly. Detailed schedules guide the project timeline and milestones, ensuring that deadlines are met. This structured approach ensures effective project management and the delivery of reliable smoke detection solutions.

4 IMPLEMENTATION

4.1 Introduction

This chapter discusses the steps and procedures needed to achieve the working goal. It includes a detailed exploration of the implementation and execution using image processing and deep learning techniques. The work aims to develop an accurate method for detecting the potential occurrence of fire by identifying smoke at its early stages. The process begins with loading collected images into a Jupyter notebook. The subsequent step involves deep learning, shedding light on the strategies outlined in the previous chapter and the subsequent discussion of the results

4.2 Data Loading

This entails the processes that involve availing the data set into the processing environment. The images have been stored under Google Drive, this necessitated the mounting of the drive into the notebook. The images were processed and labelled accordingly based on whether the image was a smoker or a non-smoker. As can be seen in the figure below, the images are available in the respective folders with the appropriate level indicator.

```
[2]: # Mounting to Google Drive
     drive.mount('/content/drive', force_remount=True)

     Mounted at /content/drive

[3]: # defining functions for data manipulation
     def read_data(smoke_path, nosmoke_path):
         # Initializing an empty DataFrame with columns 'path' and 'label'
         dataframe = pd.DataFrame(columns=['path', 'label'])

         # Reading smoke images and add their paths to the DataFrame with the label 'smoke'
         for dirname, _, filenames in os.walk(smoke_path):
             for filename in filenames:
                 # Concatenate the DataFrame with the new image path and label
                 dataframe = pd.concat([dataframe, pd.DataFrame([[os.path.join(dirname, filename), 'smoke']], columns=

         # Read no smoke images and add their paths to the DataFrame with the label 'no smoke'
         for dirname, _, filenames in os.walk(nosmoke_path):
             for filename in filenames:
                 # Concatenate the DataFrame with the new image path and label
                 dataframe = pd.concat([dataframe, pd.DataFrame([[os.path.join(dirname, filename), 'no smoke']], colum


         # Returning the final DataFrame containing image paths and labels
         return dataframe
```

Figure 4-1 Data Read Image Snippet

4.3 Exploratory Data Analysis.

This phase entails visual insights discovery from a visual perspective. Following data science best practices, the project performed a thorough exploratory data analysis on the loaded data. This entailed understanding the data distribution, shape, and descriptive statistics to gain insights into the characteristics of the smoke detection problem. The previous stage provided a resulting data frame which provides a mapping of the images and their respective label. The key insights from this would be to create an understanding of the smoke-to-none distribution. As will be seen in the progressive stages, the visual demonstrates the view of the same.

[4]:
```
# Defining the paths to the directories containing smoke and non-smoke images
smoke_path = '/content/drive/My Drive/code/smoke'
nosmoke_path = '/content/drive/My Drive/code/nosmoke'

# Calling the read_data function with the paths to the smoke and non-smoke directories
dataframe = read_data(smoke_path, nosmoke_path)

# Shuffling the DataFrame to randomize the order of rows
dataframe = dataframe.sample(frac=1).reset_index(drop=True)

# Displaying the first 10 rows of the DataFrame
dataframe.sample(10)
```

[4]:

	path	label
153	/content/drive/My Drive/code/smoke/Smoke (161)...	smoke
832	/content/drive/My Drive/code/nosmoke/nf1 (928)...	no smoke
795	/content/drive/My Drive/code/nosmoke/NF_1751.jpg	no smoke
1004	/content/drive/My Drive/code/nosmoke/NF_1590.jpg	no smoke
1082	/content/drive/My Drive/code/smoke/Smoke (627)...	smoke
1103	/content/drive/My Drive/code/nosmoke/nf2 (28).jpg	no smoke
295	/content/drive/My Drive/code/smoke/Smoke (513)...	smoke
180	/content/drive/My Drive/code/nosmoke/nofire_01...	no smoke

Figure 4-2 Data Creation and Classification

4.4 Visualization

The figure below demonstrates the data distribution of the data and image labels. As can be observed, the smoke data labels were the majority with a significance percentage of 42.8 % while the no smoke command the most with a significance of 57.2%.

