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IoT and deep learning-inspired multi-model framework for monitoring Active Fire Locations in Agricultural Activities

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ABSTRACT

This paper proposes an Internet of Things (IoT) and deep learning-inspired multi-model system for detection, dissemination, and monitoring of Active Fire Locations(AFL) in agricultural activities. The IoT module of the proposed system works on the fusion of IoT sensors-based detectors and deep learning-based detectors. Fuzzy logic is used for the fusion of various sensors and providing real-time detection and location of AFL. The deep learning detector implements IP camera-based MobilenetV2 architecture for accurate and long-distance detections trained on a novel self-created dataset. The proposed framework also provides a software module for monitoring and tracking of various AFL. The software comes with several features like automatic extraction of fire locations from remote sensing sites, assigning active fire locations to multiple stakeholders, extracting farmers' names indulged in burning, automatic sending a notification to government agencies, and provisions for citizens centric participation. The results of the proposed framework are quite encouraging.

1. Introduction

The agriculture industry plays a significant role in the overall economic development of many countries like India. India is an agrarian country with diverse farming practices depending upon agricultural-climatic zones and generates about 500 million tons [1] of crop residues per year; however, the management of agricultural waste has limited sources that lead to one of the easiest ways to decompose agricultural residue by burning also known as Stubble Burning, Farm fires or Active Fire locations (AFL).

With the least availability of resources and less time to plant Rabi crop after Kharif season, farmers are more attracted to this practice even though stubble contains a considerable amount of organic carbon, nitrogen, sulphur, phosphorus, potassium. Stubble

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burning has resulted in the high complexity of disposal of agricultural waste and contributes to global environmental pollution, leading to the release of various harmful gases like Sulphur dioxide($SO_{2)}$), Nitrogen di-oxide($NO_{2)}$), Nitrous Oxide(N_2O), Carbon Mono-oxide (CO), Methane, etc. in the atmosphere together with the destruction of different soil nutrients, decreases soil fertility [2]. Governments have been trying to fight this evil by providing agriculture incentives to farmers, providing equipment, and Indian Government has made stubble burning a crime under Section 188 of the Indian Penal Code and Air and Pollution Control Act of 1981 [3]. But despite all these efforts, a large number of farm fires have already been reported this Rabi season in the states of Haryana and Punjab as per data provided by Haryana Space Applications Centre (HARSAC) and Punjab Remote Sensing Institute, which are Nodal Agencies for reporting AFL/farm fires in these states. One of the major hurdle in stopping this malpractice is the absence of a real-time system for stubble-burning detection. These detections are currently based on studying satellite imagery and thereafter manually initiating action in the minimum possible time. Therefore, there is a need to develop a framework that could detect a fire in almost real-time and provide support for its dissemination, report submission, and surveillance activities.

Motivation of the study

Various methods for farm fire detection are in place, and most of these are based on satellite imaging that has its limitations. Satellites are located on orbits over 22,800 miles above the earth's surface; since the intensity decreases as the inverse square of the distance, it becomes difficult for the satellite to detect the optical and infrared (heat) radiation emitted by flames in early stages before its spread over a broad region. Besides, this doesn't work for cloudy areas and foggy weather conditions and provides a slow response time. Another bottleneck of these systems is the accurate and real-time extraction of fire location. The majority of the governments depend upon various remote sensing centers to disseminate AFL information and then initiate some action by asking their employees to visit AFL sites. Remote sensing centers further rely on agencies like NASA's fire product FIRMS [4] that provides Near Real-Time (NRT) active fire data within 3 hours of satellite observation from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra and Aqua satellites and NASA's Visible Infrared Imaging Radiometer Suite (VIIRS) aboard the Suomi National Polar-orbiting Partnership (Suomi NPP) and NOAA-20 satellites. This data is provided on a 24-hour basis that adds a substantial delay between the fire's time and any remedial action taken by the concerned department. There is another class of methods based on optical sensors and cameras' deployment; however, detection range and line of sight of the camera is still an issue [5]. IoT-based networks seem to be the solution, but often, sensor fusion appears to be a less powerful solution. Another drawback of such a system is that the computation of inputs is done at the server far away from the nodes, resulting in data loss during transmission [6].

Inspired by the above shortcomings, this paper proposes a multimodal framework employing deep learning and IoT-based detectors fused and deployed to present a single system for active fire detection, surveillance, and monitoring. The proposed approach can capture data from NASA's FIRMS fire product directly and provide real-time detection of farm fire using deep learning and IoT-based systems to compensate for misses made by satellite data. The deep learning-based detector has been developed using MobieNetV2 architecture and trained on a dataset of images manually collected from the fields for this task. An IoT-based module deploys several sensors to detect farm fires using fuzzy logic and communicate these to the server. The system combines the output of the deep learning-based detections with sensor-based detections to detect fire in real-time accurately. The framework is supported by a web-interface and mobile application for real-time surveillance and reporting by various state employees. The software system provides alerts to registered users after extracting longitude and latitude details and working out the respective geographical locations. The system is also capable of extracting the names of defaulting farmers for further action by the authorities. The locations get allocated to various employees, and these employees can verify fire reports, issue fines or challans to erroring farmers. Several analyses are also proposed to demonstrate the working of the proposed system.

