

Emerging Methods for Early Detection of Forest Fires

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PROJECT TITTLE	Emerging Methods for Early Detection of Forest Fires
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1. INTRODUCTION

1.1 OVER VIEW

Forests, which are diverse centre of flora and wildlife and create 1/3 of the world's oxygen, are at risk of forest fires, both natural and man-made.

The precaution of averting such a massive devastating flare can save many animals and the environment. Protecting forests before they are harmed is a method of repaying Mother Nature's everlasting gift.

Wildfires are one of the biggest catastrophes faced by our society today causing irrevocable damages.

These forest fires can be man-made or caused by mother nature by different weather conditions, torrential winds.

These fires cause damages not only to the environment they also destroy vast homes and property.

1.2 PURPOSE

Forest fires have become a major threat around the world, causing many negative impacts on human habitats and forest ecosystems.

Climatic changes and the greenhouse effect are some of the consequences of such destruction.

Interestingly, a higher percentage of forest fires occur due to human activities.

The goal of the project is to develop a forest fire detection system that can identify forest fires in their early phases.

2. LITERATURE SURVEY

2.1 EXISTING SYSTEM

Every year, there are an estimated 340,000 premature deaths from respiratory and cardiovascular issues attributed to wildfire smoke.

The increasing frequency and severity of wildfires pose a growing threat to biodiversity globally. Individuals, companies and public authorities bear great economic costs due to fires. In order to reduce all these, we need to detect the forest fire at an early stage and prevent it.

Some of the existing solutions for solving this problem are:

Technology

The present technology includes particle and smoke detection systems, which are commonly used in facilities and families. These systems detect moisture in a space and determine whether the current atmosphere is safe or if an alarm should be triggered. The same way that a fire alarm works by spraying water throughout the room to put out the fire.

Fire fighter

To tackle fire problems, highly trained humans are used. Firefighters employ techniques and trucks to suppress forest fires throughout the conditions.

The priority of a firefighter is to protect people and reduce the number of people killed or injured by fire. Firefighting and property damage are the second and third priorities, respectively.

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2.3 PROBLEM STATEMENT DEFINITION

1.JOBS-TO-BE-DONE / PROBLEMS

Satellite remote sensing offers a useful tool for forest fire detection, monitoring, management and damage assessment. During a fire event, active fires can be detected by detecting the heat, light and smoke plumes emitted from the fires. This application uses real-time satellite data to detect and monitor forest fires (sending alerts to mobile devices), and understand fire patterns.

2.TRIGGERS

Human-caused fires result from campfires left unattended, the burning of debris, equipment use and malfunctions, negligently discarded cigarettes.

3. EMOTIONS: BEFORE / AFTER

BEFORE : unsafe and worries about lives and belongings

AFTER : safety and relief

4. AVAILABLE SOLUTION

Avoid burning wastes around dry grass. Obey local law regarding open fires, including campfires Have firefighting tools nearby and handy. Use fire resistant roofing materials. undertake technical checkups regularly. Monitoring weather analytics, monitoring thermal anomalies, monitoring water stress and temperature rises

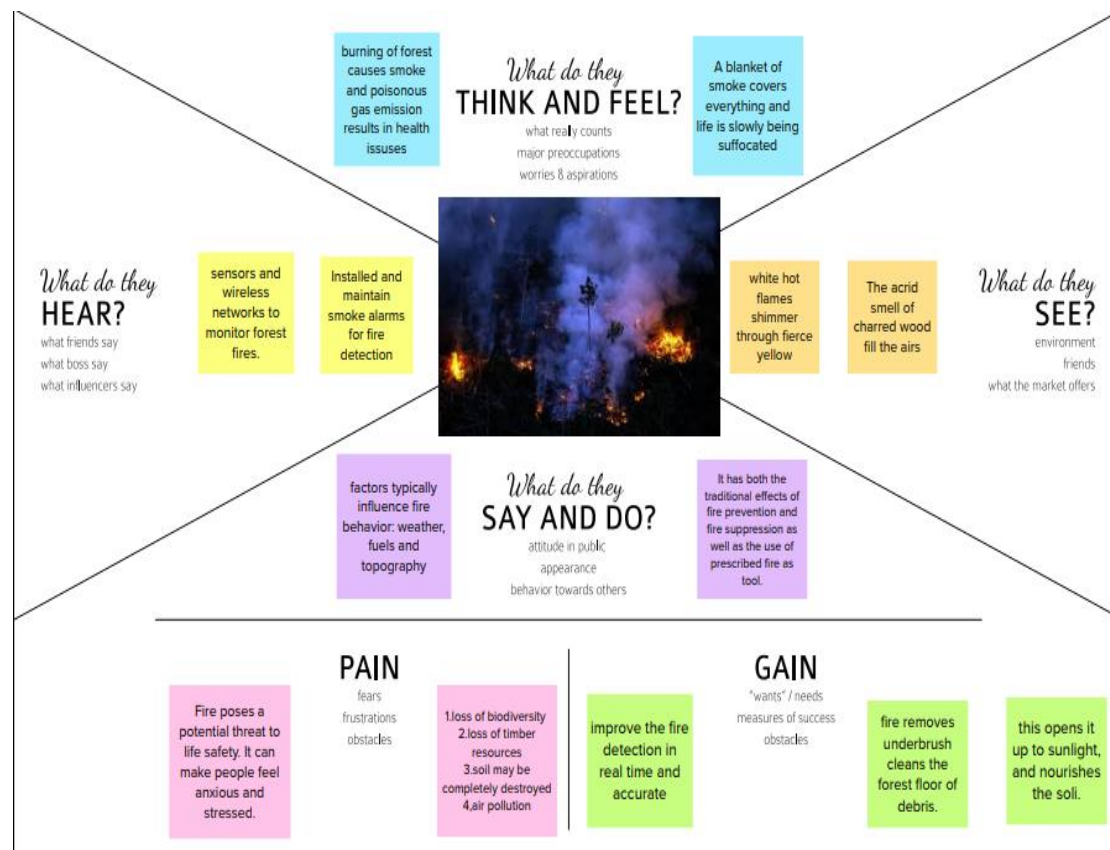
5. CUSTOMER CONSTRAINTS

Satellites allow for detecting and monitoring a range of fires , providing information about the location, duration, size, temperature, and power output of those fires that would otherwise be unavailable. Satellite data is also critical for observing and monitoring smoke from the fire

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas

An empathy map canvas helps brands provide a better experience for users by helping teams understand the perspectives and mindset of their customers. Using a template to create an empathy map canvas reduces the preparation time and standardizes the process so you create empathy map canvases of similar quality.



3.2 Ideation & Brainstorming

IDEATION:

[Ideation](#) is the process where you generate ideas and solutions through sessions such as [Sketching](#), [Prototyping](#), [Brainstorming](#), [Brainwriting](#), [Worst Possible Idea](#), and a wealth of other ideation techniques. Ideation is also the third stage in the [Design Thinking](#) process. Although many people might have experienced a “brainstorming” session before, it is not easy to facilitate a truly fruitful ideation session. In this article, we’ll teach you some processes and guidelines which will help you facilitate and prepare for productive, effective, innovative and fun ideation sessions.

Ideation is often the most exciting stage in a Design Thinking project, because during Ideation, the aim is to generate a large quantity of ideas that the team can then filter and cut down into the best, most practical or most innovative ones in order to inspire new and better design solutions and products.

IDEATION WILL HELP YOU,

- Ask the right questions and innovate with a strong focus on your users, their needs, and your insights about them.
- Step beyond the obvious solutions and therefore increase the [innovation](#) potential of your solution.
- Bring together perspectives and strengths of your team members.
- Uncover unexpected areas of innovation.
- Create volume and variety in your innovation options.
- Get obvious solutions out of your heads, and drive your team beyond them.

BRAINSTORMING:

Brainstorming can be used to generate possible solutions for simple problems, but it is unrealistic to expect it to accomplish most problem-solving or planning tasks. The technique is of value as part of a larger effort that includes individual generation of information and ideas and subsequent compilation, evaluation, and selection. Brainstorming can be used to generate components of a plan, process, solution, or approach and to produce checklists.

One of the reasons why brainstorming works is that ideas generate further ideas through the power of association—a process that has been called “hitch-hiking” or “piggybacking.” Also, the technique of “free association” is more powerful when one is working in a group than when

one is working alone. Reinforcement is another factor that leads to increased creativity. In the idea-generation phase of brainstorming, all suggestions are rewarded by being received and listed—a positive reinforcement. Nothing is criticized; there is no negative reinforcement.

THE GROUP:

The optimum size for a brainstorming group seems to be six to twelve members, and the optimum group consists of women as well as men. Brainstorming is a total-group effort. Breaking into smaller groups would defeat the purpose of the brainstorming session. **BEGINNING** Prior to the actual session, group members should be provided with a one-page memorandum that states the problem to be considered and outlines the brainstorming procedure. At the beginning of the actual session, if group members are not already acquainted with one another, they should be introduced (a getting-acquainted activity can be used for this). It is a good idea to conduct a warm-up activity, with the group members directed to brainstorm solutions to a simple problem that is unrelated to the topic of the actual session.

THE PROCESS :

The leader begins the work session by stating the problem or topic in specific, not general, terms. The problem should be simple rather than complex, so that the group can focus on a single target. The leader should have a list of categories, classifications, or leads (new uses, adaptation, modification, increase, decrease, substitute, rearrange, combine) that can be suggested to the group members if they seem to be getting off track. The leader also can have a few ideas about solutions ready to throw in when the group seems to lag. It seems to work best if one idea at a time is offered by any one member. This allows all members the space to participate and encourages “piggybacking” on previous ideas. A recorder (not necessarily the leader) lists all ideas (but not who suggested them) on newsprint as soon as they are generated. This list is positioned so that all members can see it. The session also may be tape recorded to make sure that no ideas are lost.

THE RULES OF BRAINSTORMING:

The following criteria are essential to the idea-generation phase of a brainstorming session :

1. There is no criticism, evaluation, judgment, or defense of ideas during the brainstorming session. The purpose of brainstorming is to generate as many ideas related to the topic as possible in the time allowed. Evaluation, judgment, and selection of ideas are the purposes of subsequent sessions.

2. Free wheeling and free association is encouraged. Group members are asked to voice any solutions they can think of, no matter how outrageous or impractical they seem. There is no limit on “wild” or “far-fetched” ideas. Every idea is to be expressed. It is easier to tone down an idea and to select out later than it is to think up new and creative possibilities.

3. Quantity is more desired than quality. Group members are encouraged to contribute as many ideas as they think of. The greater the number of ideas generated, the more likely it is that there will be several useful ideas.

4. Building on ideas is encouraged. Combining, adding to, and “piggybacking” on ideas is part of the creative process. Members can suggest improvements, variations, or combinations of previous ideas.

INDIVIDUAL BRAINSTORMING:

Brainstorming can be conducted on an individual basis as well (Hayes, 1981). One can write down possible solutions to a clearly outlined problem, forcing oneself to keep the ideas flowing from the pen without stopping. This use of brainstorming is effective at stopping one of the strongest drains on creativity: self-criticism or negative self-talk. People tend to criticize themselves, their thoughts, and their actions far more than they praise themselves.

3.3 Proposed Solution

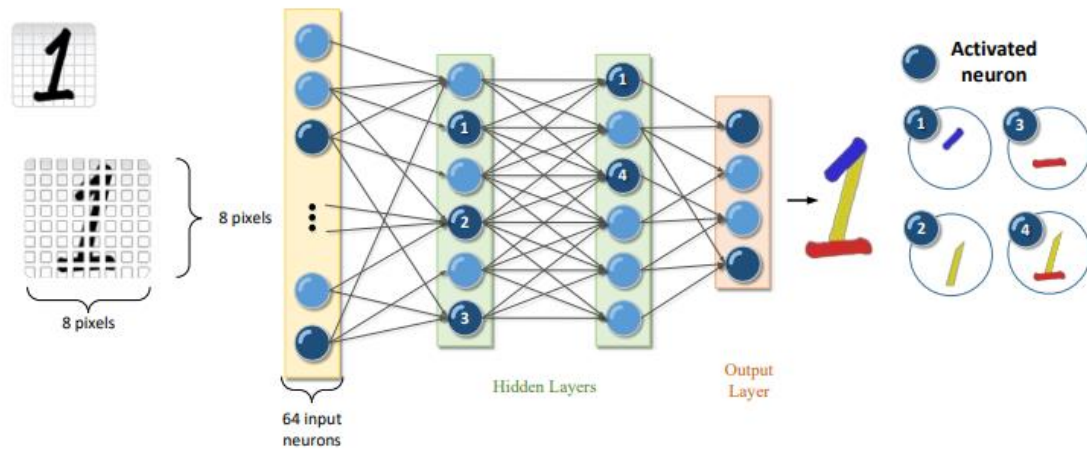
The flow of the proposed architecture is shown in Figure. The video input is captured from the camera, and the other inputs such as wind speed, wind directions, and IR image sensing are calculated using the sensors mounted on the UAV for navigation. These images are provided as input to the deep learning models, and it checks for the existence of the fire. The region is predicted clearly since there is a possibility of more projections of the images provided to the model due to the 3D modeling. Further detection is made, and the details are stored in the database for further.



3.4 Problem Solution fit

Artificial intelligence has become extremely popular in the recent years as it has the ability to perform tasks, which are inherent to a human mind. Artificial intelligence, sometime referred to as machine intelligence, is implemented by using neural networks. The neural networks are specialized computer models, which can be trained to perform different tasks. They are used for classification of images, speech recognition, translation of texts and more complex tasks, like control of autonomous vehicles, etc. There are several types of neural networks, but the most widely used for image detection and computer vision are the convolutional neural networks [7, 8]. They consists of input layer, hidden layers and output layer of interconnected neurons, as shown in Fig. Depending on the number of hidden layers, we have machine learning methods (with just one hidden layer) and deep learning methods (with

more than one hidden layers), in terms of methods for training the neural networks. For example, Fig. presents a deep neural network, since it has two hidden layers.



4. REQUIREMENT ANALYSIS

4.1 Functional requirement

Functional requirements of the proposed solution.