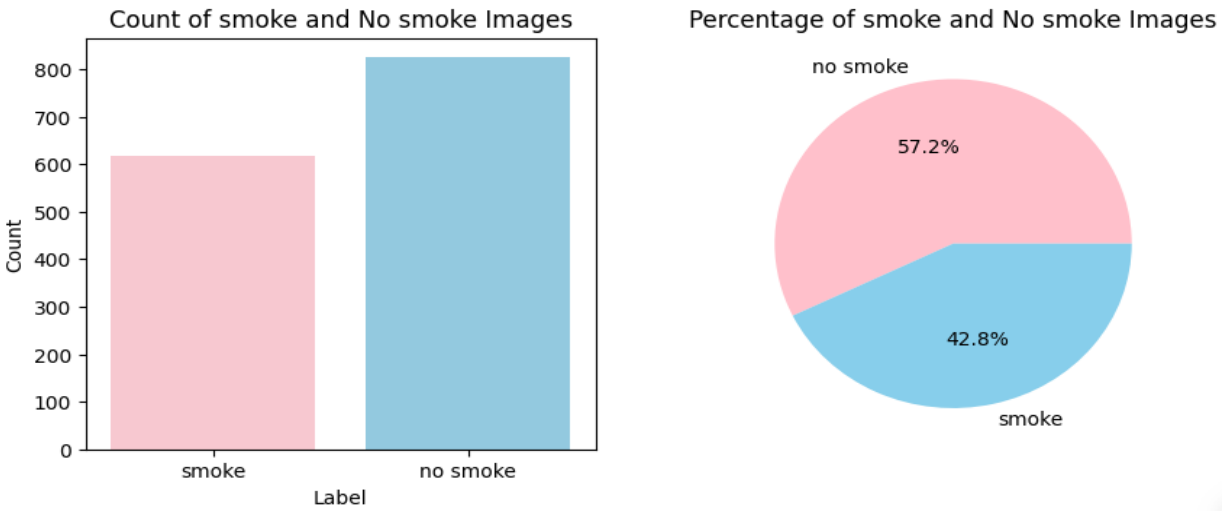


Figure 4-3 Data Visualization

From the figure below, we demonstrate the areas with smoke in the sample. There are variations in the clarity of the smoke within the image, but it is possible to identify smoke elements in the figure.

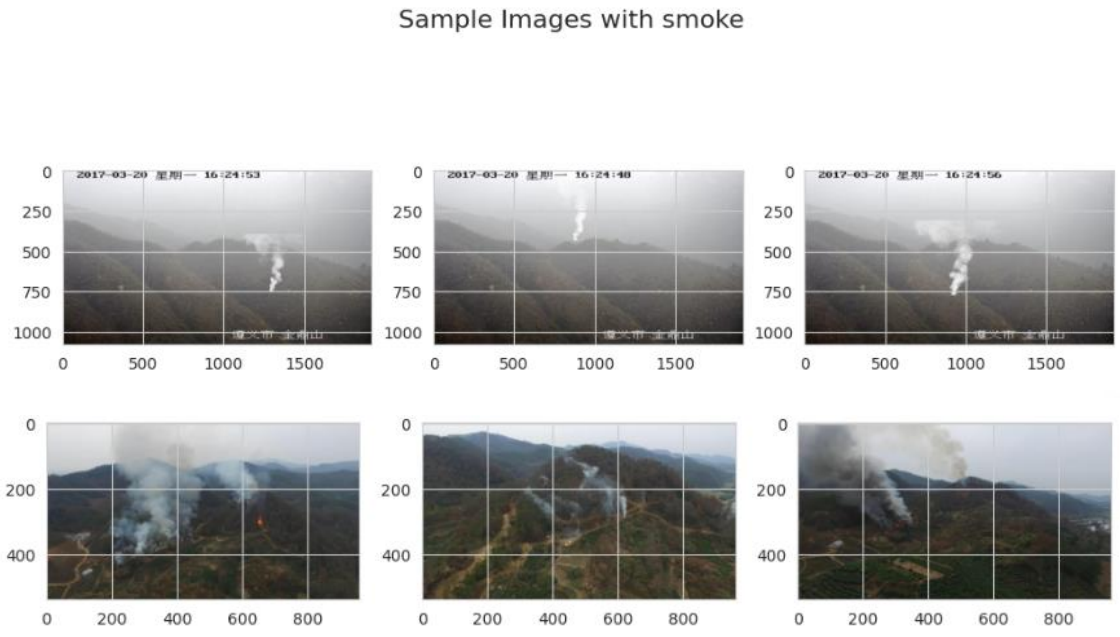


Figure 4-4 Sample images with smoke

From the Figure 4-4 we demonstrate the areas without smoke in the sample

4.5 Feature Engineering and Scaling.

The steps involved in preparing the data for the machine learning model included creating additional features derived from the data. The dataset was divided into two parts: the training set and the test set. The training set was used to train the machine learning models, and the test set was kept for evaluating the model's performance. This approach ensured that the models were tested on unknown data, providing a reliable measure of their ability to generalize.

4.6 Train test Split

In this section, the deep learning models expect the dataset to include both training data and test data. Additionally, there will be an evaluation set that is used to assess the model's performance. The images have been divided into separate training and test sets, as illustrated in the figure below.

```
[8]: # Split the DataFrame into training and testing sets
train_df, test_df = train_test_split(df, train_size=0.8, random_state=46)

# Display the first few rows of the training set DataFrame
display(train_df.head())

# Display the first few rows of the testing set DataFrame
test_df.head()
```

Figure 4-5 Data Train Test Split image

	path	label
546	/content/drive/My Drive/code/nosmoke/nofire_07...	no smoke
1266	/content/drive/My Drive/code/smoke/Smoke (817)...	smoke
494	/content/drive/My Drive/code/nosmoke/nf2 (282)...	no smoke
393	/content/drive/My Drive/code/nosmoke/nofire_03...	no smoke
596	/content/drive/My Drive/code/nosmoke/nf2 (394)...	no smoke

	path	label
785	/content/drive/My Drive/code/smoke/Smoke (138)...	smoke
172	/content/drive/My Drive/code/nosmoke/nf1 (241)...	no smoke
158	/content/drive/My Drive/code/smoke/Smoke (458)...	smoke
1144	/content/drive/My Drive/code/smoke/Smoke (618)...	smoke
1163	/content/drive/My Drive/code/smoke/Smoke (49).jpg	smoke