The paper is organized as follows: The following section discusses various available solutions in the literature. Section-III describes the proposed methodology with detailed elaborations. Section-IV is devoted to implementation details and discussion on results. The last section is dedicated to the conclusion and discussion on the future scope of the work.

2. Literature Review

The studies for fire location detections have been influenced by the work on forest fire detection. They can be categorized into three main categories: based on deployment of sensors, use of computer vision, and use of satellite data in the form of imaging and other parameters. We tend to summarize various studies under these headings separately.

The evolution of WSN technology in recent years has made it possible to use it with a potential for early fire detection, and Paul et al. [9] surveyed various strategies and measurement techniques for range-based and range-free localization of wireless sensor nodes. Lloret et al. [10] suggested a solution based on similar technology in which the author deployed a mesh network of sensors dispensed with internet protocol (IP) cameras in which an alarm signal was sent to sink on detecting fire at the beginning. The sink then reverts a message to switch 'on' the nearest camera to get actual fire images to avoid fake alarms. This paper is based on testing the execution of 4 IP cameras and their energy requirements. But the system suffers from the bottleneck of transferring data over a wireless sensor network for its limited sources of power, memory, and buffer. Another hindrance was its successful efficiency in dark, foggy, or rainy weather.

Table 1
Comparison of various studies in literature

Comparison	Satellite Systems	Optical Camera	Wireless Sensor Network	Proposed framework
Technique Used	Satellite's optical and infrared sensors	Optical and thermal Cameras	Various sensors like smoke, temperature etc.	Sensors with IP camera fusion
Studies	[18], [19], [20], [22], [23]	[10], [11], [25]	[9], [12], [13], [14], [15], [16]	-
Cost	Very High	High	Medium	Low
Probability of Faulty Alarms	Low	Medium	Medium	very Low
Images for the place of Ignition	heat maps are available	Can be obtained	No	Yes, heat maps and sample filed images
Impact of Weather Conditions	Yes	Yes	No	Minimal
Availability of Real-time information	No	Yes	Yes	Yes
Coverage Area	Depends on the orbit of the satellite or maybe intermittent with substantial gaps in time	Depends on the number of cameras and their range	Can cover any area size	Combines advantages of satellite, optical, and sensor network
Delay in Detection	Very Long	Long	Small	Small

Sahin et al. [11] proposed a continuous monitoring and early detection of forest fires by generating thermal maps using a radio-acoustic sounding system. The RASS (radio-acoustic sounding system technique) can directly and continuously measure air temperature profiles, including increased temperature due to fire with its high-resolution volume. The system was suitable for crown and surface, but not ground fires, and may not effectively work on sunny days. Zhu et al. [12] proposed a wireless sensor network with GPRS capabilities to monitor forest fires. The system collected real-time data for smoke, temperature, humidity, with few other environmental parameters which are transmitted in a multihop fashion to the central node and then to the monitoring center to produce reports, graphs, and curves in helping fire-fighters make an appropriate decision. Wenning et al. [13] proposed a dynamic routing method for wireless sensor networks to be used in case of a node failure, and the system could adapt routes in such cases. Grover et al. [14] outlined a WSN system that collects data using multiple sensors to monitor temperature, humidity, and smoke and oxygen levels in several spots in a forest environment divided into square-shaped clusters for monitoring containing a sensor system. The node's localization was done using satellite communication to reduce coverage holes and ensure maximum range with the least latency. Still, the fire could only be detected when it resolves half a pixel, i.e., roughly an area of 7 hectares. Antonio Molina-Molina-Pico et al. [15] proposed a WSN system with two nodes: Sensor Nodes, to collect data from the field, and Central Nodes, to collect data from the sensor nodes and transmit it to a Control Centre for early forest fire detection. It ensured a seamless configuration of the network with full geographical coverage in the deployment zone. Shinghal [16] proposed a two-network system for far fire detection where one network gathers data from sensors, and another one was used for sensor network data utilization for timely alerting farmers. The author successfully simulated the system for detecting fire in agricultural fields using Multisim. In practice, heat is detected mainly in the smoldering fire, and the temperature is detected primarily in the flaming fire, and the proposed system seemed to be more efficient for detecting flame fire. The use of fuzzy logic also finds mentioned in various studies to utilize inputs from various sensors and Sowah et al. [17] proposed fuzzy inspired system consisting of smoke, temperature, and flame sensors integrated with a re-engineered mobile CO2 air-conditioning unit with its testing being done on a medium-sized physical car.