S.No	Functional Requirement	Sub Requirement
1.	User Registration	Registration through Twilio services
2.	User Confirmation	Confirmation via Mobile number Confirmation via OTP
3.	User Login	Login using credentials
4.	User Search	Search for Info on forest fire occurrence
5.	User Profile	User shall be given a live feed of the forest
6.	User Application	User is alerted if there is an forest fire occurrence in their surroundings

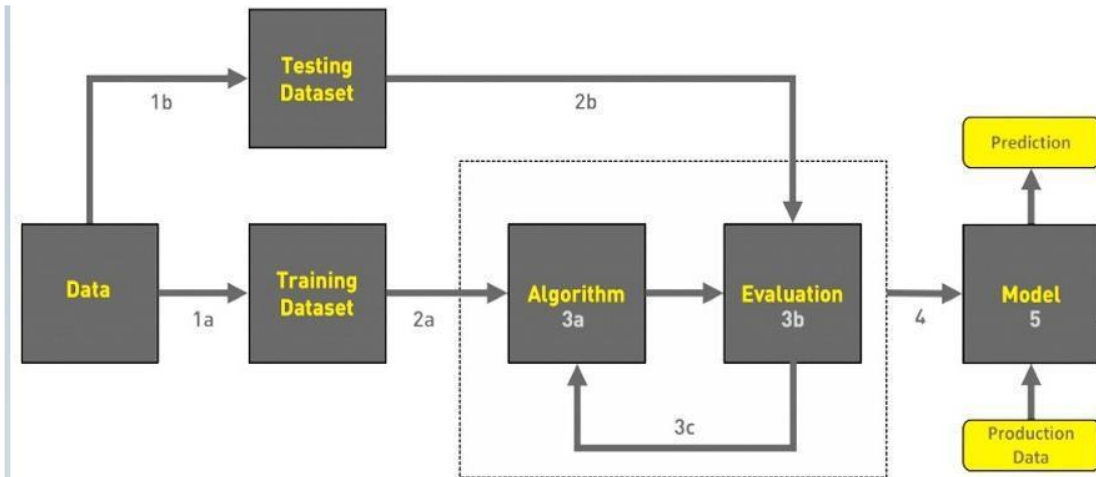
4.2 Non-Functional requirements

Non-functional requirements of the proposed solution.

S.No	Non-Functional Requirement	Description
1.	Usability	Alerts according to the user location
2.	Security	Instant live feed with alert of the situation
3.	Reliability	The prediction of the forest fire is 87% accurate
4.	Performance	The feed and the alert message is an immediate action without a lag
5.	Availability	The application gives alerts and live feeds 24/7

5. PROJECT DESIGN

5.1 Data Flow Diagrams



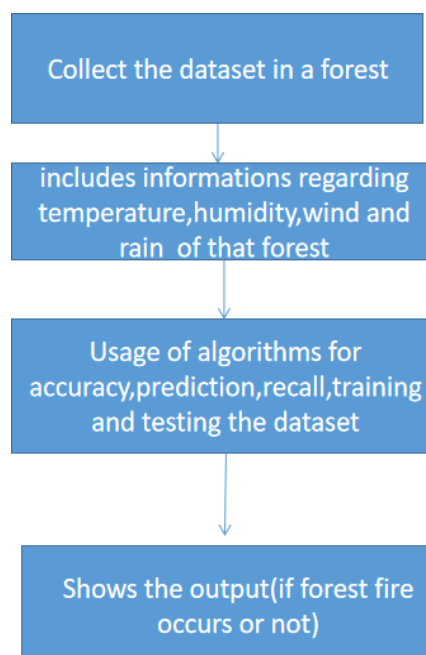
1. COLLECT DATA

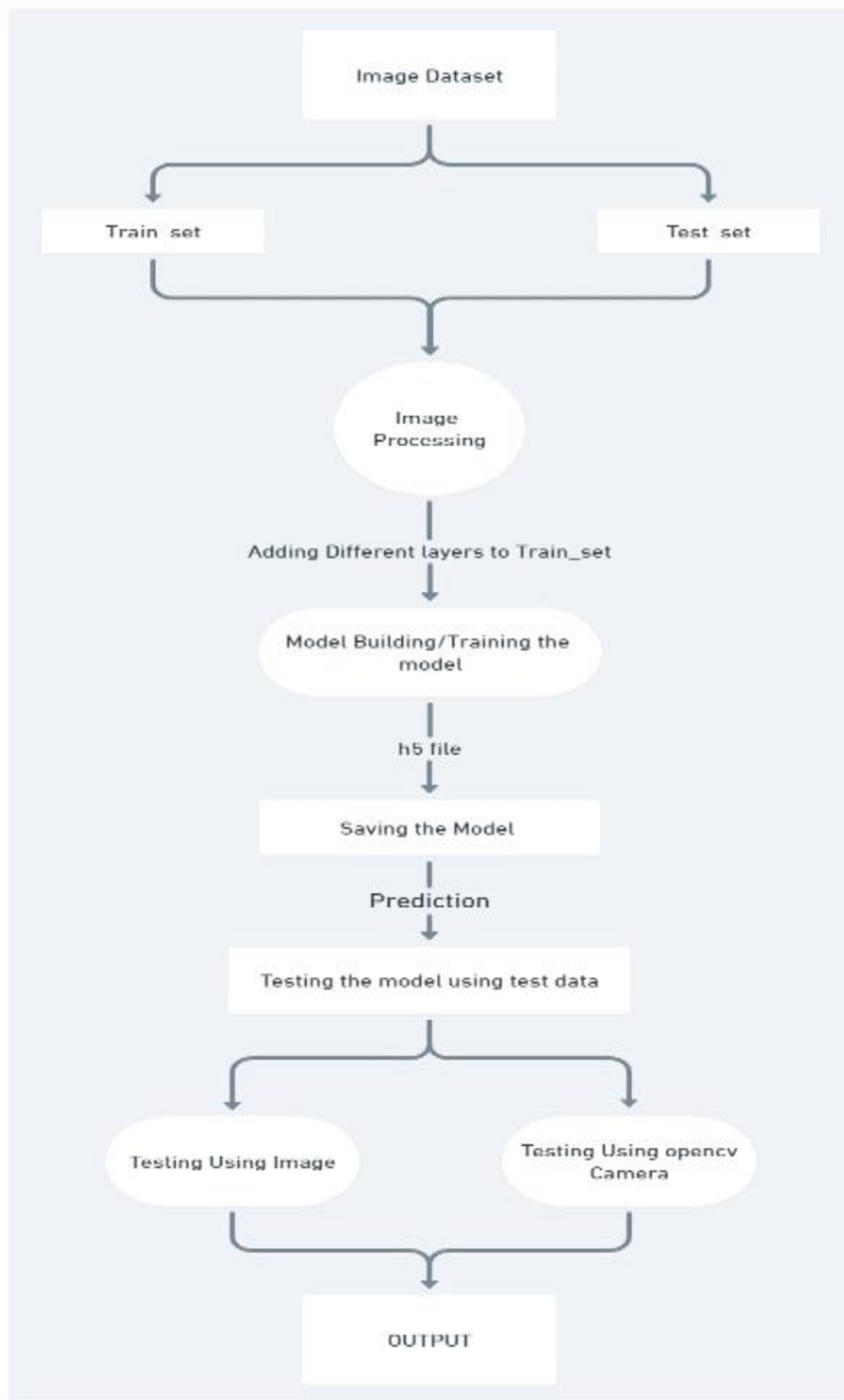
2. EVALUATE DATA SET

3. IMPLEMENT ALGORITHMS

4. EVALUATE THE ACCURACY OF EACH ALGORITHMS

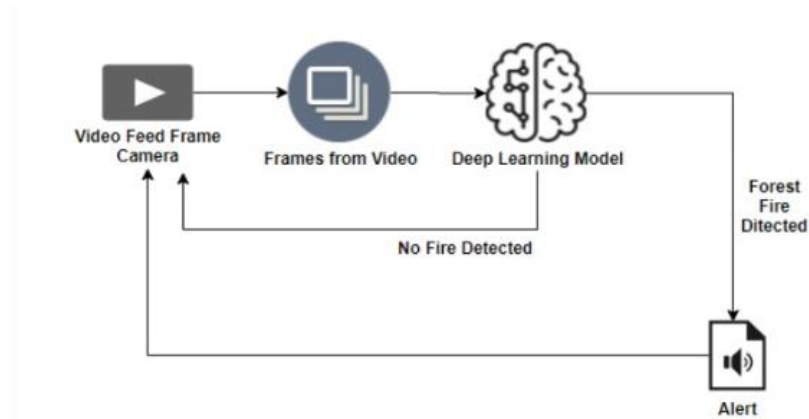
5. DISPLAY RESULTS





5.2 Solution & Technical Architecture

Detection of forest fire and smoke in wild land areas is done through remote sensing-based methods such as satellites, high-resolution static cameras fixed on the ground, and unmanned aerial vehicles (UAVs).



The video input is captured from the camera, and the other inputs such as wind speed, wind directions, and IR image sensing are calculated using the sensors mounted on the UAV for navigation. These images are provided as input to the deep learning models, and it checks for the existence of the fire. The region is predicted clearly since there is a possibility of more projections of the images provided to the model due to the 3D modeling. Further detection is made, and the details are stored in the database for further.

5.3 User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Environmental	Collect the data	USN-1	As an Environmental list, it is necessary to collect the data of the forest which includes temperature, humidity, wind and rain of the forest	It is necessary to collect the right data else the prediction may become wrong	High	Sprint-1
		USN-2	Identify algorithms that can be used for prediction	To collect the algorithm to identify the accuracy level of each algorithms	Medium	Sprint-2
		USN-3	Identify the accuracy of each algorithms	Accuracy of each algorithm-calculated so that it is easy to obtain the most accurate output	High	Sprint-2
		USN-4	Evaluate the Dataset	Data is evaluated before processing	Medium	Sprint-1
		USN-5	Identify accuracy, precision, recall of each algorithms	These values are important for obtaining the right output	High	Sprint-3
		USN-6	Outputs from each algorithm are obtained	It is highly used to predict the effect and to take precautionary measures	High	Sprint-4

6. PROJECT PLANNING & SCHEDULING

6.1 Sprint Planning & Estimation

Sprint Planning

When we first came to learn that our proposal for developing an early warning system to detect forest fires was selected, it seemed an almost surreal moment. An idea that came about in random workplace discussions was now finally becoming reality.

Our first Sprint was divided into 4 experiments to explore the viability of project implementation, 2 of which were quite straight forward. These included identifying a technical partner to design and develop the forest fire management system (which was easy as we were already working on a simultaneous project to develop another early warning system to detect leopards), and identifying and engaging a research consultant to conduct a study into forest fire incidents for the past 5 years (this would allow us to gather the data necessary to develop a robust forest fire management system). The latter simply required us to develop the requisite Terms of Reference and have them advertised through our internal processes.

Estimation

Forest fires have major impact on ecosystems and greatly impact the amount of greenhouse gases and aerosols in the atmosphere. This presents an overview in the forest fire detection, emission estimation, and fire risk prediction using satellite imagery, climate data, and various simulation models. Some developed algorithms have been utilized for detecting the forest fire hot spots at a sub-pixel level. With respect to modeling the forest burning emission, a remote sensing data-driven Net Primary productivity (NPP) estimation model was developed for estimating forest biomass and fuel. In order to improve the forest fire risk

modeling , real-time meteorological data, such as surface temperature, relative humidity, wind speed and direction, have been used as the model input for improving prediction of forest fire occurrence and its behavior. Shortwave infrared (SWIR) and near infrared (NIR) channels of satellite sensors have been employed for detecting live fuel moisture content (FMC).

6.2 Sprint Delivery Schedule

Sprint-1

Registration

USN-1

As a user ,I can register for the application by entering my email, password, and confirming my password.

USN-2

As a user, I will receive confirmation email once I have registered for the application usage.

Sprint-2

Input

USN-3

Whenever the fire is detected, the information is given to the database.

USN-4

When it is the wildfire then the alarming system is activated.

Sprint-3

Output

USN-5

And the alarm also sent to the corresponding departments and made them know that the wildfire is erupted.

Sprint-4

USN-6

Required actions will be taken in order to controlled erupted wildfire by reaching as early as possible to the destination with the help of detecting systems.

6.3 Reports from JIRA

FIRESENSE aims to develop an automatic early warning system integrating multiple sensors to remotely monitor areas of archaeological and cultural interest for the risk of fire and extreme weather conditions.

FIRESENSE will take advantage of recent advances in multi-sensor surveillance technologies by employing both optical and infrared cameras to monitor the site and the surrounding area as well as a wireless sensor network capable of measuring different environmental parameters(e.g. temperature, humidity).

The signals and measurements collected from these sensors will be transmitted to a monitoring center, which will employ intelligent computer vision and pattern recognition algorithms as well as data fusion techniques to automatically analyze and combine sensor information.

The control centre will be capable of generating automatic warning signals whenever a dangerous situation arises, i.e. when fire or smoke is detected. Moreover, the system will read weather data from official meteorological services as well as from local weather stations installed at the site and will issue alerts in case of extreme weather conditions.

It will also provide real-time information about the evolution of the fire based on wireless sensor network data. Furthermore, it will be able to estimate the propagation of the fire based on the fuel model of the area and other important parameters such as wind speed and direction and ground morphology.

Finally, the estimated fire propagation will be visualized on a 3D Geographic Information System (GIS) environment.

7. CODING AND SOLUTIONING

7.1 Features 1

The features of a fire alarm system is to detect a fire outbreak as soon as one occurs and alert the occupants immediately.

Therefore when purchasing a fire alarm system you need a reliable one. The most important feature to look for in a fire alarm is detectors and sensors that can accurately identify fire outbreaks. This can help with the automatic initiating process.

The system should also have the ability to initiate the alarm manually. It must have a notification system which is loud and visible enough to alert almost every occupants in the building.

If you want the fire alarm for a commercial building, then you should purchase addressable fire alarm systems.

These systems can accurately locate the zone in which the fire starts with the help of its addressable detectors connected to its main control panel.

This enables you to prioritize each zone according to the level of urgency. The main goal of these activities was to raise awareness about the protection of cultural heritage from natural disasters such as wildfires, disseminate the project's results, educate the inhabitants and exploit the FIRESENSE product.

7.2 Features 2

High reliability: The system utilizes different sensing technologies (CCTV cameras, PTZ cameras, IR cameras, PIR sensors, temperature and humidity sensors, and meteorological sensors). The different types of sensors operate independently

- Early detection of fire: Automatic detection of flame/smoke/rise in temperature.
- Forest fire management: The system estimates and visualizes the fire propagation based on the area's fuel model (vegetation), the local weather conditions and ground morphology.

- Automation of the fire fighting: The output of the FIRESENSE system can activate waterpipe networks for watering, like the fire sprinkler in buildings. Such water pipe networks are usually organized in sectors, which can be timely and separately activated in the areas threatened by the fire.
- Early warning for extreme weather conditions: Local weather stations provide useful sensor readings like temperature, wind direction and speed, relative humidity, barometric pressure, rain gauge etc.

External weather forecasting is made available to the system as well, which makes it straightforward to use it as an early warning system for extreme weather conditions.

Furthermore, two significant features of the FIRESENSE system, which make it applicable to numerous archaeological sites across Europe

- Modular architecture that allows for easy system upgrades and extensions depending on the particular needs of different archaeological sites.
- Protection of archaeological sites through non-destructive and non-intrusive intervention

8. TESTING

8.1 Test Cases

Large scale will always cause a loss of worth crores which will turn the net asset of forest into ashes. Therefore, greater emphasis is laid on the survey that can be used for the purpose of design and development of detection and monitoring system.

It is because of some activities such as an uncontrolled anthropogenic which makes a fire in the forest to occur at regular intervals.