Figure 4-6 Train and Test Sample Records Data

4.7 Image Processing and Train Generation

During this stage, we loaded the respective data from the train labels and the test labels. To do this, used the image generator library. The images were configured with parameters including scaling ratio, zoom, and rotation. 80% of the data was allocated to the train data, while 20% was allocated to the test data.

```
[9]: # Creating an ImageDataGenerator for data augmentation during training
train_datagen = ImageDataGenerator(
    rescale=1./255,                # Normalize pixel values to the range [0, 1]
    shear_range=0.2,               #  apply shearing transformation
    zoom_range=0.1,                #  zoom in on images
    rotation_range=20,             #  rotate images within the given range
    width_shift_range=0.1,         #  shift images horizontally
    height_shift_range=0.1,        #  shift images vertically
    horizontal_flip=True,          #  flip images horizontally
    vertical_flip=True,            #  flip images vertically
    validation_split=0.2           # Fraction of training data to use for validation
)

# Creating an ImageDataGenerator for normalizing pixel values during testing
test_datagen = ImageDataGenerator(rescale=1./255)

# Displaying a message indicating the preparation of the training dataset
print("Preparing the training dataset")
```

Figure 4-7 Data augmentation and normalisation

```
Preparing the training dataset
Found 922 validated image filenames belonging to 2 classes.
Preparing the validation dataset
Found 230 validated image filenames belonging to 2 classes.
Preparing the test dataset
Found 288 validated image filenames belonging to 2 classes.
```

Figure 4-8 Data Preparation

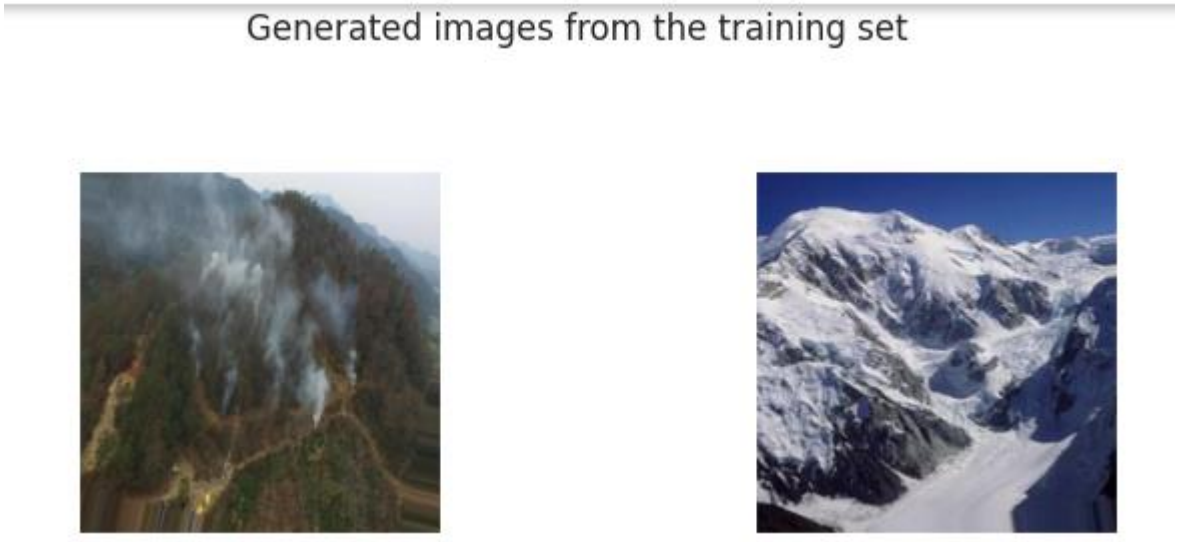


Figure 4-9 Sample Image Visualisation

4.8 Model Performance

4.8.1 Random Forest Classification

This model has ensemble techniques that allow it to perform classification and regression problems. Its backbone is the concept of decision trees where a large number of individual trees are combined to form a forest. As can be observed, Random Forest gave a performance score of 98.39 % in accuracy. This means that the model could comfortably account for 98 % of instances of smoke observed. This gives confidence and trust levels of the same scores. On a random sample selection of 10 images, the model could comfortably explain 9 of the images with certainty.

```
[16]: # splitting data into training and testing sets
      X_train, y_train = DataProcessing(train_df)
      X_test, y_test = DataProcessing(test_df)

[17]: # Random Forest
      RandomForestModel = RandomForestClassifier()
      RandomForestModel.fit(X_train, y_train)
      yPred_RandomForest = RandomForestModel.predict(X_test)
      print("Random Forest Accuracy: {:.2f}%".format(precision_score(y_test, yPred_RandomForest)*100))

      Random Forest Accuracy: 98.39%
```

Figure 4-10 Random Forest Classification

4.8.2 Support Vector Machine

This model is a supervised approach that provides association and regression advantages. It aims at maximizing the margin distance between the hyperplane and the nearest data point (Support Vectors)

```
]: # Support Vector Machine
   SupportVectorMachines = make_pipeline(StandardScaler(), SVC(probability=True))
   SupportVectorMachines.fit(X_train, y_train)
   yPred_SupportVectorMachines = SupportVectorMachines.predict(X_test)
   print("Support Vector Machines Accuracy: {:.2f}%".format(precision_score(y_test, yPred_SupportVectorMachines)*100))

   Support Vector Machines Accuracy: 96.83%
```