The use of satellite imaging and other parameters captured from various satellites is also one of the key areas explored by researchers and major remote sensing agencies of the country provides several products for the benefit of researchers like NASA's FIRMS, MODIS [7], ISRO's Geoportal - Bhuvan [8], etc. FIRMS fire product offers two types of services/fire products Modis (Moderate-resolution imaging spectroradiometer) and VIIRS (Visible Infrared Imaging Radiometer Suite) , with major differences being higher resolution images. The thermal band of MODIS is 1000 meter resolution per pixel, but VIIRS provides 375m resolution per pixel. This higher resolution enables the detection of fires by VIIRS that are generally overlooked by MODIS. Though detection of fire location by VIIRS is better as compared to MODIS, MODIS can still provide crisp background images. MODIS products are capable of capturing data in 36 spectral bands ranging from 400nm to 1440m at different spatial resolutions (2 bands at 250m, 5 bands at 500m, and 29 bands at 1Km). The instrument takes earth images every 1 to 2 days. MODIS is the key instrument on Terra and Aqua satellites. Terra's orbit around the earth from north to south across the equator in the morning, whereas Aqua passes from south to north over the equator in the afternoon. Terra MODIS and Aqua MODIS capture the entire earth surface every 1 to 2 days. VIIRS is one of the five instruments available on the SNPP satellite platform that was launched in October 2011. JPSS-1(Joint Polar Satellite System, NOAA-20) hosts a VIIRS instrument as part of their payload. The VIIRS instrument was designed to improve and extend the functionality initiated by its predecessor, MODIS(Moderate-resolution imaging spectroradiometer), AVHRR(Advanced very high-resolution radiometer), and SeaWiFS(Sea-viewing Wide field-of-view Sensor). The instrument can capture earth images that span from visible to infrared regions across land, sea, and atmosphere. It uses a whiskbroom radiometer to capture images over 22 channels varying from 410nm to 1201nm. Five of these channels are high-resolution images band or I-bands, 16 bands are moderate or M-bands, and one band is panchromatic Day/night band. VIIRS is well suited for monitoring fire activity, and it enables scientists and firefighters to model and predicts shifts during fire activity more accurately.

Byun et al. [18] worked on the theory of spatial outlier detection on satellite images to work out places of fire. The Scatter plot and Moran's scatter plot were used to evaluate the applicability of this algorithm, and the results were compared with the MODIS fire product provided by NASA MODIS Science Team. Badrinath et al. [19] studied the burning of agricultural crop residue of wheat and rice in Punjab and analyzed the data from the Indian Remote Sensing Satellite (IRS-P6) Advanced Wide Field Sensor (AWiFS) for the

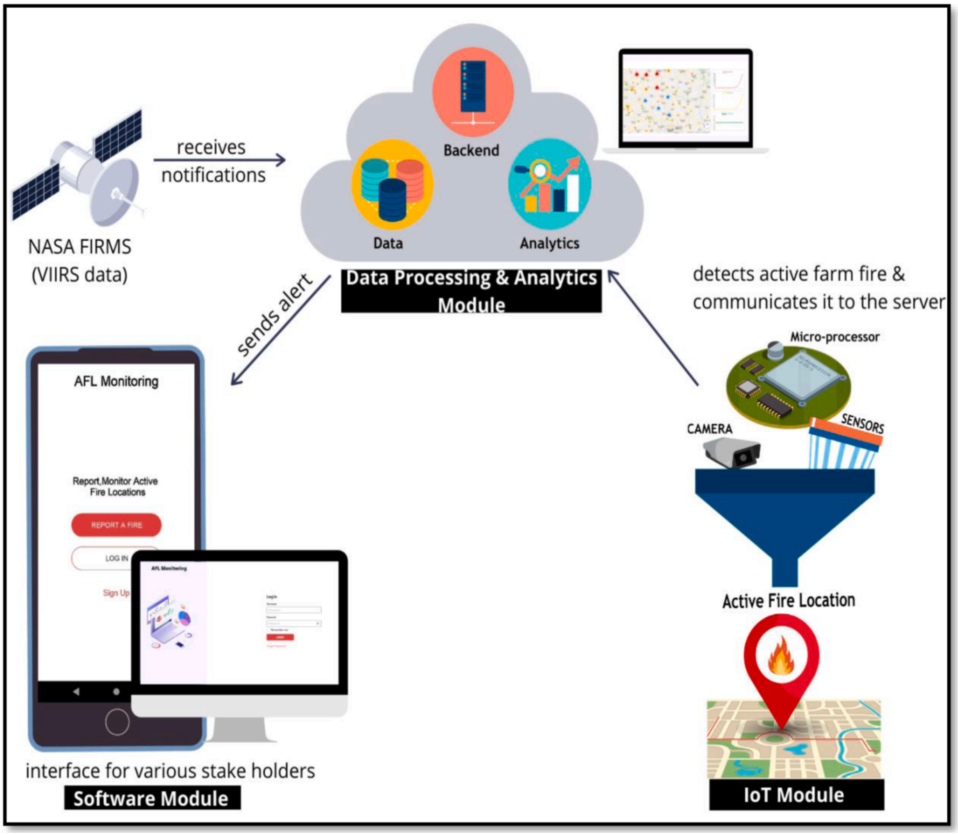


Fig. 1. Proposed framework architecture

months from May to October 2005 to estimate the amount of greenhouse gas (GHG) emissions from stubble burning. The authors then compared their findings with the emission factors outlined in the literature of Wang et al. [20], Dennis et al.[21], and Reddy et al. [22] for estimating the emissions. As a result, they found that emissions from paddy crop residue burning are higher than that of wheat crop residue in Punjab.

Flannigan et al. [23] worked on satellite images and used a multispectral technique that used AVHRR's channels 3 and 4 to identify fires and estimate fire size during a severe fire outbreak in north-central Alberta. Similarly, Chhabra et al. [24] made attempts to monitor and map the real-time active fire locations of 3 states by gathering thermal datasets provided by the IARI Satellite Ground Station during the Kharif crop harvest season (October-November) 2018 from 3 different sensors.