Incidents which lead to regular forest fires include man-made incidents, climate changes, and other factors; there has been a constant increase in the frequency of forest fires.

Out of the incidents mentioned above, man-made incidents, i.e., deliberate cause is the most common one.

In general fires that occur in the forest can be classified into three types which are:

1. Ground fires,
2. Surface fires, and
3. Crown fires.

Ground fires as given in Fig. 1 occur basically on the floor of forest which will produce much heat but without flames.

This type of fire is a result of peaty leaves which will be always found on the floor of forest.

One more cause can be the organic component of soil which will be formed by the process of decomposition of leaves and other plant materials by soil microorganisms.

Ground type of fires is rarest of the three and has been rarely recorded because they normally occur at forests which are situated at very high altitudes such as Himalayan forests.

To detect this type of fires, which is a very difficult task, sensors which can record and measure even a temperature difference of as small as 1 °C also should be used. There fore, one can go for the implementation of thermal sensors and radiation sensors for this purpose.

Figure 1: Ground fires



Figure 2: Surface fire



Figure 3: Crown fires



8.2 User Acceptance Testing

Thermal detection of burning vegetation

Our Fire detection identifies heat sources in thermal images captured by LWIR (long-wavelength infrared) thermal sensor. The temperature of burning vegetation is between 300 and 800 degrees Celsius. The burning plants will emit more intense infrared radiation than the surrounding environment.

Thermal detection detects early-stage forest fires after the initial ignitions. It is fast and accurate. We can detect a burning vegetation surface as small as 2-meter square size at a 5km distance. Infrared radiation, like all other radiations, travels in a straight line. Hence thermal detection requires LOS (line of sight) between the burning object and the thermal sensor.

With all the safety measures in place, if the detection distance is 2km or less, we suggest the following field test setup: wood logs with dimensions

1 m x 1 m x 1 m. The wood logs should be around 10 cm to 15 cm thick in diameter and should be arranged and stacked as shown below:



Figure 1: fire test setup for thermal detection of forest fire

Visual detection of wildfire flame and smoke

Our AI Wildfire Detection uses Machine Learning object detection to detect forest fires. We used about half a million visual images of wildfires to train our AI models. They are small flame or smoke photos of distance surface fires. The smoke rise above tree canopies is a important visual signal of distant forest fire.



Figure 2: smoke of distant fire

With all safety measures implemented, we suggest the following field test setup: wood logs with dimensions 1 m x 1 m x 1 m.

The wood logs should be around 10 cm to 15 cm thick in diameter and should be arranged and stacked. When the wood logs are burned, completely charred and visible flames extinguished, add damp green leaves and grass on top of the charred wood left over. White smoke will be generated as shown below:



Figure 3: fire test setup for AI visual detection of forest fire

Water should be sprayed on the greens from time to time to prevent them from drying and starting to burn.

The smoke column can be generated for at least 15 minutes.

9. RESULTS

9.1 Performance Metrics

In this section, comprehensive experiments are carried out in order to detect forest fire using conventional machine learning algorithms, object detection techniques, deep and hybrid deep learning models.

Accuracy (AC), f-measure (FM), precision (PR), mean average precision (mAP), and recall (RC) are employed as evaluation metrics to demonstrate the performance of the models. To calculate evaluation metrics for each model, the number of true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) values are obtained using confusion matrix.

The TP refers to the number of operations extracted from the result of the fire by the model for visual data that actually contains the fire in the sample space collected within the scope of the study. TN is the number of visual data that does not actually contain a fire image and is determined by the model to contain no fire. FP refers to the number of visual data that the model classifies as if it were containing fire, although it does not actually contain fire data. FN refers to the number of visual data that is classified as if it does not contain fire data on the model side, even though it actually contains fire data. The ratio of the number of data that a model can classify as false when false and true when true to the total number of data gives the accuracy value given in equation 1.

$$Accuracy = \frac{TP+TN}{TP+NP+TN+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+NP} \quad (2)$$

Recall is used to measure the precision of the model. It gives the ratio of correctly predicted positive estimates to the number of all images that are actually correct (containing fire) given in equation 3.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F-measure is a value obtained as a result of the weighted ratio of positive interpretive strength and sensitivity values. Both false-positive and falsenegative values are taken into account when calculating the F-measure. When the distribution of classes is not balanced, it gives more realistic results compared to the total accuracy criterion when measuring the success of the model. The formula should be given as in equation 4.

$$F - measure = \frac{2 \cdot Recall \cdot Precision}{Recall + Precision} \quad (4)$$

Intersection over Union (IoU) is defined as the area of the intersection divided by the area of the union of a predicted bounding box (B_p) and a ground-truth box (B_{gt}). Formula is presented in equation 5.

$$IOU = \frac{area(B_p \cap B_{gt})}{area(B_p \cup B_{gt})} \quad (5)$$

To observe how the hyperparameters effect the performance of the system, different combinations are tested such as the number of convolution layer, the number of neurons in the hidden layers and dense layer, The best performance result is determined to construct the proposed model. In the experiments, dataset is divided into 70% as training and remaining is test.

The following abbreviations are used in the tables:

AC: Accuracy,

FM: F-measure,

PR: Precision,

RC: Recall,

SVM: Support vector machine,

RF: Random Forest,

CNN: Convolutional neural network,

CNNGRU: Convolution Neural Network-Gated Recurrent Unit,

CNN-LSTM: Convolutional neural network-long short-term memory,

SSD: Single shot detector,

Faster R-CNN: Faster recurrentconvolutional neural network,

Avg: Average.

The best results are obtained for each dataset in the Table 1 and Table 2 after experiments of hyperparameter tuning. The best performance results are also demonstrated in boldface in all tables.

In Table 1, the performance results of all classification models according to evaluation metrics in the first dataset (DS1) are demonstrated. As it is clearly seen that in Table 1, convolutional neural network model outperforms other models with 98.32% of accuracy result.

Table 1. Classification performance results of each method in terms of evaluation metrics on DS1.

DS1	Evaluation Metrics			
Models	AC	FM	PR	RC
SVM	72.75	75.86	78.22	83.26
RF	80.26	81.22	83.17	84.35
CNN	98.32	98.12	98.30	98.34
CNN-GRU	53.08	66.34	34.66	66.21
CNN-LSTM	53.45	30.15	15.24	24.68
Avg.	71.24	70.15	62.18	71.96

It is followed by RF with 80.26%, SVM with 72.24 %, CNN-GRU with 53.45%, and CNN-LSTM with 53.08% of accuracy results.

Although the RF is the model with the second-best classification ability, it cannot be said to be competitive due to nearly an 18% accuracy difference between them compared to CNN.

As another result of Table 1, hybrid deep learning models exhibit poor performance with approximately 53.08% of accuracy in the image classification task for DS1, both compared to traditional machine learning techniques and CNN as a deep learning model.

In Table 2, the performance results of all classification models according to evaluation metrics in the second dataset (DS2) are demonstrated.

Table 2. Classification performance results of each method in terms of evaluation metrics on DS2.

DS2	Evaluation Metrics			
Models	AC	FM	PR	RC
SVM	75.29	78.48	70.29	89.15
RF	81.45	83.08	78.49	88.66
CNN	99.32	99.32	99.22	99.42
CNN-GRU	55.11	52.26	46.48	57.78
CNN-LSTM	54.73	34.25	17.48	37.78
Avg	73.35	69.52	62.46	74.18

As it is obviously observed that in Table 2, convolutional neural network model outperforms other models with 99.32% of accuracy result. It is followed by RF with 81.45%, SVM with 75.29%, CNN-GRU with 55.11%, and CNN-LSTM with 54.15% of accuracy results.

Although the RF is the second-best classification technique, RF is not competitive because of about an 18% accuracy decrement when compared to CNN method. As another result of Table 2, hybrid deep learning techniques present the poorest classification success with approximately 54.15% of accuracy for CNNLSTM and 55.11% of accuracy for CNN-GRU in DS2, both compared to conventional machine learning techniques and CNN model. The classification performance of models is ordered as: CNN> RF> SVM> CNN-GRU> CNN-LSTM.

When we compare Table 1 and Table 2 in terms of datasets, there is no remarkable change in accuracy for the CNN model when the total number of data increases. On the other hand, the traditional machine learning models exhibit an enhancement in accuracy values of nearly 1% for the RF, about 3% for the SVM model, and almost 2% and roughly 1 for the CNN-GRU and CNN-LSTM models when the number of data increases.

In addition, when the average accuracy value is considered in Table 1 and Table 2, an increase of almost 2% is also noticeable. Experiment results demonstrate that the utilization of CNN model for detection of forest fire significantly contributes to classification success of the system.

For this reason, experiments are carried out on detailed parameter settings of CNN model as a next step. Table 3 and Table 4 present detailed parameter experiments for DS1 and DS2, respectively.

The parameters employed in the experiments are the number convolution layer, the number of neurons and dense layer.

In order to ensure the best scores of CNN model, different combinations are tested by varying epoch sizes. Epoch size is arranged as 20 for CNN and 50 for hybrid deep models, 32 batch sizes for CNN and 8 batch sizes for hybrid deep models, the number of convolution layer, the number of neurons contained in each layer, and the number of dense layers.

The following abbreviations are used in the Table 3 and Table 4: CNV: The number of convolution layer, ND: The number of neurons contained in each layer, DNS: the number of dense layers.

Table 3. Classification performance results of each parameter combination in terms of evaluation metrics on DS1.

CNN	Evaluation Metrics			
Parameters	AC	FM	PR	RC
2 CNV-32 ND-1 DNS	98.32	98.12	98.30	98.34
2 CONV-32 ND-2 DNS	97.26	90.79	90.79	90.79
2 CNV-64 ND-1 DNS	97.26	97.26	97.26	98.26
2 CNV-64 ND-2 DNS	95.29	85.89	80.45	92.28
3 CNV-32 ND-1 DNS	90.42	95.08	93.47	97.74
3 CNV-32 ND-2 DNS	93.13	94.10	94.15	94.13
3 CNV-64 ND-1 DNS	84.46	95.19	93.73	98.19
3 CNV-64 ND-2 DNS	93.54	95.46	98.31	94.46

In Table 3, the combination of 2 convolution layer, 32 nodes, and 1 dense layer exhibits the best classification success with 98.32% of accuracy. When the number of dense layers and convolution layers are set to 1, and 2, respectively, the only change is observed in number of nodes. When the number of nodes increases from 32 to 64, the performance is decreased nearly 1%.

If the number of node and dense layers are adjusted as 32 and, 1, the number of convolutions varies to 3 from 2, which causes approximately 8% decrement in classification accuracy.

When the number convolution layers, nodes, and dense layers are set to 3, 64, and 1, the fire detection system exhibits the poorest classification success with 84.15% of accuracy.

As a result of Table 3 and Table 4, the raise of number of convolution layer and nodes affect the classification performance of the system, negatively. Finally, CNN experiments are carried out by setting the number of convolution layer, nodes, and dense layer as 2, 32, and 1, respectively for DS1 and DS2. In Table 4, classification results of each parameter combination in terms of evaluation metrics on DS2 are presented.

Similar to Table 3, the combination of 2 convolution layer, 32 nodes, and 2 dense layers exhibits the best classification success with 99.32 % of accuracy. Although there is a modification in the number of nodes and hidden layers, no significant increase or decrease in classification performance is observed.

However, the increase in the number of convolution layers caused a decrease in classification performance of about 5%.

Table 4. Classification performance results of each parameter combination in terms of evaluation metrics on DS2.

CNN	Evaluation Metrics			
Parameters	AC	FM	PR	RC
2 CNV-32 ND-1 DNS	99.16	98.60	99.52	98.61
2 CNV-32 ND-2 DNS	99.32	99.32	99.22	99.42
2 CNV-64 ND-1 DNS	98.96	99.41	99.34	99.16
2 CNV-64 ND-2 DNS	99.46	99.42	99.49	99.83
3 CNV-32 ND-1 DNS	96.59	95.19	95.24	96.81
3 CNV-32 ND-2 DNS	94.26	94.49	94.34	93.28
3 CNV-64 ND-1 DNS	95.76	96.64	97.57	95.19
3 CNV-64 ND-2 DNS	97.78	96.15	97.42	97.26

In addition to classification task in order to detect forest fire, object detection techniques are also evaluated. For this purpose, SSD and Faster R-CNN models are performed in the experiments.

In Table 5, performance results of object detection techniques are presented in terms of evaluation metrics. The mAP metric compares the ground-truth bounding box to the detected box and returns a score. The results demonstrated in Table 5 are ensured employing 1,605 fire images with 300*300 size. Test data contains 232 fire images and train data has 1,379 fire images.

Common Objects in Context dataset (MS COCO), which contains 80k training images (“2014 train”) and 40k validation images (“2014 val”) is released by Microsoft. There is an associated MS COCO challenge with an evaluation metric, that averages mAP when is used calculate object detection accuracy over different IoU thresholds, from 0.5 to 0.95.

This emphasizes a significantly larger emphasis on localization compared to COCO metrics. Every model has a performance number for training dataset.

When Faster R-CNN model is trained on the dataset, the result of mAP is lower than 28%. Actually, this means that the Faster R-CNN model gives result of mAP score 13.36% for 0.5 intersection on unit (IOU).

The same dataset is also trained on other object model single shot detector (SSD).

The experiment result shows that the usage of SSD technique outperforms Faster R-CNN with 22.2% of mAP. Furthermore, precision of SSD model performs better than Faster R-CNN method with 19.26%. Figure 2 demonstrates the fire detection results of SSD model on test images.

Table 5. Performance results of object detection techniques in terms of evaluation metrics.

Models	Evaluation Metrics		
	mAP	Precision	Recall
SSD	22.20	19.26	43.00
FasterR-CNN	13.36	14.22	43.22



Figure 2. SSD fire detection model on test images.

In authors propose multi-scale prediction for fire detection utilizing convolutional neural network. 97.89% of F-measure score is reported while our study demonstrates 98.12% of F-score. In convolutional neural network (CNN) is proposed to detect fire by classifying both fire and smoke in videos. The training procedure is performed with the videos including both fire and smoke.

The experiment results indicate that the model used in the study is able to classify the fire, smoke and fire with smoke with a recognition rate of up to 94%, 95% and 93%, respectively. In Saponara et. al present real-time video fire/smoke detection system employing YOLOv2 convolutional neural network. Authors employ a large scale of fire/smoke and negative videos in different environments, both indoor (e.g., a railway carriage, container, bus wagon, or home/office) and outdoor (e.g., storage or parking area).

They report that the achieved experimental results show that the proposed system is suitable real-time video-surveillance system for fire/smoke detection with 96.02% of accuracy that surpasses of our object detection models because of using different model and different experiment settings, and datasets.

10. Advantage :

Slash and burns fires are set every day to destroy large section of forest. These forests don't just remove trees they kill and display wildlife alter water cycles and soil fertility and endanger the lives and livelihoods of local communities and they also can rage out of control.