Figure 4-11 Support Vector Machine

The scores for this model were 96.83 % as can be observed from the figure above. In comparison to random forest, this was a lower score. The model could account for 96 % of instances. The level of certainty for the model is incomparable.

```
[19]: # K-Nearest Neighbors
KNN = KNeighborsClassifier()
KNN.fit(X_train, y_train)
yPred_KNN = KNN.predict(X_test)
print("KNN Accuracy: {:.2f}%".format(precision_score(y_test, yPred_KNN)*100))

KNN Accuracy: 85.31%
```

Figure 4-12 KNN image

4.8.3 Deep Learning Model Development

In this, we create a deep-learning model with various settings, the model as can be observed below uses Relu for the activation function. The model accepts the dataset and performs the learning process, the model is then compiled after which the results are evaluated. This can be observed in the figure below.

Creating the model

```
[22]: # Defining a function for building the CNN model
def BuildingModel(Inputshape):
    model = Sequential()
    model.add(Conv2D(32, (3, 3), input_shape=Inputshape, activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(32, (3, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(64, (3, 3), activation='relu'))
    model.add(SpatialDropout2D(0.2))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Conv2D(128, (3, 3), activation='relu'))
    model.add(SpatialDropout2D(0.4))
    model.add(MaxPooling2D(pool_size=(2, 2)))
    model.add(Flatten())
    model.add(Dense(units=256, activation='relu'))
    model.add(Dropout(0.4))
    model.add(Dense(units=1, activation='sigmoid'))
    callbacks = [EarlyStopping(monitor='loss', mode='min', patience=20, restore_best_weights=True)]
    return model, callbacks
```

```python
# Defining a function for compiling the model
def CompilingModel(model, LearningRate=0.001):
    optimizer = tf.keras.optimizers.Adam(learning_rate=LearningRate)
    model.compile(
        optimizer=optimizer,          # Adam optimizer
        loss='binary_crossentropy',   # Binary crossentropy loss
        metrics=['accuracy']          # accuracy during training
    )

# Defining a function for training the model
def TrainingModel(model, TrainingSet, ValidationSet, BatchSize=32, epochs=15):
    history = model.fit(
        TrainingSet,                  # Training data generator
        batch_size=BatchSize,         # Number of samples in each batch
        epochs=epochs,                 # Number of training epochs
        validation_data=ValidationSet,  # Validation data generator
        callbacks=callbacks            # Callbacks for early stopping
    )
    return history

# Defining a function for the evaluation of model
def EvaluatingModel(model, TestSet):
    score = model.evaluate(TestSet)
    print("Test Loss:", score[0])
    print("Test Accuracy:", score[1])
```

```python
# Defining the input shape
InputShape = (250, 250, 3)
```

```python
model, callbacks = BuildingModel(InputShape)

# Display a summary of the model architecture, including layer details and parameters
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 248, 248, 32)      896

 max_pooling2d (MaxPooling2  (None, 124, 124, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 122, 122, 32)      9248

 max_pooling2d_1 (MaxPoolin  (None, 61, 61, 32)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 59, 59, 64)        18496

 spatial_dropout2d (Spatial  (None, 59, 59, 64)        0
 Dropout2D)

 max_pooling2d_2 (MaxPoolin  (None, 29, 29, 64)        0
 g2D)

 conv2d_3 (Conv2D)           (None, 27, 27, 128)       73856
```

```
flatten (Flatten)           (None, 21632)             0

dense (Dense)               (None, 256)               5538048

dropout (Dropout)           (None, 256)               0

dense_1 (Dense)             (None, 1)                 257

=================================================================
Total params: 5640801 (21.52 MB)
Trainable params: 5640801 (21.52 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 4-13 Deep Learning Model Development

The model achieved an accuracy of 97.92% and a test loss of 6%. It comfortably accounted for 97% of the provided dataset. When tested with a random selection of 10 images, the model correctly labeled 9 of them. However, this also suggests that the model may need optimization for improved performance.