In the past few years, due to an increase in the number of wild and indoor fire incidents, few studies have dealt with video processing to detect fire, particularly employing the usage of machine learning and convolutional neural networks. Frizzi et al. [25] proposed a 9-layered convolutional neural network for video fire and smoke detection. A small network was preferred to improve classification time, and a sliding window of size 12×12 was applied to the last feature map generated from the network to detect fire and smoke in a video frame. The proposed system was, however, only capable of detecting red-fire and had few challenges with smoke detection.

For readers' understanding, we had compared various studies available in the literature based on common attributes, as shown in table 1. The table also lists the advantages the proposed system provides as compared to these studies.

Inspired by the literature discussed above, this paper adopts the strengths of deep learning methods and IoT sensors in developing a system for accurate and real-time detection of active fire locations. The complete framework proposes a web-interface for real-time monitoring and reporting of such locations by issuing alerts notification with approximate geographic coordinates to the scene of fire and names of various farmers for use by multiple users. The next section proposes the complete system.

3. Proposed Architecture

Fig. 1 presents the complete framework with all details used in this model. The proposed framework comprises three sub-units: - IoT Module, Data processing and analytics module, and Software module. The major task of the IoT module is to detect AFL with a combination of sensors and an IP camera-based deep learning detector. The data processing and analytics module deals with the storage of fire locations as either extracted directly from the NASA website or reported by IoT module. This module is also responsible for the issuance of notifications and other backend tasks. The software module provides web and app interfaces to various stakeholders

Input: Sensory data, images
Output: AFL locations with geographical details, notifications, and analysis
Procedure:

Step 1: Detection of Fire Location by IoT Module
- Various sensors at general nodes (GN) sense physical conditions using sensors and communicate it to deployed fuzzy logic to get a response.
- IP camera captures images at regular intervals and deep learning-based detector processes it to output its response.
- Exact location of active farm fire is calculated.

Step 2: Central Node (CN) communicates this information to the data processing and analysis module
Step 3: Periodic notifications are received from FIRMS and processed by data processing and analysis module for removal of false cases.
Step 4 : Data processing and analysis module updates its database with new locations.
Step 5: Data processing module works out further details, performs analysis and issues alerts in real time.
Step 6: Stakeholders receive alerts using software module and act accordingly.

Fig. 2. Steps for working of the proposed framework

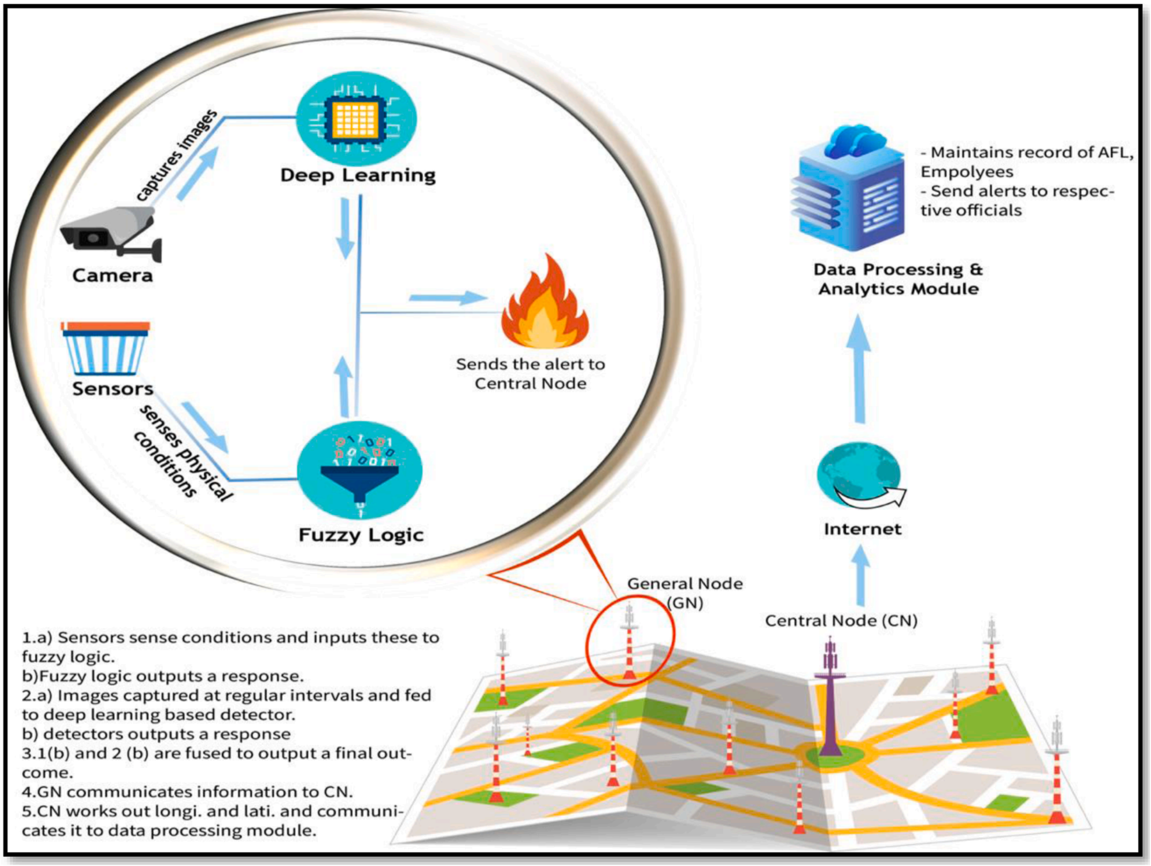


Fig. 3. IoT module details

like employees, government agencies, and citizens. Fig. 2 elaborates steps for working on the proposed framework. The following sub-sections explain these modules in greater detail.