The very huge area of forest is destroyed by fire every year and monitoring of the potential risk is sand an early detection of fire can significantly shorten the reaction time and also reduce the potential damage as well as the cost of fire fighting .

Fire kills diseases and insects that prey on trees and provides valuable nutrients that enrich the soil and the cleaning the forest floor the fire removes low growing underbrush cleans the forest floor of debris opens it up to sunlight and nourishes the soil .

Fires occurring in nature can restore ecological balance and facilitate regeneration the over time of forest floor become littered with debris and choked by heavy undergrowth that competes with trees for nutrients and water .

Wildlife can even be displaced from its natural habits of low intensity fires clear forest floor with minimal damage to the trees fires can also rid forest of insects infestation and potential diseases .

Fires require oxygen and fuel to be ignited with oxygen and fuel to be ignited with oxygen presents in the air faulty electrical wiring cigarette butts static electricity and even concentrated sunlight can act as fuel and destructive fire can start and fires are made more deadly by smoke and toxic gases emitted from material .

Disadvantages :

The fire can be deadly, destroying homes, wildlife habitat and timber, and polluting the air with emissions harmful to human health. Fire also releases carbon dioxide—a key greenhouse gas—into the atmosphere. One of the most significant negative effects of wildfires is the loss of land and property, including homes, crops, animals, and resources. In the United States, wildfires burn an average of 7.4 million acres annually.

The main effect of prescribed burning on the water resource is the potential for increased rainfall runoff. When surface runoff increases after burning, it may carry suspended soil particles, dissolved inorganic nutrients, and other materials into adjacent streams and lakes reducing water quality.

It harms wildlife and destroys their habitat. Naturally, trees serve as homes, food source and protection for animals and insects. High risk of forest fires due to human negligence. High cost involved in maintaining forests. Impact on wildlife due to human activities that leads to the destruction of natural habitats. There is a risk of soil erosion and landslides. The cutting down of forests leads to a loss in biodiversity. leaves a scar on the environment. It contributes to the problem of climate change and It causes soil erosion. It affects the water cycle.

The solution used in wet chemical extinguishers is alkaline, which means it can cause corrosion of some metals. the solution can cause irritation to the skin and eyes. not suitable for electrical fires.

One of the limitations of decision trees is that they are largely unstable compared to other decision predictors. A small change in the data can result in a major change in the structure of the decision tree, which can convey a different result from what users will get in a normal event.

Despite its socioeconomic significance, wood is sometimes regarded as an inferior source of energy. For example, the traditional woodfuel* sector is often associated with unsustainable and often illegal production that leads to deforestation, forest degradation and, in some areas, woodfuel scarcity.

11. Conclusion :

The system for early forest fire detection is still in its development stage. We are still waiting for some equipment to be purchased, but we have planned and discussed the actual implementation.

We have performed a thorough research and some simulation experiments and we believe that we follow the right way to achieve the goal. We also believe that we apply adequate approach that is also up-to-date.

We think that the system could enhance the available platforms for fire detection and we hope that such improvement could significantly reduce the damages caused by untimely or late fire detection.

12. FUTURE SCOPE

This project is far from complete and there is a lot of room for improvement. Some of the improvements that can be made to this project are as follows:

Additional pump can be added so that it automatically sends water when there is a fire breakout.

Also industrial sensors can be used for better ranging and accuracy. \ This project has endless potential and can always be enhanced to become better.

Implementing this concept in the real world will benefit several industries and reduce the workload on many workers, enhancing overall work efficiency.

13. APPENDIX

13.1 Source code

Home.html

```
<!DOCTYPE html>
<html lang="en">
<head>
<title>Early Detection of Forest Fires</title>
<meta charset="UTF-8">
<meta name="viewport" content="width=device-width, initial-scale=1">
<link rel="stylesheet"
href="https://www.w3schools.com/w3css/4/w3.css">
<link rel="stylesheet"
href="https://fonts.googleapis.com/css?family=Lato">
<link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-
awesome/4.7.0/css/font-awesome.min.css">
<style>
body { font-family: "Lato", sans-serif}
.mySlides {display: none}
</style>
</head>
<body>

<!-- Navbar -->
<div class="w3-top">
  <div class="w3-bar w3-black w3-card">
    <a class="w3-bar-item w3-button w3-padding-large w3-hide-medium
w3-hide-large w3-right" href="javascript:void(0)"
onclick="myFunction()" title="Toggle Navigation Menu"><i class="fa
fa-bars"></i></a>
    <a href="#" class="w3-bar-item w3-button w3-padding-
large">HOME</a>
    <a href="#band" class="w3-bar-item w3-button w3-padding-large w3-
hide-small">PROJECT DETAILS</a>
    <a href="/detect" class="w3-bar-item w3-button w3-padding-large w3-
hide-small">DETECT</a>
    <a href="#contact" class="w3-bar-item w3-button w3-padding-large
w3-hide-small">CONTACT</a>
  </div>
```

```
<a href="javascript:void(0)" class="w3-padding-large w3-hover-red
w3-hide-small w3-right"><i class="fa fa-search"></i></a>
</div>
</div>
```

```
<!-- Navbar on small screens (remove the onclick attribute if you want
the navbar to always show on top of the content when clicking on the
links) -->
```

```
<div id="navDemo" class="w3-bar-block w3-black w3-hide w3-hide-
large w3-hide-medium w3-top" style="margin-top:46px">
  <a href="#band" class="w3-bar-item w3-button w3-padding-large"
onclick="myFunction()">BAND</a>
  <a href="#contact" class="w3-bar-item w3-button w3-padding-large"
onclick="myFunction()">CONTACT</a>
  <a href="#" class="w3-bar-item w3-button w3-padding-large"
onclick="myFunction()">MERCH</a>
</div>
```

```
<!-- Page content -->
```

```
<div class="w3-content" style="max-width:2000px;margin-top:46px">
```

```
<!-- Automatic Slideshow Images -->
```

```
<div class="w3-container w3-content w3-center w3-padding-64"
style="max-width:800px" id="band">
  <h2 class="w3-wide">Emerging Methods for Early Detection of
Forest Fires</h2>
  <p class="w3-opacity"><i>Save a Forest, Save the World</i></p>
</div>
```

```
<div class="mySlides w3-display-container w3-center">
  
  <div class="w3-display-bottommiddle w3-container w3-text-white w3-
padding-32 w3-hide-small">
```

```
</div>
```

```
</div>
```

```
<div class="mySlides w3-display-container w3-center">
  
  <div class="w3-display-bottommiddle w3-container w3-text-white w3-
padding-32 w3-hide-small">
</div>
```

```
</div>
<div class="mySlides w3-display-container w3-center">
  
  <div class="w3-display-bottommiddle w3-container w3-text-white w3-
padding-32 w3-hide-small">
</div>
</div>
```

```
<div class="mySlides w3-display-container w3-center">
  
  <div class="w3-display-bottommiddle w3-container w3-text-white w3-
padding-32 w3-hide-small">
</div>
</div>
```

```
<!-- The Band Section -->
<div class="w3-container w3-content w3-center w3-padding-64"
style="max-width:800px" id="band">
  <p class="w3-justify">
```

Forest fires are occurring throughout the year with an increasing intensity in the summer and autumn periods.

These events are mainly caused by the actions of humans, but different nature and environmental phenomena, like lightning strikes or spontaneous combustion of dried leafs or sawdust, can also be credited for their occurrence.

Regardless of the reasons for the ignition of the forest fires, they usually cause devastating damage to both nature and humans.

Forest fires are also considered as a main contributor to the air pollution, due to the fact that during every fire huge amounts of gases and particle mater are released in the atmosphere.

To fight forest fires, different solutions were employed throughout the years. They ware primary aimed at the early detection of the fires.

The simplest of these solutions is the establishment of a network of observation posts - both cheap and easy to accomplish, but also time-consuming for the involved people.

```
</p>
```

```
</div>
```

```
<!-- The Contact Section -->
```

```

<div class="w3-container w3-content w3-padding-64" style="max-
width:800px" id="contact">
  <h2 class="w3-wide w3-center">CONTACT</h2>
  <p class="w3-opacity w3-center"><i>How? Drop a note!</i></p>
  <div class="w3-row w3-padding-32">
    <div class="w3-col m6 w3-large w3-margin-bottom">
      <i class="fa fa-map-marker" style="width:30px"></i>
NagarCoil,India<br>
      <i class="fa fa-phone" style="width:30px"></i> Phone: +91 8754X
XXXXX<br>
      <i class="fa fa-envelope" style="width:30px"> </i> Email:
asuvanaraj02@gmail.com<br>
    </div>
    <div class="w3-col m6">
      <form action="/action_page.php" target="_blank">
        <div class="w3-row-padding" style="margin:0 -16px 8px -16px">
          <div class="w3-half">
            <input class="w3-input w3-border" type="text"
placeholder="Name" required name="Name">
          </div>
          <div class="w3-half">
            <input class="w3-input w3-border" type="text"
placeholder="Email" required name="Email">
          </div>
        </div>
        <div class="w3-half">
          <input class="w3-input w3-border" type="text"
placeholder="Message" required name="Message">
        </div>
        <button class="w3-button w3-black w3-section w3-right"
type="submit">SEND</button>
      </form>
    </div>
  </div>
</div>

<!-- End Page Content -->
</div>

```

```

<!-- Footer -->
<footer class="w3-container w3-padding-64 w3-center w3-opacity w3-
light-grey w3-xlarge">
  <i class="fa fa-facebook-official w3-hover-opacity"></i>

```

```

<i class="fa fa-instagram w3-hover-opacity"></i>
<i class="fa fa-snapchat w3-hover-opacity"></i>
<i class="fa fa-pinterest-p w3-hover-opacity"></i>
<i class="fa fa-twitter w3-hover-opacity"></i>
<i class="fa fa-linkedin w3-hover-opacity"></i>
<p class="w3-medium">Powered by <a
href="mailto:asuvanaraj02@gmail.com" target="_blank">Atchuu</a></p>
</footer>

```

```

<script>
// Automatic Slideshow - change image every 4 seconds
var myIndex = 0;
carousel();

function carousel() {
  var i;
  var x = document.getElementsByClassName("mySlides");
  for (i = 0; i < x.length; i++) {
    x[i].style.display = "none";
  }
  myIndex++;
  if (myIndex > x.length) {myIndex = 1}
  x[myIndex-1].style.display = "block";
  setTimeout(carousel, 4000);
}

// Used to toggle the menu on small screens when clicking on the menu
button
function myFunction() {
  var x = document.getElementById("navDemo");
  if (x.className.indexOf("w3-show") == -1) {
    x.className += " w3-show";
  } else {
    x.className = x.className.replace(" w3-show", "");
  }
}

// When the user clicks anywhere outside of the modal, close it
var modal = document.getElementById('ticketModal');
window.onclick = function(event) {
  if (event.target == modal) {
    modal.style.display = "none";
  }
}

```

```
}  
</script>
```

```
</body>  
</html>
```

Detect.html

```
<html lang="en">  
  <head>  
    <meta charset="utf-8">  
    <meta name="viewport" content="width=device-width, initial-scale=1,  
shrink-to-fit=no">  
    <link rel="stylesheet"  
href="https://cdn.jsdelivr.net/npm/bootstrap@4.4.1/dist/css/bootstrap.min  
.css">  
    <title>  
      Page of Detect  
    </title>  
    <style>  
  
      #bg  
      {  
background-image: url('static/img/p1.jpg');  
position: fixed;  
left: 0;  
top: 0;  
width: 100%;  
height: 100%;  
background-size: cover;  
filter: blur(0px);  
}  
  
#myButton1 {  
  letter-spacing: 1px;  
  
}  
#myButton11 {  
  letter-spacing: 1px;  
  left: -30px;  
  
}  
</style>
```



```
<script>
function clearFunc()
{
document.getElementById("wave").value="";
}
function Func()
{
alert(" The Area'are under in Fire zone ");

}

function lFunc()
{
alert(" The Area'are not under in Fire zone ");

}

</script>
</head>
<body id="bg">
<div class="container">
<br>
<br>
<br>
<br>
<br>
<br>
<center><form>
<div class="form-group col-md-3">
<label><b>Upload The Wave Image</b></label><br>
<br>
<input type="file" class="form-control-file" id="wave"
name="wave"></div>

<div class="form-row">
```



```
model = load_model('forest1.h5')
```

```
print('Model loaded. Check http://127.0.0.1:5000/')
```

```
@app.route('/', methods=['GET'])
def index():
    # Main page
    return render_template('digital.html')
```

```
@app.route('/predict', methods=['GET', 'POST'])
def upload():
    if request.method == 'POST':
        # Get the file from post request
        f = request.files['image']

        # Save the file to ./uploads
        basepath = os.path.dirname(__file__)
        file_path = os.path.join(
            basepath, 'uploads', secure_filename(f.filename))
        f.save(file_path)
        img = image.load_img(file_path, target_size=(64,64))

        x = image.img_to_array(img)
        x = np.expand_dims(x, axis=0)

        #with graph.as_default():
        preds = np.argmax(model.predict(x))
        index = ["forest", "with fire"]
        print(preds)
        text = index[preds]
        return text
```

```
@app.route('/video', methods=['GET', 'POST'])
def opencv():
    video = cv2.VideoCapture(0)
    name = ['forest', 'with fire']

    while(1):
```

```

success, frame = video.read()
cv2.imwrite("image.jpg",frame)
img = image.load_img("image.jpg",target_size = (64,64))
x = image.img_to_array(img)
x = np.expand_dims(x,axis = 0)
pred=np.argmax(model.predict(x),axis=1)
#pred = model.predict_classes(x)
pred=model.predict(x)
#p = pred[0]
p=int(pred[0][0])
print(pred)
#cv2.putText(frame, "predicted class = "+str(name[p]), (100,100),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0,0,0), 1)

pred = model.predict(x)
pred=np.argmax(model.predict(x),axis=1)
print(pred)
#cv2.putText(frame, "predicted class = "+str(name[pred]),
(100,100), cv2.FONT_HERSHEY_SIMPLEX, 1, (0,0,0), 1)
if pred[0]==1:

    cv2.putText(frame, "predicted class = Fire Detected" ,(100,100),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0,0,0), 1)
    account_sid = 'ACe5315c2184c5d92ab3e08ac1ef393549'
    auth_token = 'd3a2959a5b7ad750efabf53525588579'
    client = Client(account_sid, auth_token)

    message = client.messages \
    .create(
        body='Forest Fire is detected, stay alert',
        from_=' +12567877044', #twilio free number
        to= '+91XXXXXXXXXX')
    print(message.sid)

    print('Fire Detected')
    print ('SMS sent!')
    #return 'Fire Detected'
    return render_template('video.html',pred="Fire Detected Aler
Notification Sent")
    break
else:

```

```

        cv2.putText(frame, "predicted class = No Danger",(100,100),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0,0,0), 1)
        print("no danger")
        #break
        cv2.imshow("image",frame)

        if cv2.waitKey(1) & 0xFF == ord('a'):
            break

    video.release()
    cv2.destroyAllWindows()
    return render_template('digital.html')

if __name__ == '__main__':
    app.run(threaded = False)

```

Final main

```

# Create a VideoCapture object and read from input file
# If the input is the camera, pass 0 instead of the video file name
cap = cv2.VideoCapture('/content/drive/MyDrive/Forest with fire.mp4')

# Check if camera opened successfully
if (cap.isOpened()== False):
    print("Error opening video stream or file")

# Read until video is completed
while(cap.isOpened()):
    # Capture frame-by-frame
    ret, frame = cap.read()
    if ret == True:
        x=image.img_to_array(frame)
        res=cv2.resize(x,dsize=(128,128),interpolation=cv2.INTER_CUBI
C)

        #expand the image shape
        x=np.expand_dims(res,axis=0)
        model=load_model("/content/forest1.h5")
        cv2_imshow(frame)
        pred=model.predict(x)
        pred = int(pred[0][0])
        pred
        int(pred)

```

```

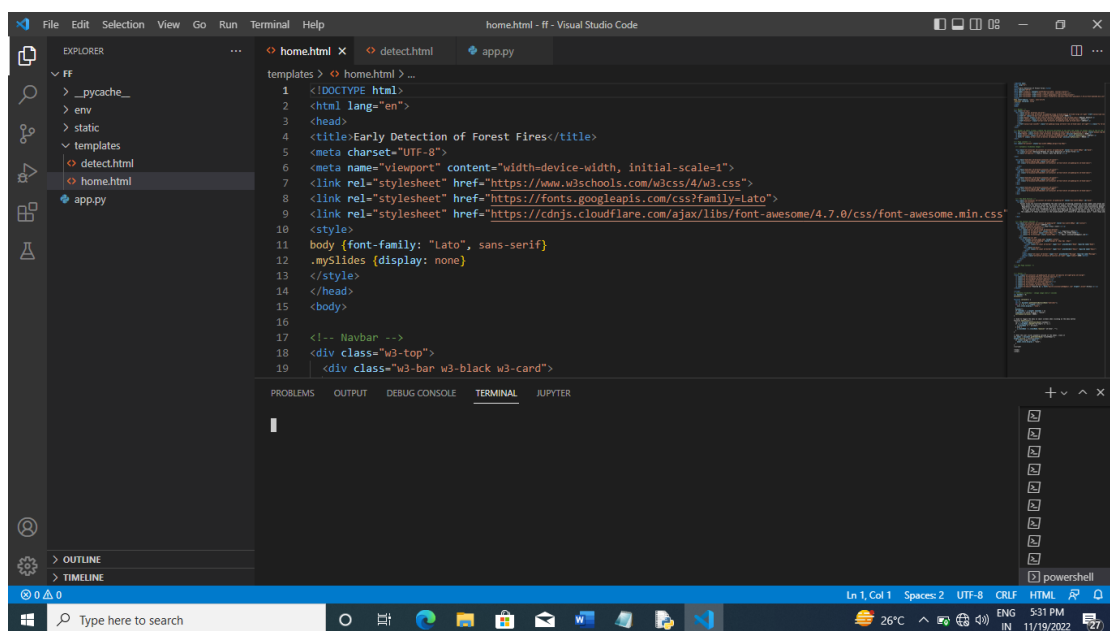
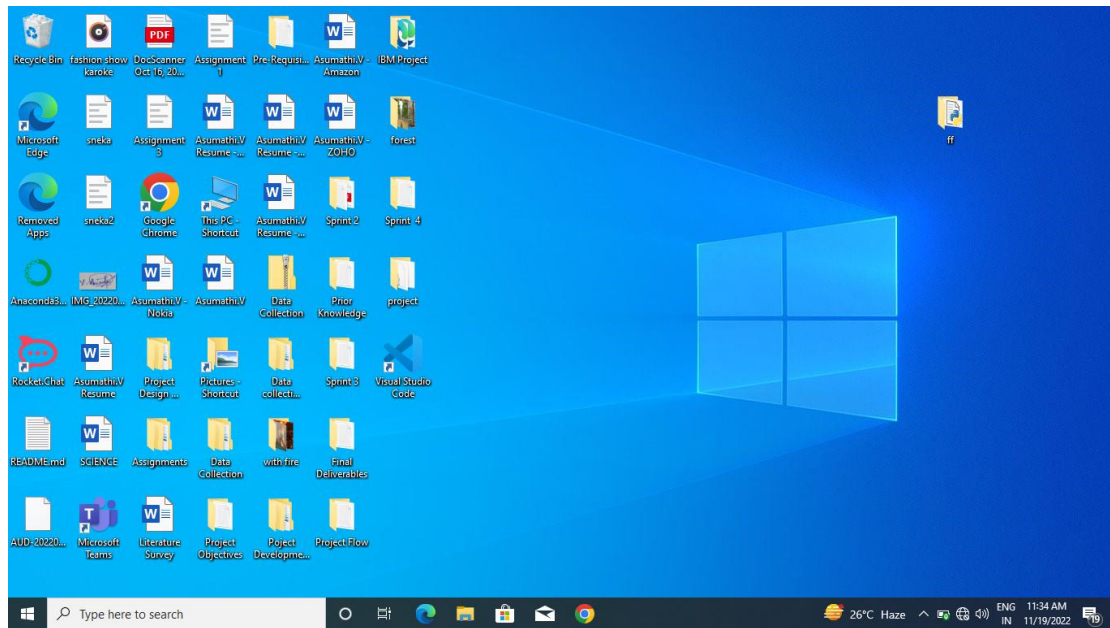
    if pred==0:
        print('Forest fire')
        break
    else:
        print("danger")
        break

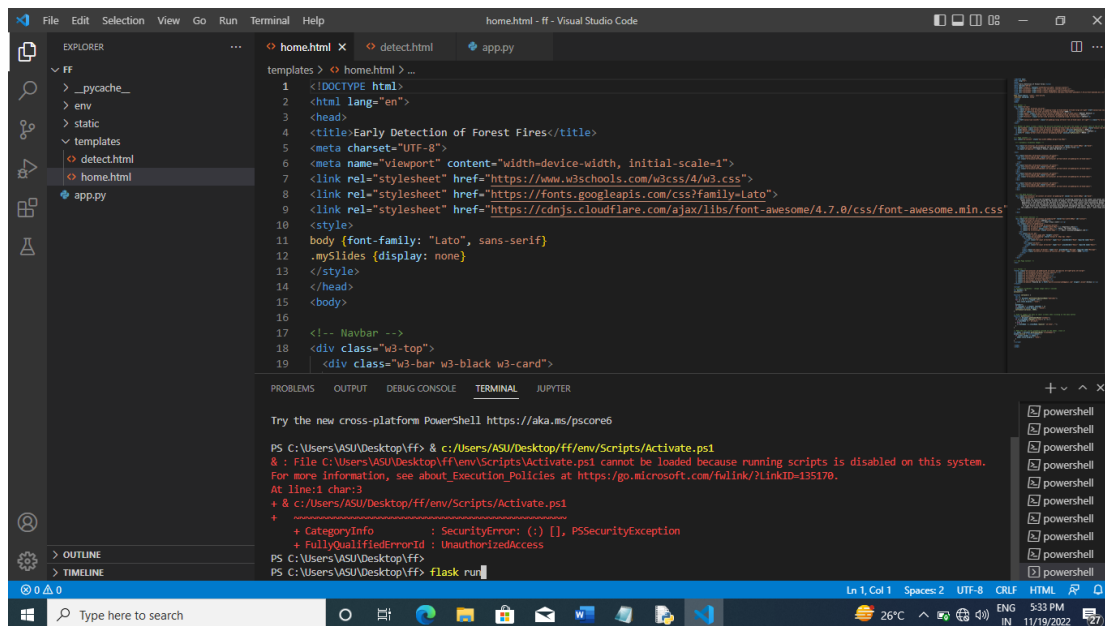
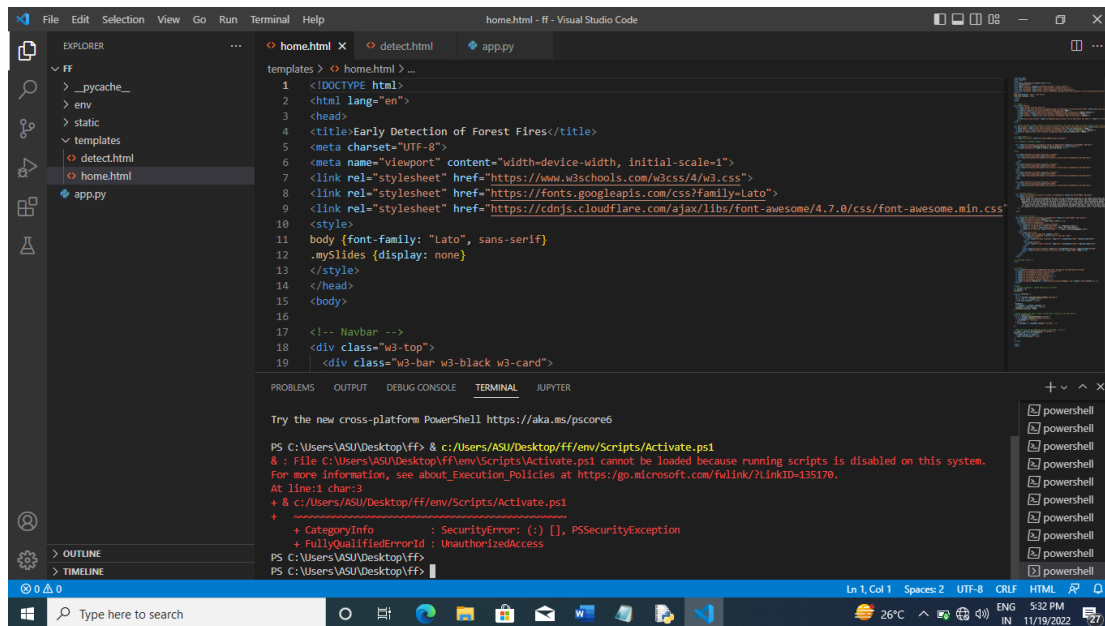
# When everything done, release the video capture object
cap.release()

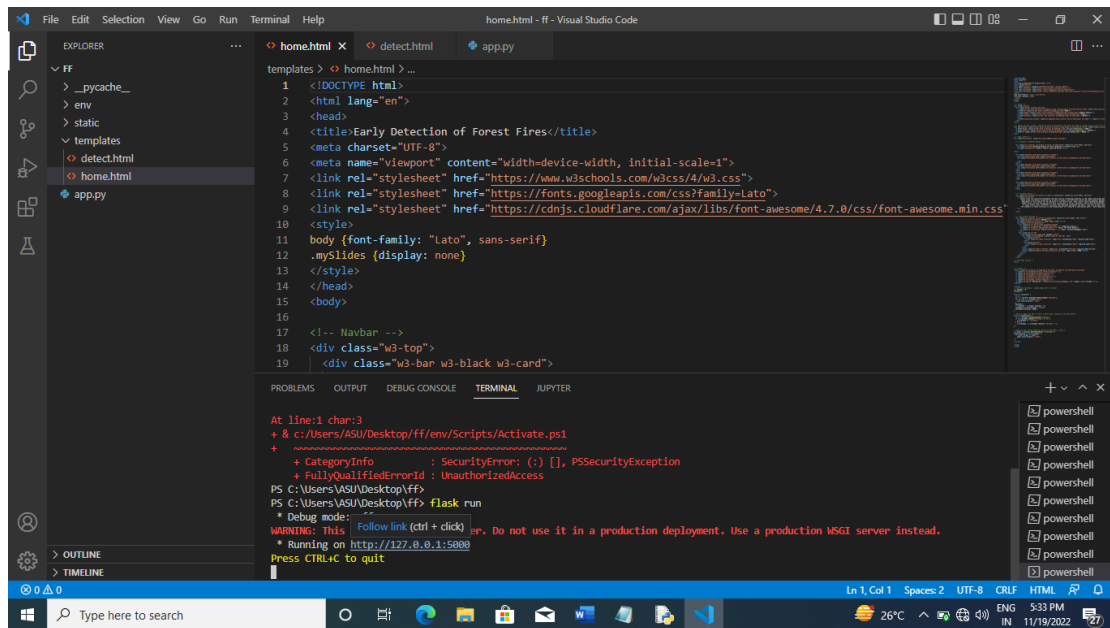
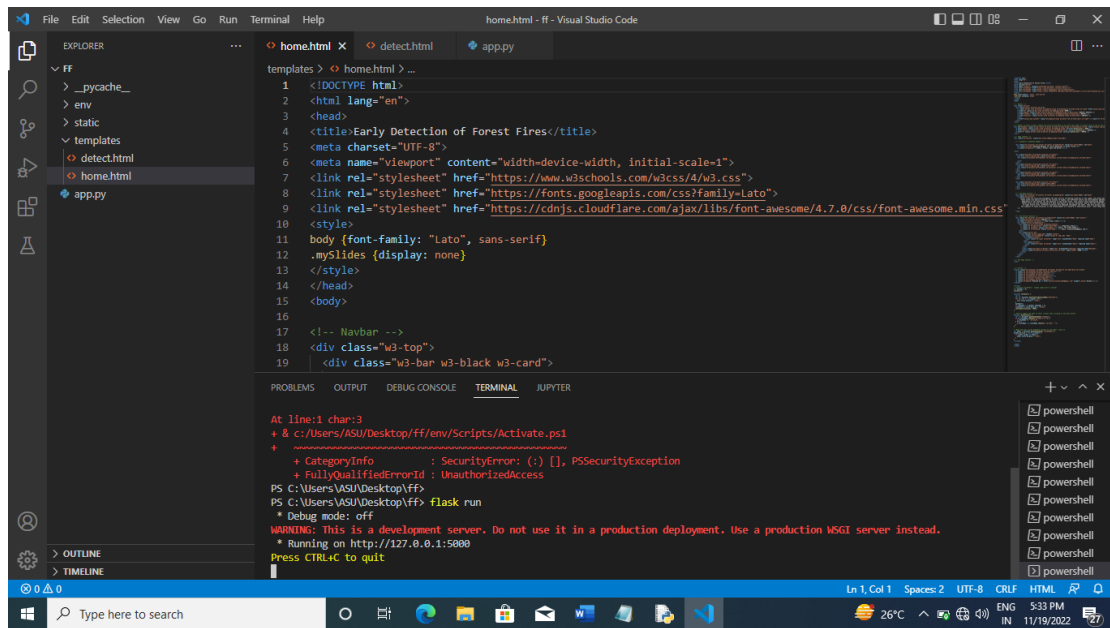
# Closes all the frames
cv2.destroyAllWindows()
from twilio.rest import Client
from playsound import playsound
if pred==0:
    account_sid='AC793bc11a38751a7b2a8c3fc7f18105c5'
    auth_token='26391d62b2b327c5a97725cad8a769ef'
    client=Client(account_sid,auth_token)
    message=client.messages \
        .create(
            body='forest fire is detected,stay alert',
            #use twilio free number
            from_='+18176708550',
            #to number
            to='+918754125453')
    print(message.sid)
    print("Fire detected")
    print("SMS Sent!")

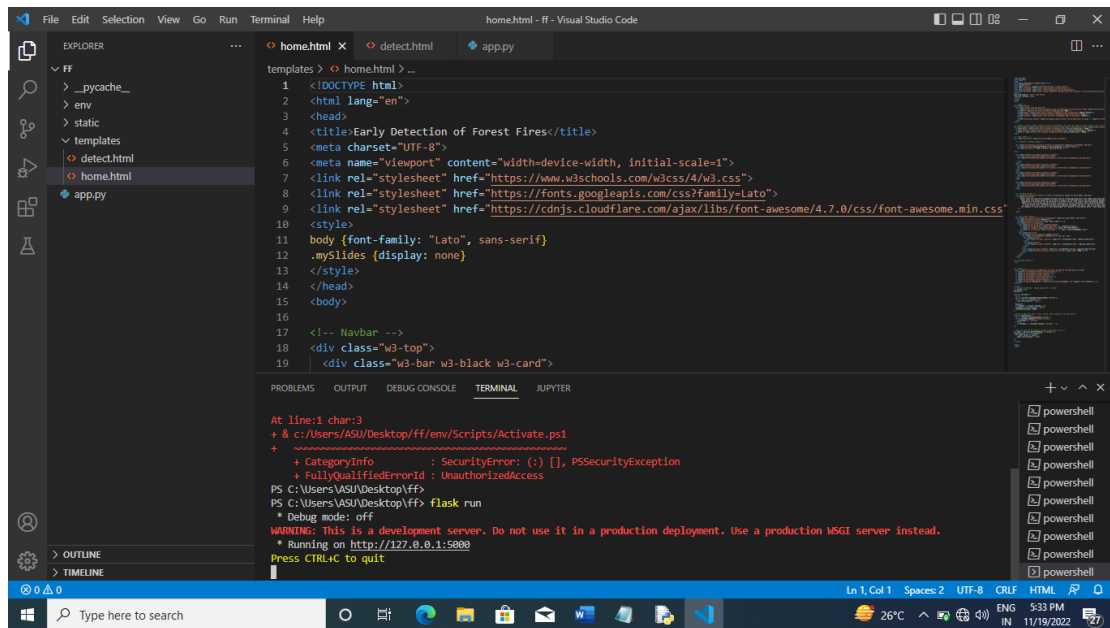
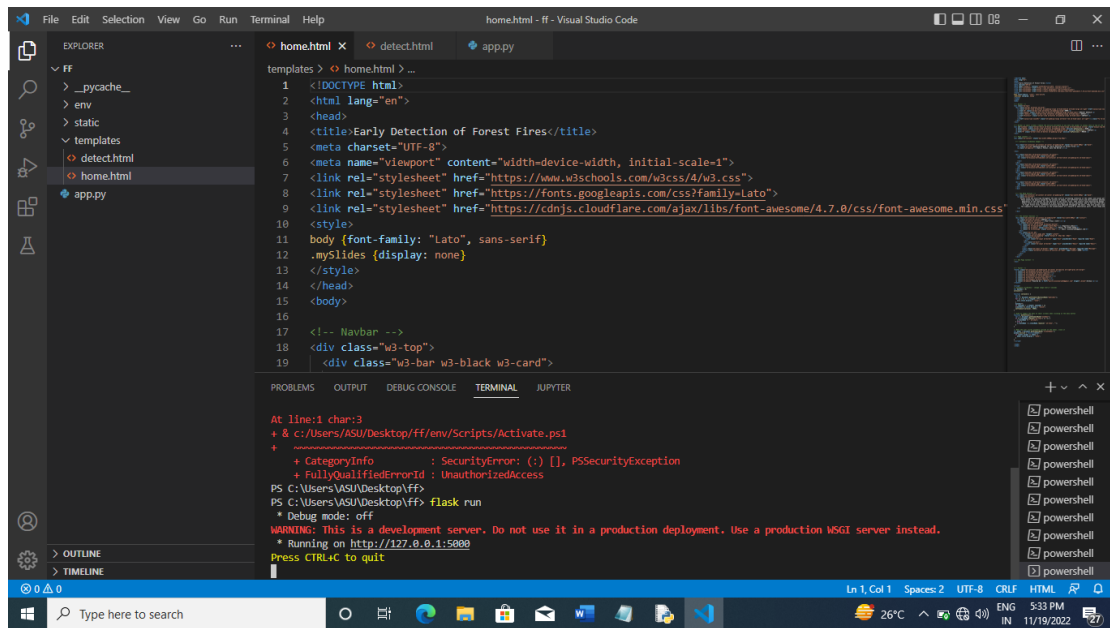
```