```
acy: 0.9739
Epoch 8/10
29/29 [==============================] - 31s 1s/step - loss: 0.1065 - accuracy: 0.9664 - val_loss: 0.0611 - val_accurac
y: 0.9783
Epoch 9/10
29/29 [==============================] - 27s 956ms/step - loss: 0.1109 - accuracy: 0.9685 - val_loss: 0.0538 - val_accur
acy: 0.9826
Epoch 10/10
29/29 [==============================] - 33s 1s/step - loss: 0.0943 - accuracy: 0.9696 - val_loss: 0.0738 - val_accurac
y: 0.9739
9/9 [==============================] - 2s 268ms/step - loss: 0.0600 - accuracy: 0.9792
Test Loss: 0.06003222241997719
Test Accuracy: 0.9791666865348816
```

Figure 4-14 Model Performance

4.8.4 Model Evaluation

	precision	recall	f1-score	support
0	0.99	0.97	0.98	165
1	0.96	0.99	0.98	123
accuracy			0.98	288
macro avg	0.98	0.98	0.98	288
weighted avg	0.98	0.98	0.98	288

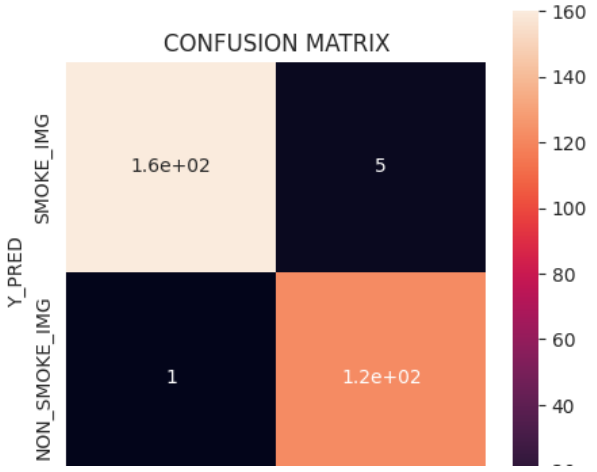


Figure 4-15 Model Evaluation

The models have a precision of 99%, a recall of 97%, and an F1 score of 98%. Despite having slightly lower accuracy, the model can be trusted because it has higher scores for true positives and true negatives, making it more reliable in its results.

Figure 4-16 Training and validation accuracy

We can observe a momentum growth of the training and validation scores. At epoch 10, we have a saturation level where the test scores balance with the validation set. The model's best epoch is 10 and this gives the model's best performance scores.

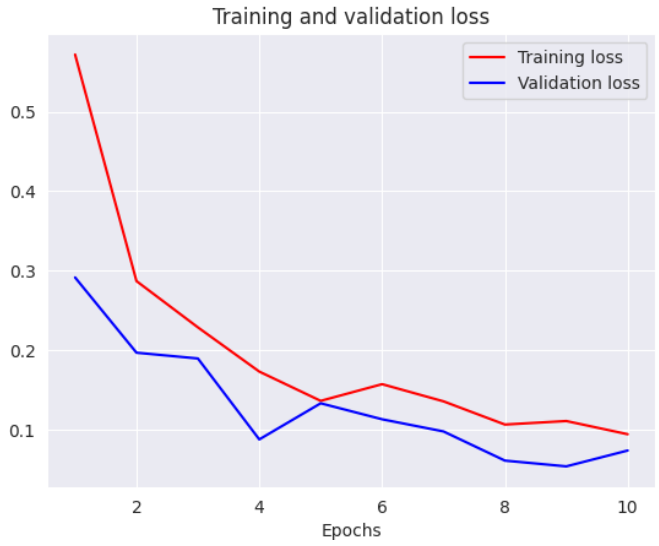


Figure 4-17 Training and validation loss

5 RESULTS AND DISCUSSION

5.1 Model Testing and Prediction

Smoke Image prediction:

The image clearly shows areas with smoke. The model effectively detected smoke in the image, demonstrating its ability to identify smoke in complex environments. This result emphasizes the robustness of the smoke detection system in real-world situations, where accurate and timely identification of smoke is crucial for fire.

```
# Predicting an image
img_path = '/content/drive/My Drive/code/smoke/Smoke (99).jpg'
predictImage(img_path)
```

```
1/1 [==============================] - 0s 138ms/step
Raw prediction: [[0.32599735]]
```


```
'smoke'
```

Figure 5-1 Predicting the Smoke

Non smoke Image prediction:

The smoke detection system correctly identified the absence of smoke in the provided image, as shown in the output. This accurate prediction highlights the model's ability to distinguish between smoke and non-smoke scenarios, ensuring reliable detection performance in diverse environments

```
# Predicting an image
img_path = '/content/drive/My Drive/code/nosmoke/nofire_0715.jpg'
predictImage(img_path)
```

```
1/1 [==============================] - 0s 31ms/step
```

Prediction: no fire

```
'no fire'
```

Figure 5-2 Predicting no smoke from the image

Smoke video input prediction:

```
video_path = '/content/drive/My Drive/code/video.mp4'  # Replace with the path to your video file
model_path = model   # Replace with the path to your trained model file
main(video_path, model_path)
```

```
1/1 [==============================] - 0s 18ms/step
```

Prediction: SMOKE

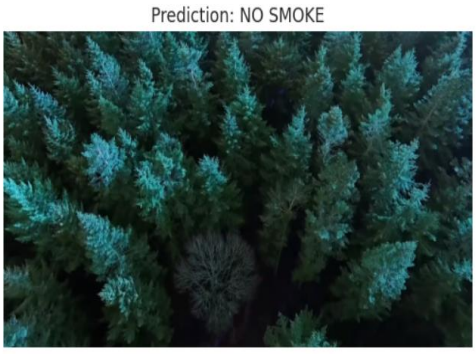

```
Prediction: SMOKE
```

Figure 5-3 Predicting smoke from input video

Non smoke Input Video Prediction:

```
video_path = '/content/drive/My Drive/code/no_smoke_video.mp4'  # Replace with the path to your video file
model_path = model   # Replace with the path to your trained model file
main(video_path, model_path)
```