3.1. IoT Module

The IoT module is hardware-based and performs the task of detecting active fire locations on the field in almost real-time. It detects a fire location by fusing the outputs of two separate units:

- A state of art deep learning-based fire detection unit employing computer vision
- IoT-based detection unit Output of various IoT sensors deployed on the field

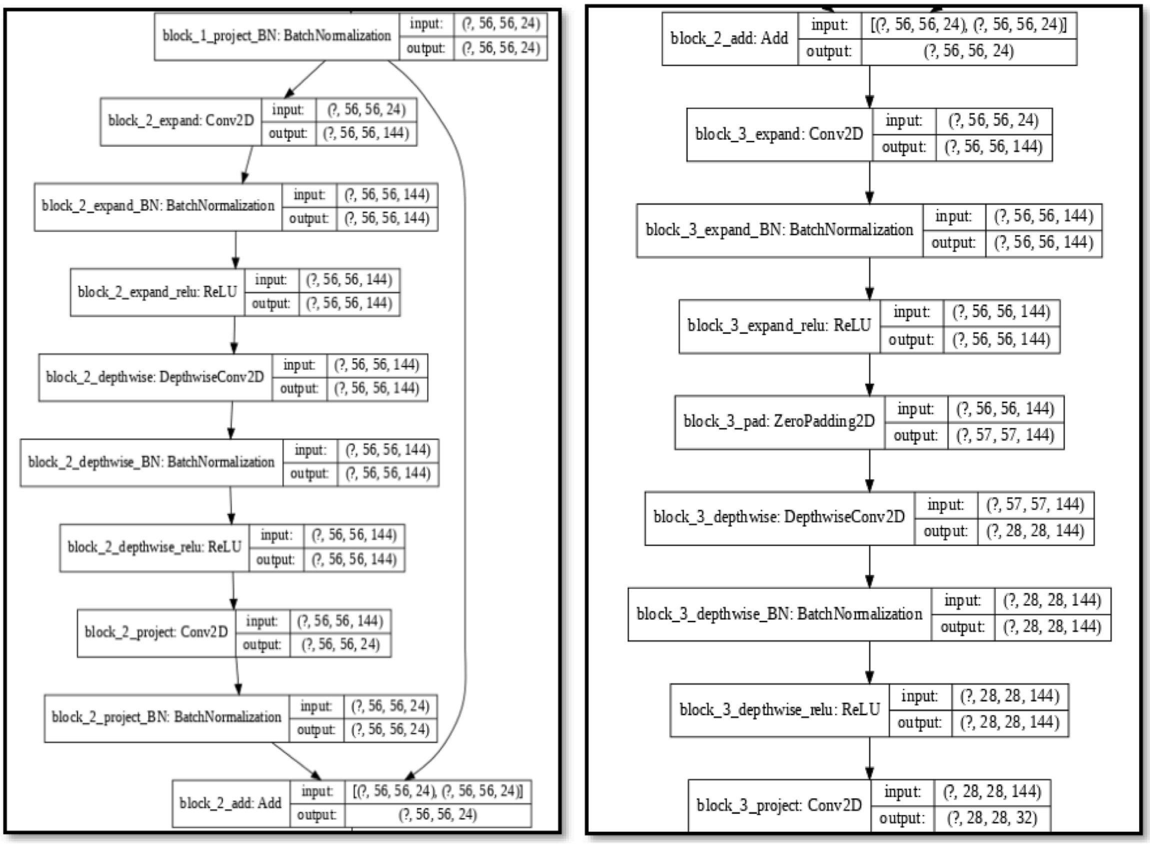


Fig. 4. Convolution blocks in MobileNetV2: Residual (left), Bottleneck (Right)