OUTPUT SCREENSHOTS :





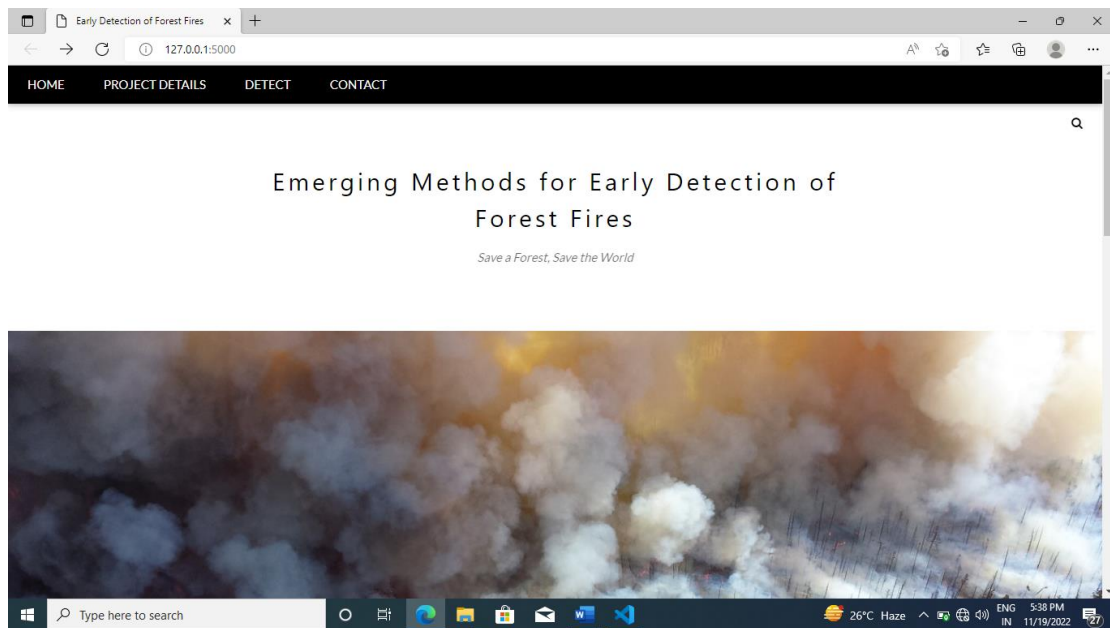


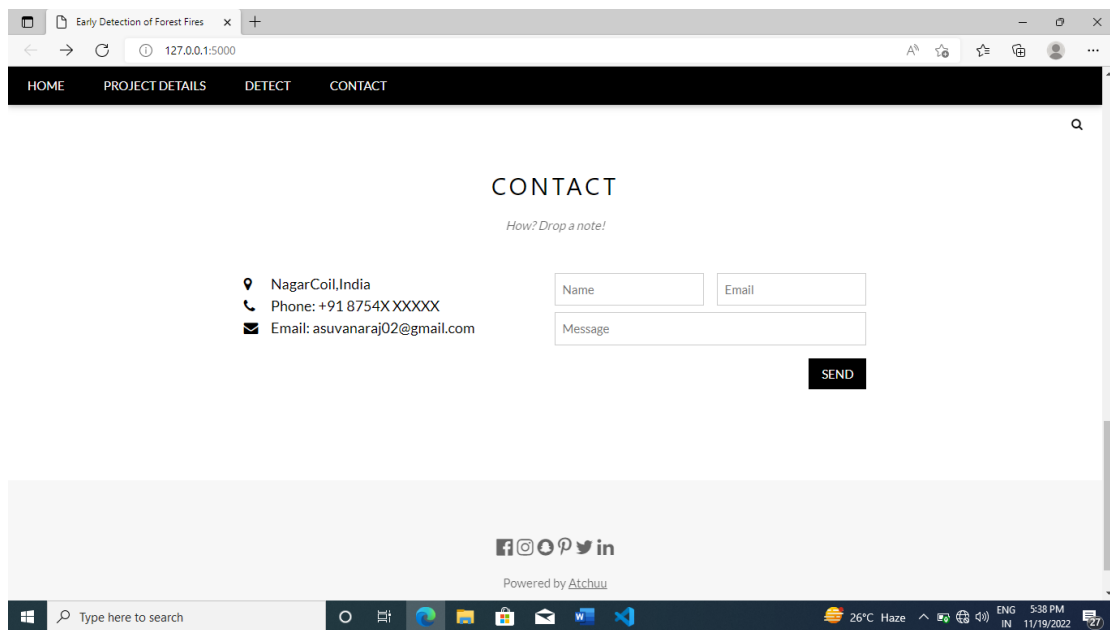
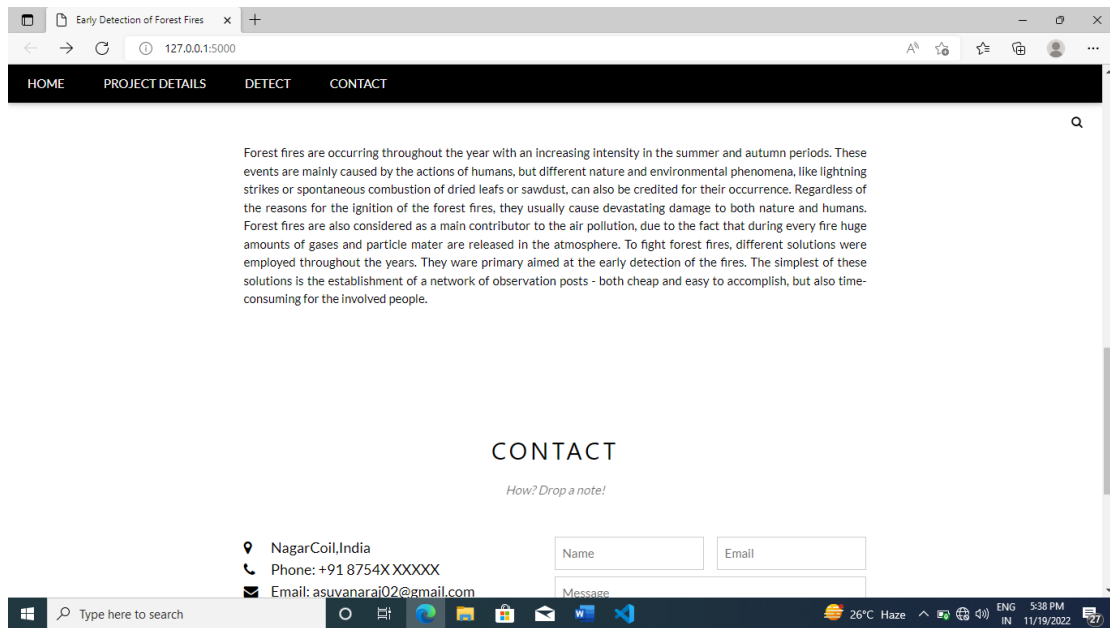


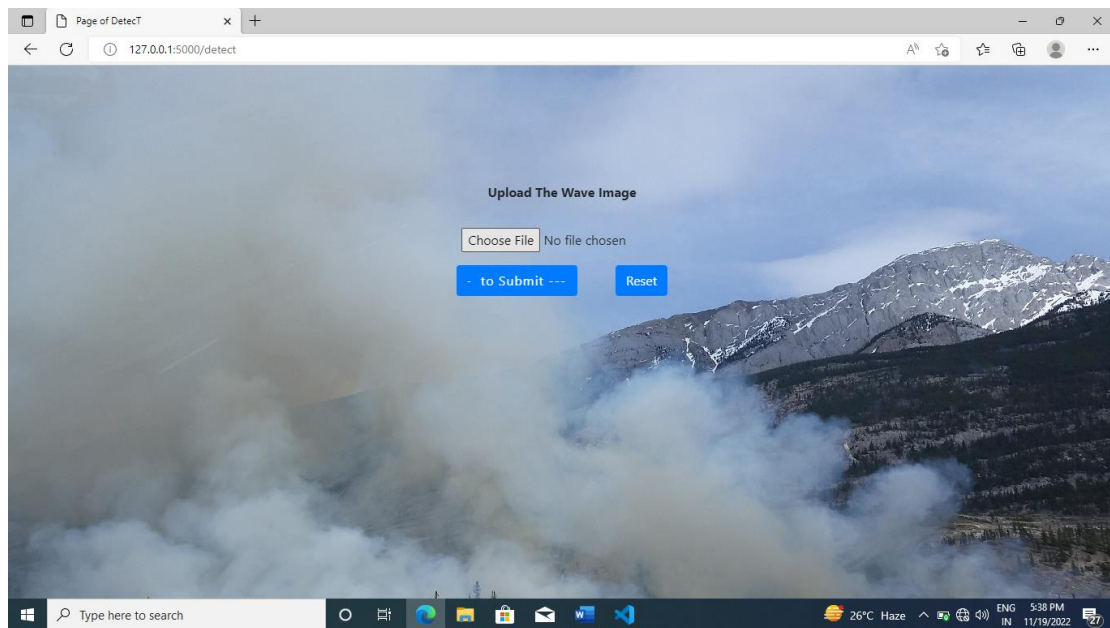
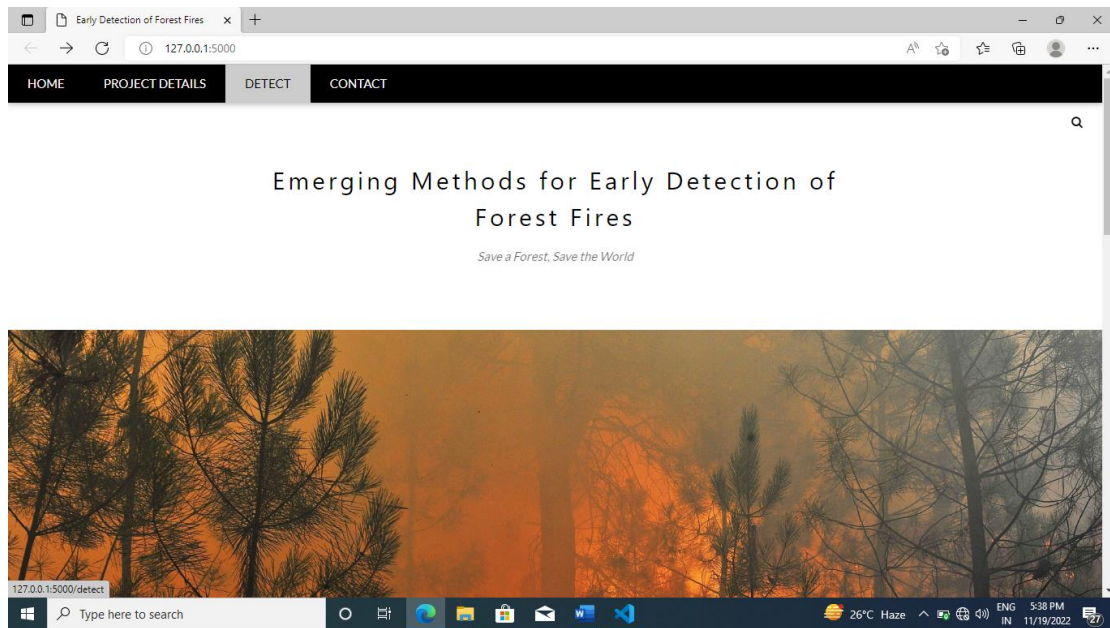
The screenshot shows the Visual Studio Code editor with the file explorer on the left. The main editor window displays the code for `home.html`. The code is an HTML document with a title "Early Detection of Forest Fires" and includes links to external stylesheets and fonts. The terminal at the bottom shows the output of the `flask run` command, indicating the application is running on `http://127.0.0.1:5000`. The terminal also shows several GET requests from `127.0.0.1` to various image files and the favicon.