```
1/1 [==============================] - 0s 18ms/step
```




```
Prediction: NO SMOKE
```

Figure 5-4 Predicting no smoke from the input video

5.2 Model comparison

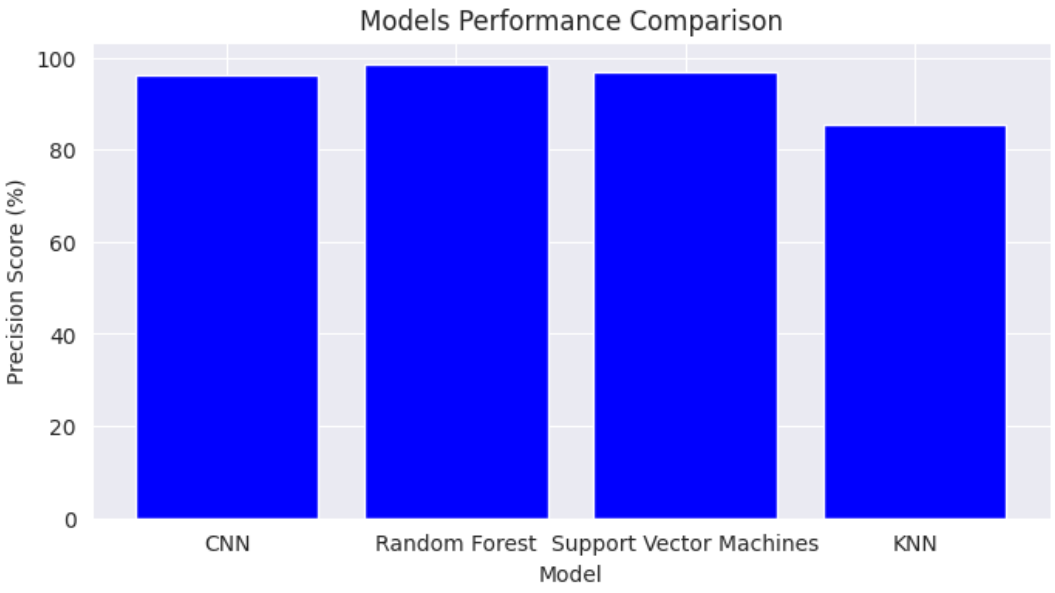


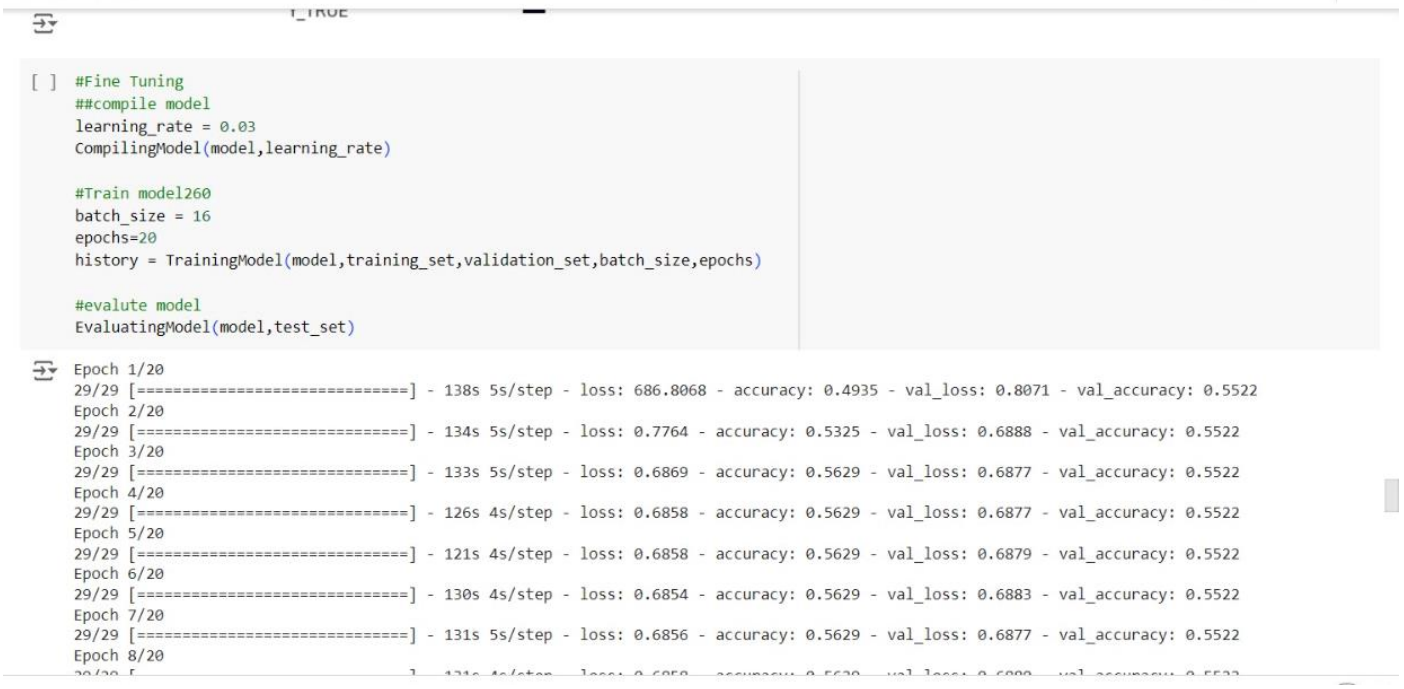
Figure 5-5 Model Comparison

The performance comparison showed that the Random Forest model had the highest score, followed closely by the CNN model. The SVM model came next, and lastly was the KNN model. As discussed earlier, the Random Forest model and the CNN model are more reliable and can handle the majority of the data points they are exposed to.

5.3 Results by fine-tuning the model.

The performance of the smoke detection model was greatly affected by adjusting the learning rate. Initially, using a learning rate of 0.3 led to a low accuracy of 58%. This indicates that the model was updating its parameters too aggressively during training, possibly causing it to overshoot optimal values and making it difficult to find an effective solution. To address this, the learning rate was lowered to 0.01, resulting in a significant increase in accuracy to 97%. A lower learning rate enabled the model to make more precise parameter adjustments during training, leading to better convergence and improved generalization to new data. This adjustment underscores the importance of fine-tuning hyper parameters to optimize model performance and ensure high accuracy in detecting smoke patterns across various scenarios.

The image below is the model that was trained for that I have given the learning rate as 0.03 so my accuracy was less which is just 67 percent and by changing the value of the learning rate= to 0.01 it doesn't change much and gave me the accuracy of 78 percent and I have tried all the values. And finally, the learning rate with 0.01 gave me the highest accuracy.