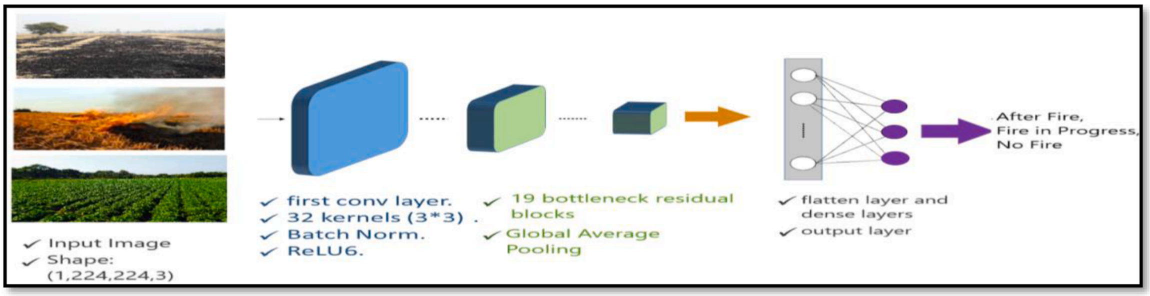


Fig. 5. MobileNetV2 based framework for AFL detection

Fig. 3 illustrates the IoT module's design and portrays the above two units separately with their respective responsibilities. Fig. 3 also explains two types of nodes that get deployed on the field: General and Central Node. The general node (GN) detects the location in terms of longitude and latitude for the place of fire. It communicates it to the central node (CN) connected to the internet and communicates the locations to the data processing and analytics module. The general node works with inputs from various IoT sensors and outputs probability of fire using suitably designed membership functions and fuzzy rule-base. The fuzzy system's output is further combined with output from the deep learning framework, which employs a trained version of the MobilenetV2 network. A final decision regarding the presence of fire is communicated to the central node which is connected to the internet, and necessary updates are made to the database.

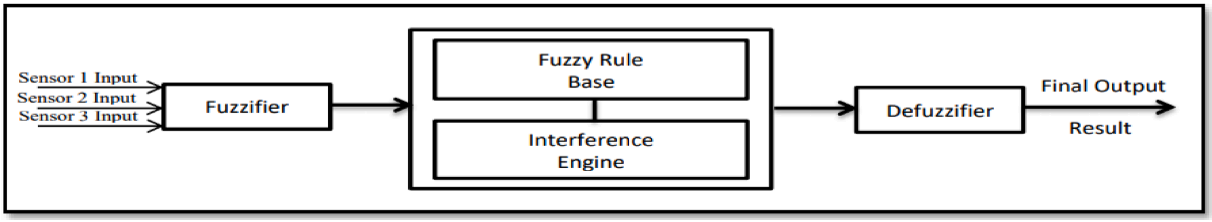


Fig. 6. Fuzzy logic architecture

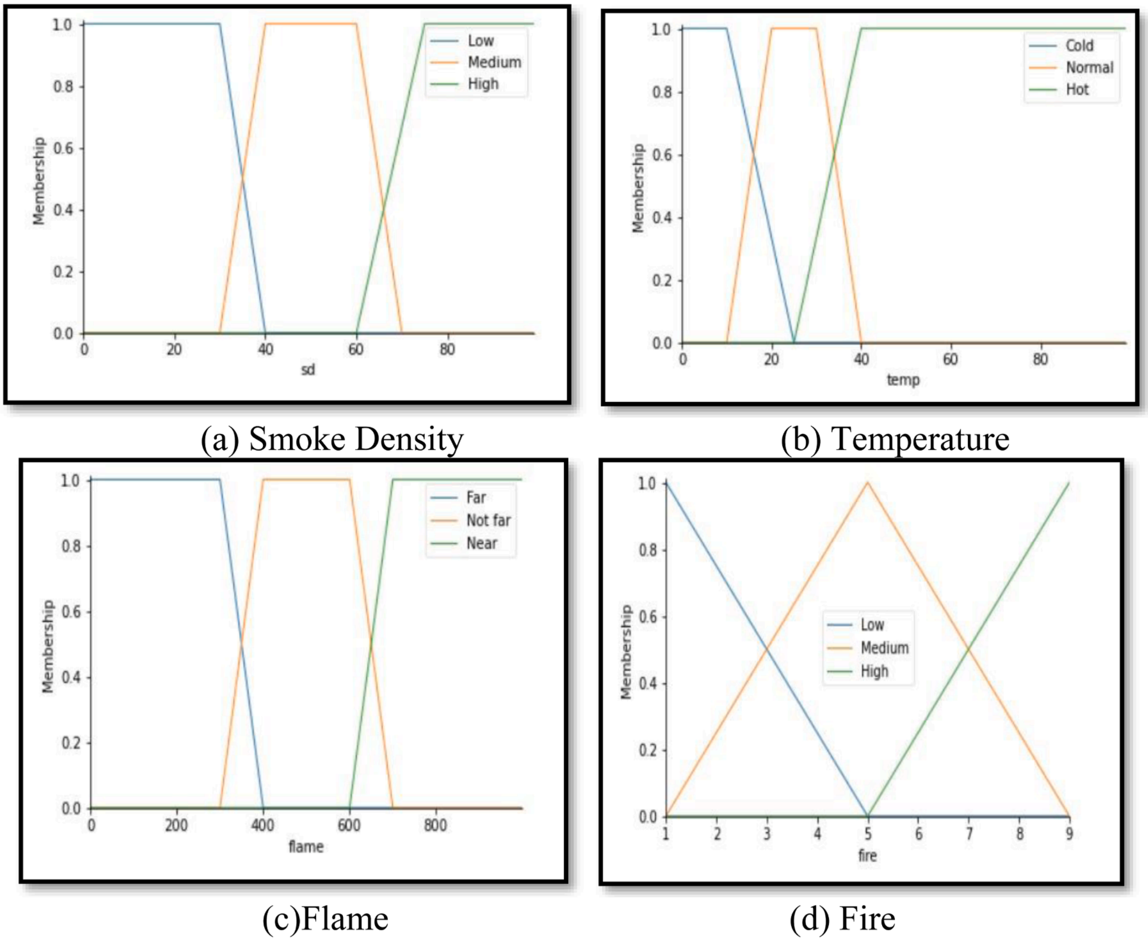


Fig. 7. Input Membership Function (Smoke Density, Temperature, Flame) and Output Membership Function (Fire)