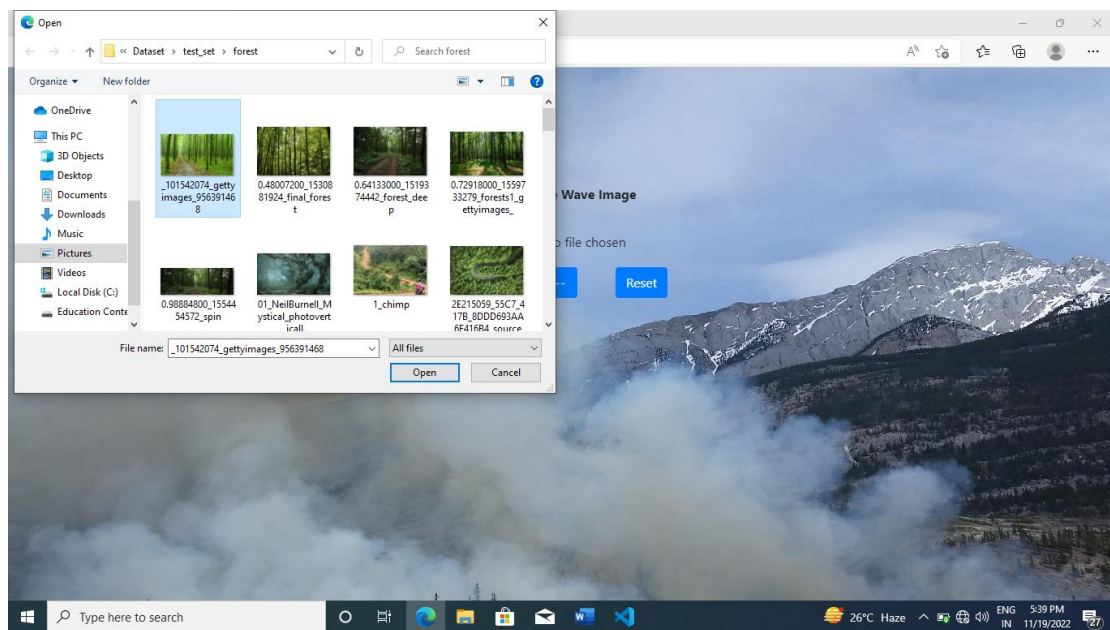
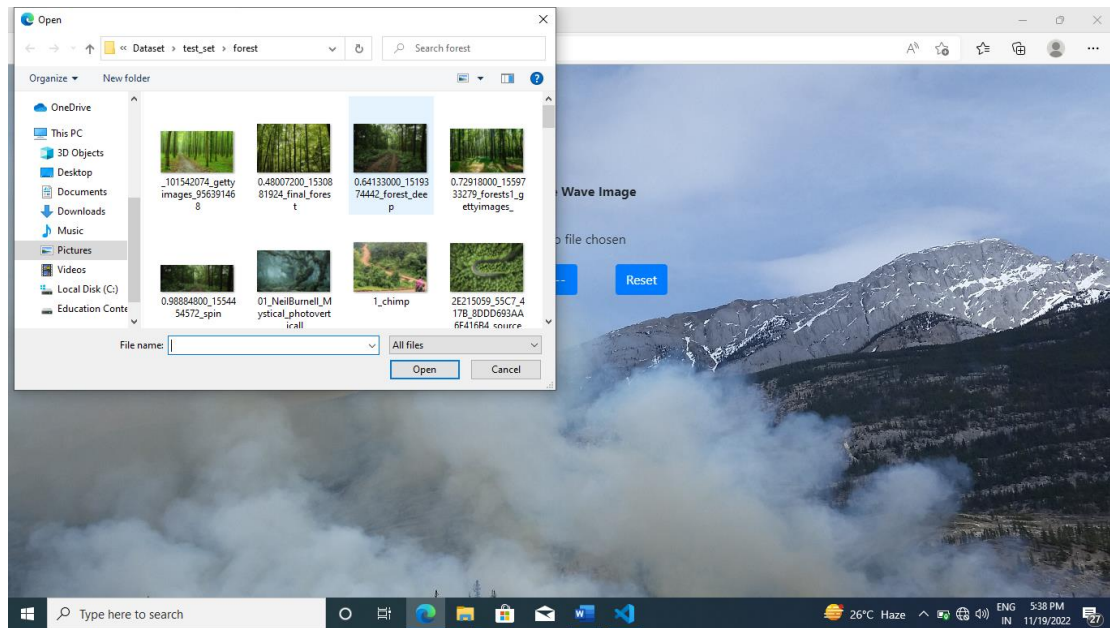
```
1 <!DOCTYPE html>
2 <html lang="en">
3 <head>
4 <title>Early Detection of Forest Fires</title>
5 <meta charset="UTF-8">
6 <meta name="viewport" content="width=device-width, initial-scale=1">
7 <link rel="stylesheet" href="https://www.w3schools.com/w3css/4/w3.css">
8 <link rel="stylesheet" href="https://fonts.googleapis.com/css?family=Lato">
9 <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/4.7.0/css/font-awesome.min.css">
10 <style>
11 body {font-family: "Lato", sans-serif}
12 .mySlides {display: none}
13 </style>
14 </head>
15 <body>
16
17 <!-- Navbar -->
18 <div class="w3-top">
19   <div class="w3-bar w3-black w3-card">
```

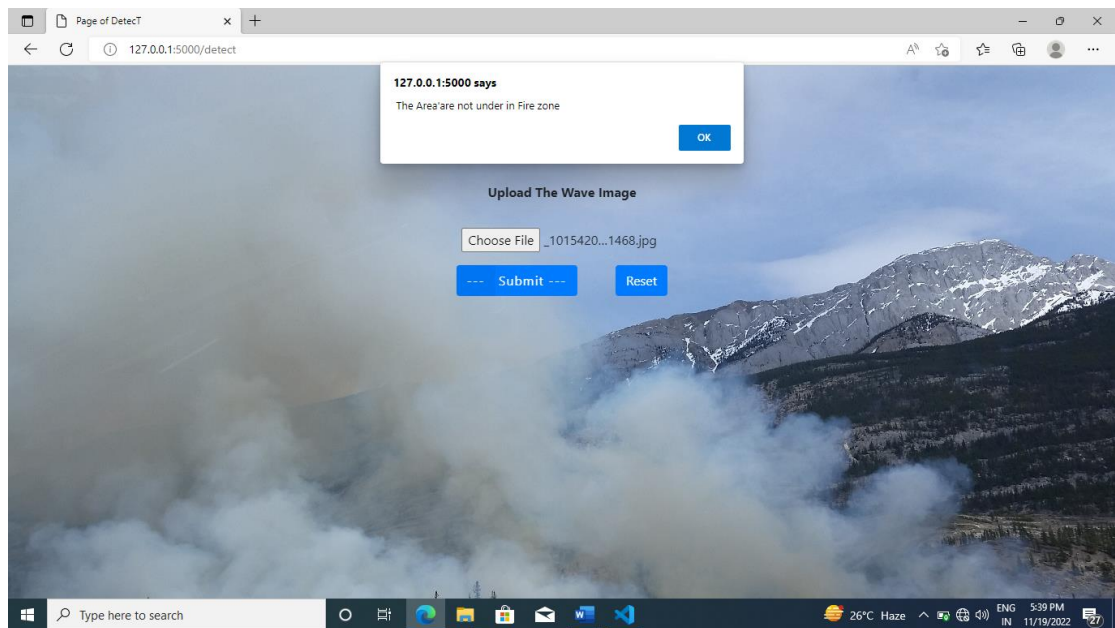
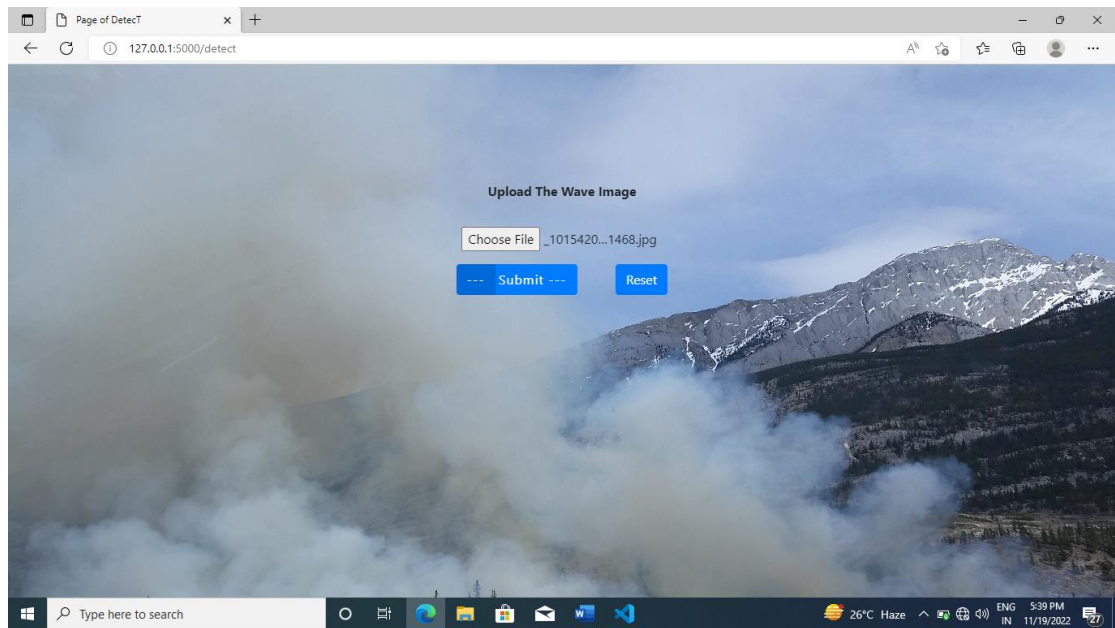
```
PS C:\Users\VASU\Desktop\ff> flask run
* Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
* Running on http://127.0.0.1:5000
Press CTRL+C to quit
127.0.0.1 - - [19/Nov/2022 17:33:35] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [19/Nov/2022 17:33:37] "GET /static/img/p6.jpg HTTP/1.1" 304 -
127.0.0.1 - - [19/Nov/2022 17:33:37] "GET /static/img/p4.jpg HTTP/1.1" 304 -
127.0.0.1 - - [19/Nov/2022 17:33:37] "GET /static/img/p5.jpg HTTP/1.1" 304 -
127.0.0.1 - - [19/Nov/2022 17:33:37] "GET /static/img/p3.jpg HTTP/1.1" 304 -
127.0.0.1 - - [19/Nov/2022 17:33:39] "GET /favicon.ico HTTP/1.1" 404 -
```

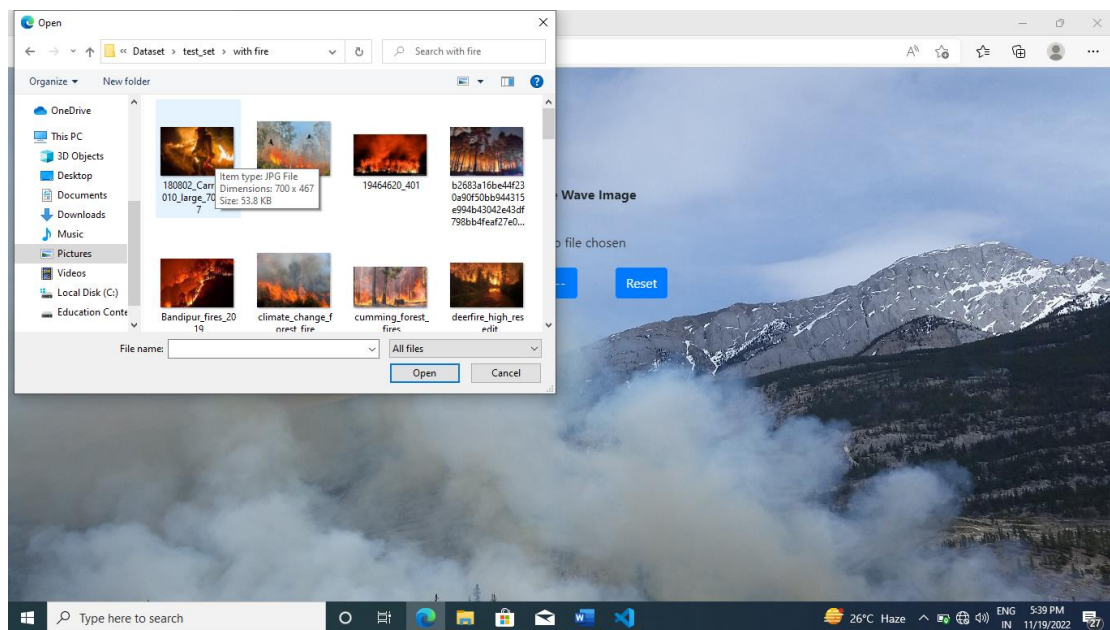
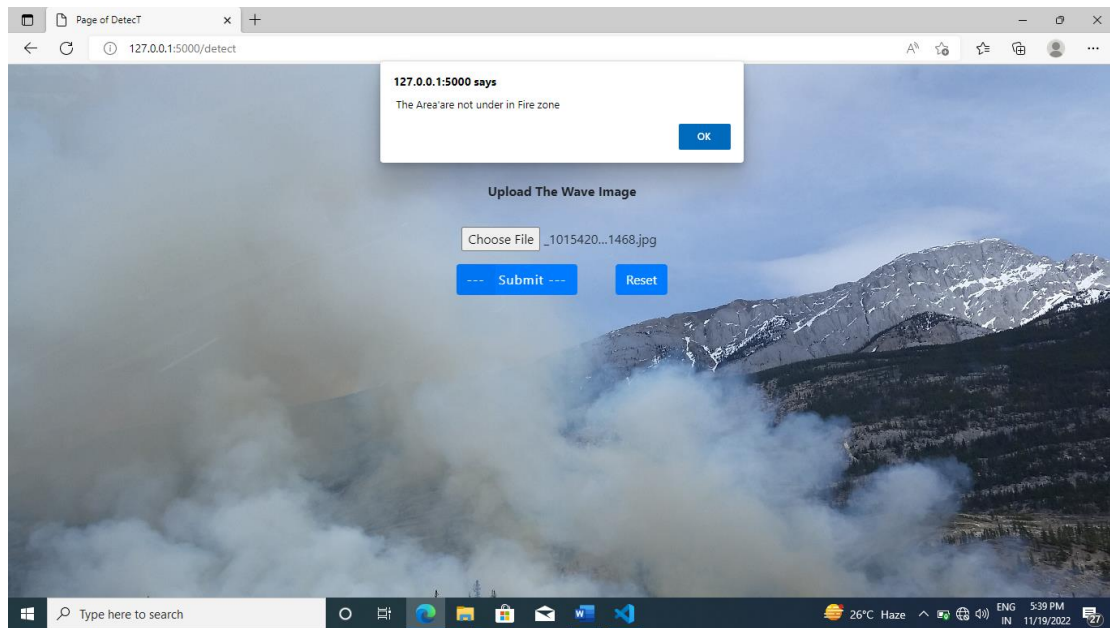