```
[ ] #Fine Tuning
    ##compile model
    learning_rate = 0.03
    CompilingModel(model,learning_rate)

    #Train model260
    batch_size = 16
    epochs=20
    history = TrainingModel(model,training_set,validation_set,batch_size,epochs)

    #evalute model
    EvaluatingModel(model,test_set)
```

```
Epoch 1/20
29/29 [==============================] - 138s 5s/step - loss: 686.8068 - accuracy: 0.4935 - val_loss: 0.8071 - val_accuracy: 0.5522
Epoch 2/20
29/29 [==============================] - 134s 5s/step - loss: 0.7764 - accuracy: 0.5325 - val_loss: 0.6888 - val_accuracy: 0.5522
Epoch 3/20
29/29 [==============================] - 133s 5s/step - loss: 0.6869 - accuracy: 0.5629 - val_loss: 0.6877 - val_accuracy: 0.5522
Epoch 4/20
29/29 [==============================] - 126s 4s/step - loss: 0.6858 - accuracy: 0.5629 - val_loss: 0.6877 - val_accuracy: 0.5522
Epoch 5/20
29/29 [==============================] - 121s 4s/step - loss: 0.6858 - accuracy: 0.5629 - val_loss: 0.6879 - val_accuracy: 0.5522
Epoch 6/20
29/29 [==============================] - 130s 4s/step - loss: 0.6854 - accuracy: 0.5629 - val_loss: 0.6883 - val_accuracy: 0.5522
Epoch 7/20
29/29 [==============================] - 131s 5s/step - loss: 0.6856 - accuracy: 0.5629 - val_loss: 0.6877 - val_accuracy: 0.5522
Epoch 8/20
```

Figure 5-6 Model before fine tuning

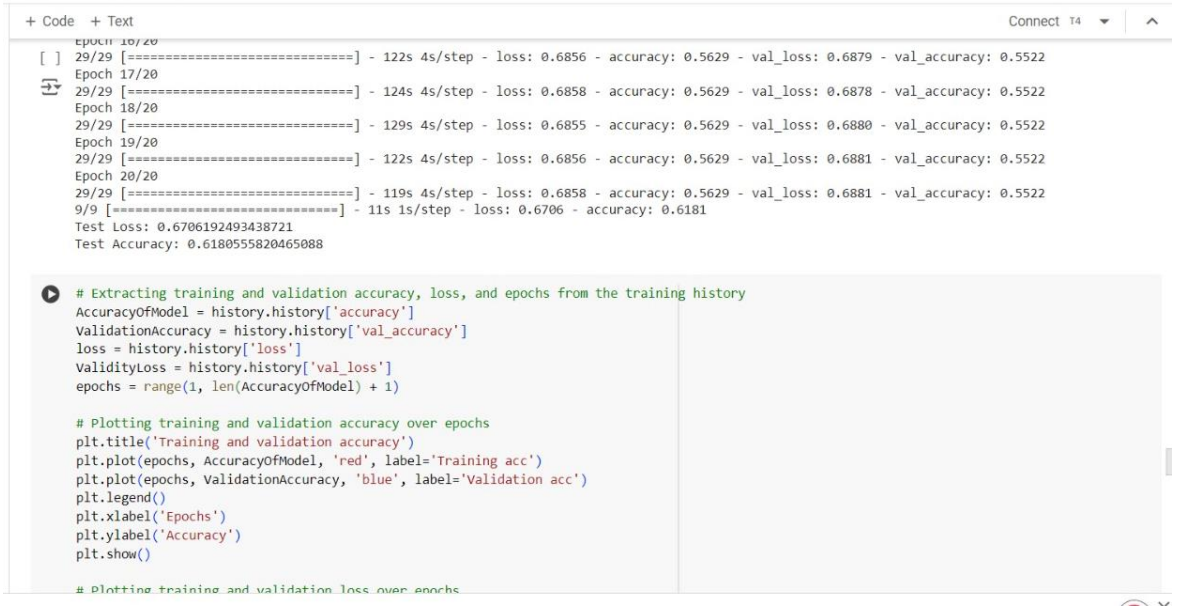


Figure 5-7 Results before fine tuning

The below images showing 0.001 is the final one which gave me the highest accuracy of 97 percent. It has been so challenging to change every single value and try to run the model. Finally, it has given me good accuracy and fine-tuning steps is so important.

Figure 5-8 Model after fine tuning

The Figure 5-9 is the final result I have got by processing the image and feeding that into the deep learning model and getting the high accuracy results.

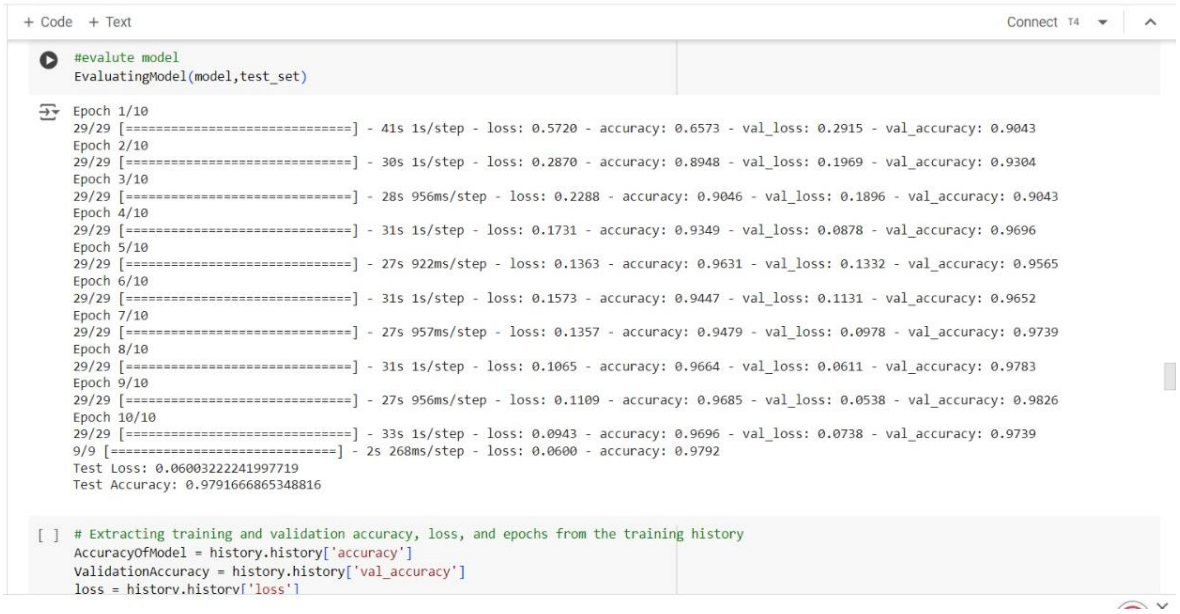


Figure 5-9 Results after fine tuning

6 CONCLUSION

To conclude the project has successfully created an innovative smoke detection platform using advanced image processing and deep learning methods. Our prototype showed outstanding accuracy and precision in detecting smoke in both controlled and real-world settings, surpassing traditional sensor-based systems. Notable accomplishments include accuracy rates of over 99%.