3.1.1. *Deep Learning-based detector*

The fire detection system makes use of convolutional neural networks for accurate and precise detection of fires. We decided to use MobileNetV2 as our backbone network to detect farm fire keeping in mind the necessity of its deployment on computationally low-end devices and its state-of-the-art performance. MobileNetV2 is a small, low-latency, low-power model parameterized to meet the resource constraints of various use cases. MobileNetV2 builds upon the ideas from MobileNetV1 using depthwise separable convolution as efficient building blocks for reducing complexity and model size for its deployment on mobile devices. However, MobileNetV2 introduced two new features to the architecture: Linear bottlenecks between the layers and shortcut connections between the bottlenecks.

The convolutional blocks in MobileNetV2 consist of two blocks (as illustrated in Fig. 4): a residual block with stride =1 and another with a stride of 2 (bottleneck), and the architecture provided three layers for both types of blocks. The first layer is a convolutional layer with a filter size of 1×1 followed by depth wise convolution layer of filter size 3×3, both implementing Relu activation. The last layer is another convolutional layer with a filter size of 1×1 without any linearity, and an expansion factor of 6 has been used for all

Table 2
Fuzzy Rulebase

	Inputs			Output
	Smoke Sensor	Temperature Sensor	Flame Sensor	Fire
1	Low	Cold	Far	Low
2	Low	Cold	Not Far	Low
3	Low	Cold	Near	Low
4	Low	Normal	Far	Low
5	Low	Normal	Not Far	Low
6	Low	Normal	Near	Low
7	Low	Hot	Far	Low
8	Low	Hot	Not Far	Low
9	Low	Hot	Near	Medium
10	Medium	Cold	Far	Low
11	Medium	Cold	Not Far	Low
12	Medium	Cold	Near	Low
13	Medium	Normal	Far	Low
14	Medium	Normal	Not Far	Low
15	Medium	Normal	Near	Low
16	Medium	Hot	Far	Medium
17	Medium	Hot	Not Far	Medium
18	Medium	Hot	Near	High
19	High	Cold	Far	Medium
20	High	Cold	Not Far	Medium
21	High	Cold	Near	High
22	High	Normal	Far	Medium
23	High	Normal	Not Far	High
24	High	Normal	Near	High
25	High	Hot	Far	High
26	High	Hot	Not Far	High
27	High	Hot	Near	High

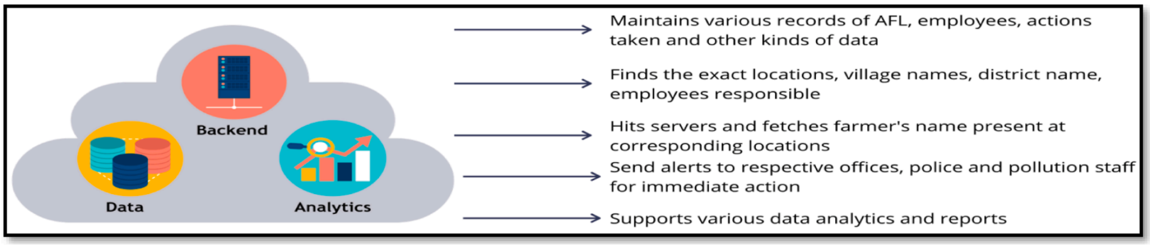


Fig. 8. Data processing & analytics module

experiments. We extracted convolution layers of the pre-trained MobileNetV2 model and added two fully connected layers over it, thereby utilizing the concept of transfer learning for minimizing training time.

Fig. 5 represents the proposed system's final model architecture that predicts one out of three categories. The architecture of MobileNetV2 contains the initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers giving 2,223,872 trainable parameters and 34,112 non-trainable parameters. The fully connected layers are dense layers with 'Relu' activation, a dropout ratio of 0.25, and batch normalization for regularization. The final model consisted of 8,037,123 trainable parameters and 2,258,368 non-trainable parameters. Details about the proposed network dataset's training and observed results are discussed in detail in the next section.

3.1.2. IoT-based detector

IoT systems had attracted a lot of attention nowadays as they can be used in various applications. It is a wireless network consisting of multiple devices for controlling and monitoring applications. The node is installed containing flame, temperature, and smoke sensors connected to a microprocessor which runs the fuzzy logic program to get the combined result. During the time of installation of nodes, a database has been created to store the node's exact location for extraction of the location of active fire. Due to multiple sensors' involvement, there comes a need to fuse the data to get better results, and fuzzy logic has been chosen for aggregating data from various sensors to make decisions.