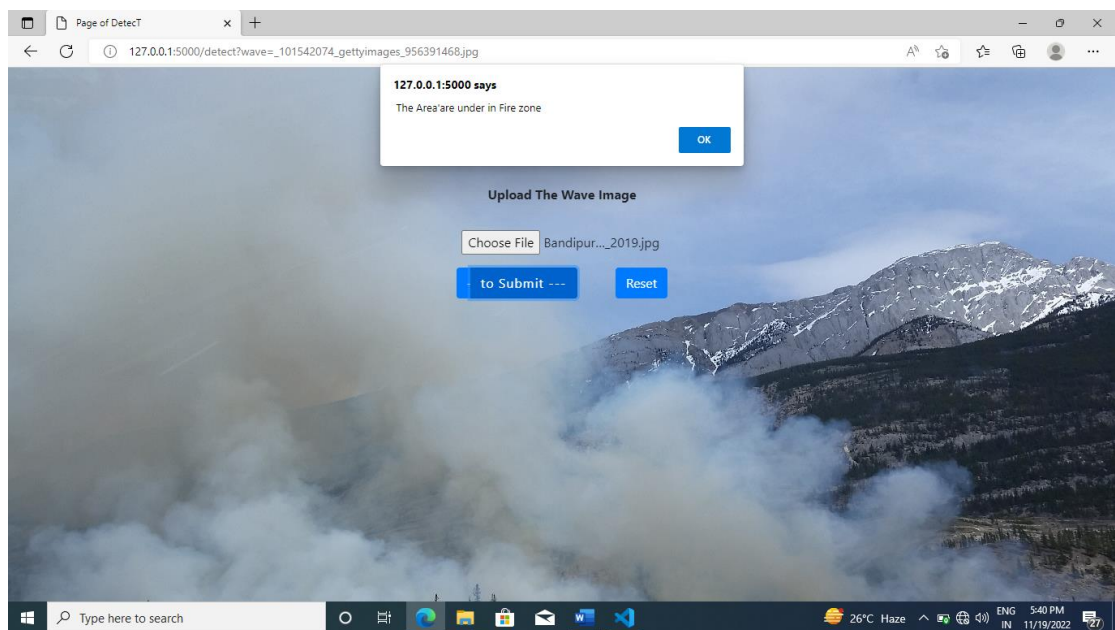
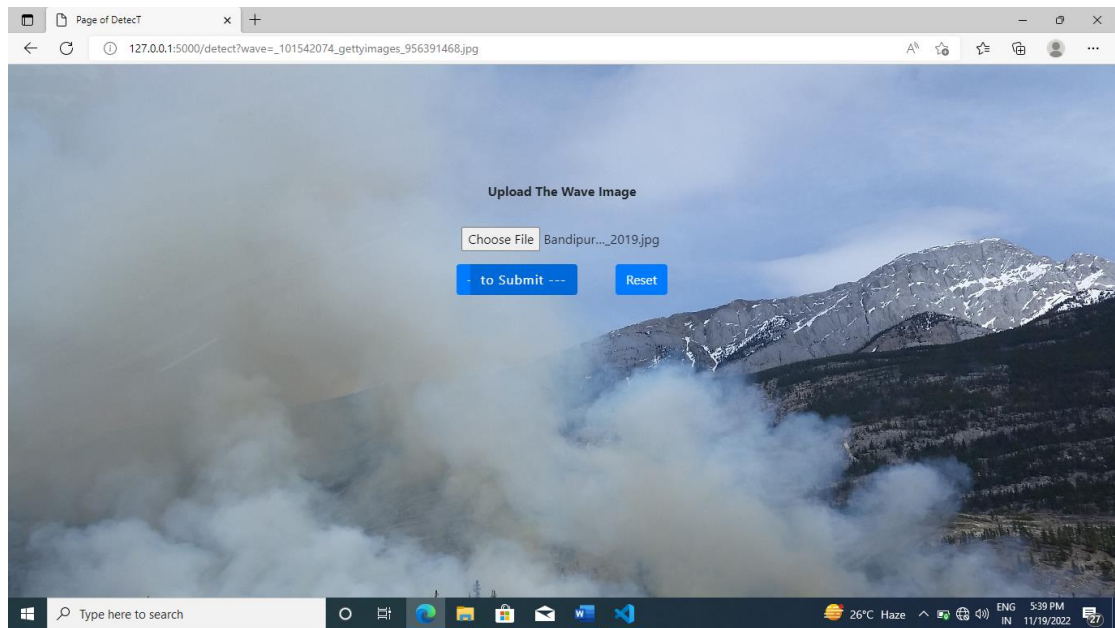


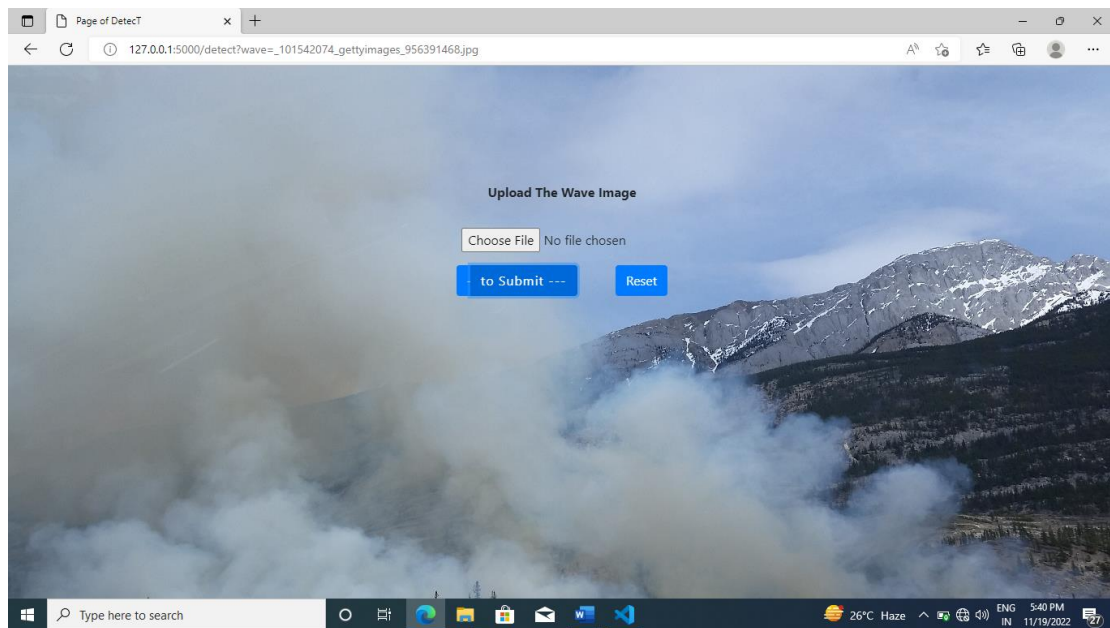
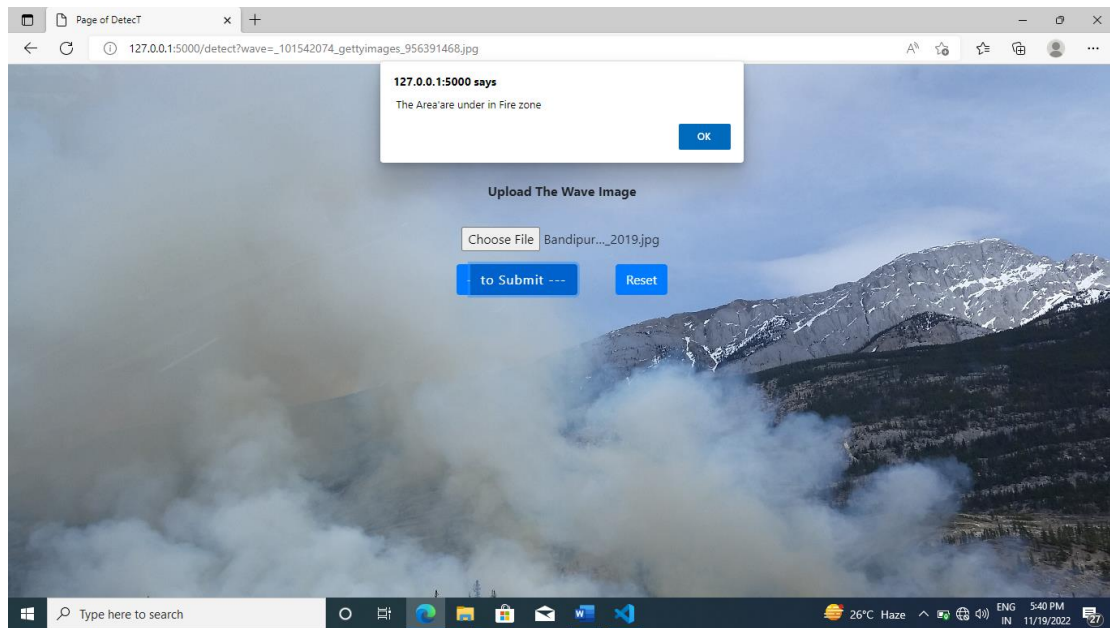




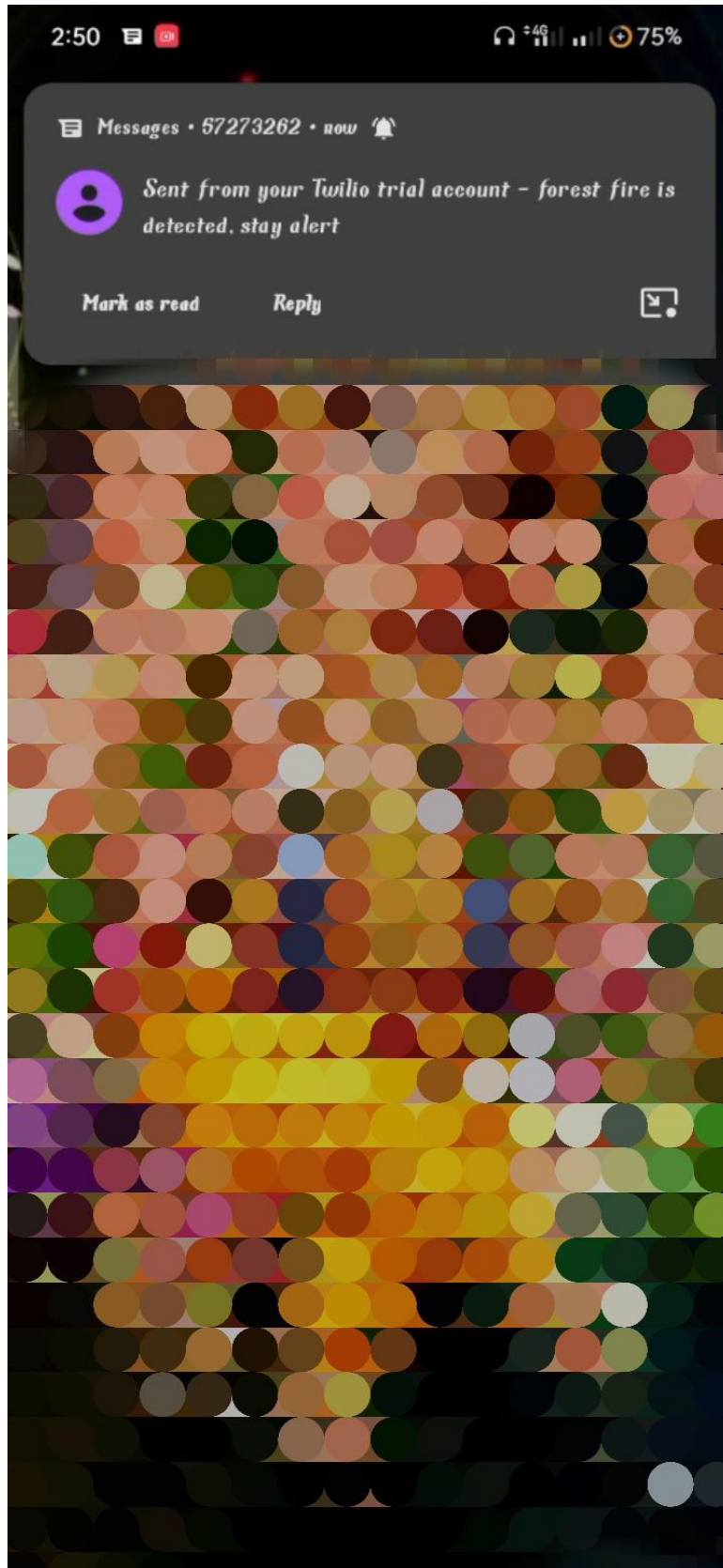








Alert Message from Twilio Account



2:50



4G 75%

← 57273262



2:50 pm

Texting with 57273262 (SMS/MMS)



Sent from your Twilio trial
account - forest fire is
detected,stay alert



Now



Text (Atchuu)

1



GITHUB Link:

<https://github.com/IBM-EPBL/IBM-Project-11032-1659255238.git>

DEMO VIDEO Link:

https://drive.google.com/file/d/1Fvd9RhLpux6Yiac1RsdJJFPS51z0jM0f/view?usp=share_link