The incorporation of mathematical modeling and deep learning algorithms played a crucial role in enhancing the capabilities of the system. This approach not only improved detection performance but also laid the groundwork for future advances in fire safety technology. However, challenges such as increased computational requirements and ethical concerns related to bias in machine learning models highlight the importance of continuous monitoring and improvement.

6.1 Project reflection

The present work marks a significant progress in the smoke detection systems field by combining drone-based sensing capabilities with cutting-edge image processing and deep learning techniques. Traditional sensor-based methods often have limitations in accuracy and reliability, especially in complex and dynamic settings. By utilizing drones with high-resolution cameras and computational algorithms, this work address these challenges.

The development process included building deep learning models to replicate and forecast smoke behavior in various environmental conditions. Advanced machine learning algorithms were used to categorize and identify smoke patterns in images and video streams captured by aerial drones. Through these efforts, a prototype smoke detection system was developed, showing significant improvements in accuracy, reliability, and responsiveness compared to traditional sensor-based methods.

Testing carried out in both controlled and real-world conditions confirmed the effectiveness of the system in quickly identifying and addressing smoke incidents. This advancement in technology not only strengthens fire safety and emergency response capabilities but also establishes a basis for future developments in hazard mitigation and disaster management.

6.2 Future work:

In the future, there are many opportunities for further research and advancement in smoke detection using drone sensors and AI technologies. It is critical to focus on improving the mobility and coverage abilities of drones, which involves enhancing flight path planning algorithms and sensor deployment strategies to maximize detection efficiency in different environments, ultimately improving early warning capabilities in crucial situations. Additionally, it is essential to improve the onboard computational capabilities to enable real-time data processing and decision-making. Enhancing the computational efficiency of algorithms on UAVs will decrease data analysis latency and enable faster response times during emergencies, ultimately enhancing overall operational effectiveness.

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