The fuzzy system can be viewed as four tasks as shown in Fig. 6: fuzzification; fuzzy rule base; fuzzy inference; and defuzzification. The sensor data fed as input to a fuzzy system acts as fuzzy sets, and in the fuzzification step, the degree of membership and factors like range, resolution, etc., are determined. A rulebase describes the expert knowledge which is used by the inference engine to infer the strength of particular input. Defuzzifier will provide a final fire status that will be provided. Three types of IoT sensors, namely Smoke

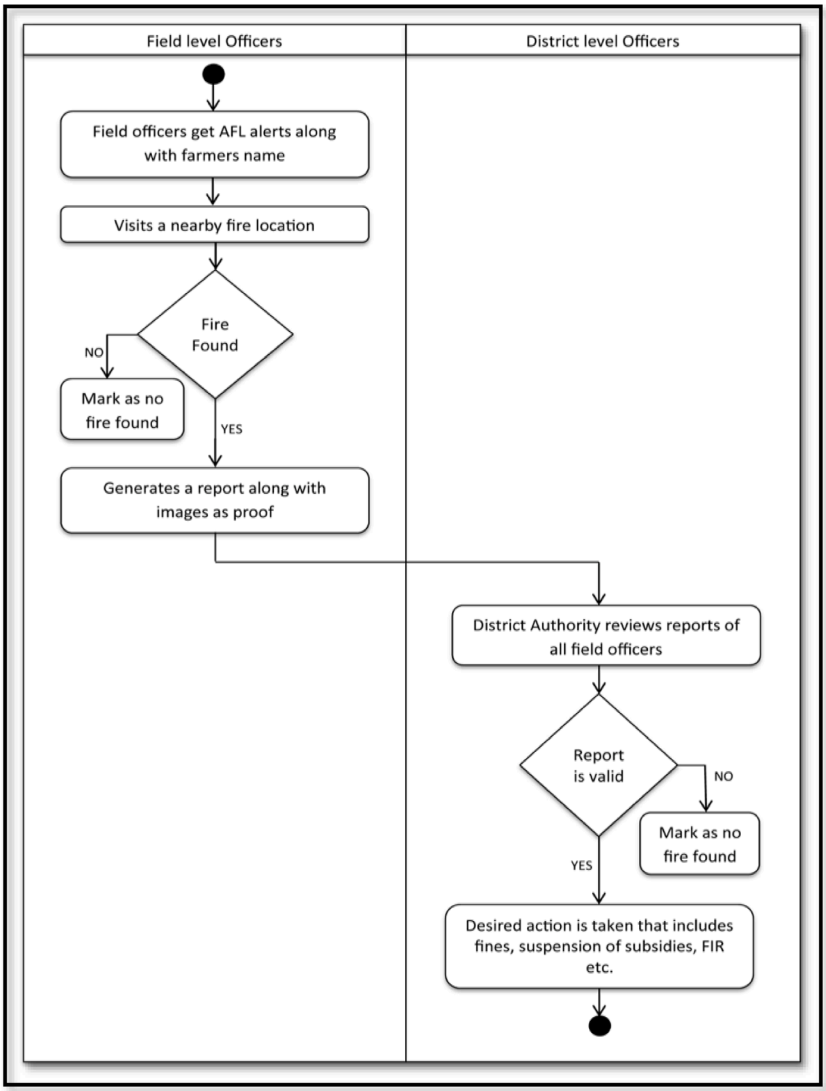


Fig. 9. Use-case diagram of the software module

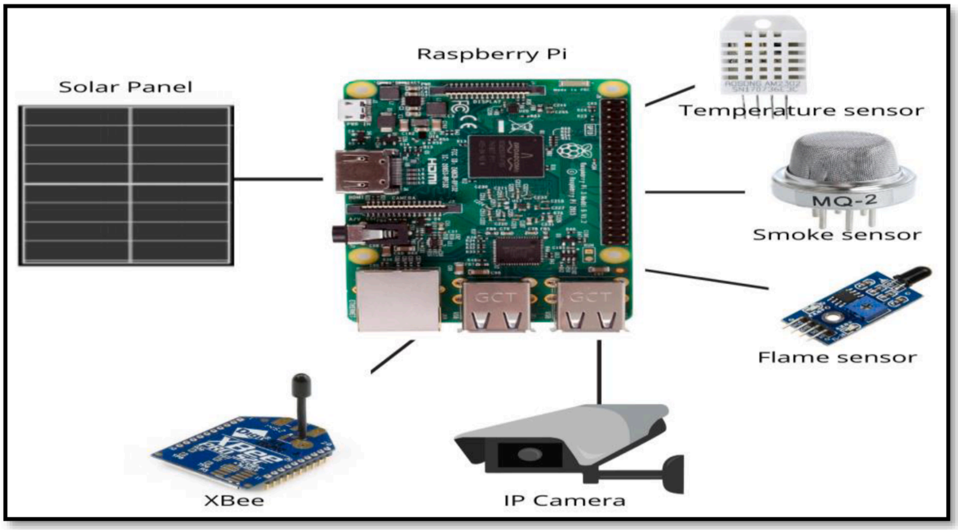


Fig. 10. Proposed node architecture

Table 3
Sample results observed by IoT module

Sr. No.	Smoke Density	Temperature	Flame
1.	77.23	51.822	912.63
2.	31.20	30.69	546.3
3.	68.32	28.364	756.15
4.	82.10	37.03	369.32
5.	29.465	22.69	398.98
6.	50.442	17.898	223.36
7.	71.994	16.120	456.58
8.	37.66	26.36	454.225
9.	32.346	33.222	400.23
10.	53.589	36.74	269.854
11.	60.65	40.36	731.23
12.	57.21	35.3	53.122
13.	29.364	19.36	456.32
14.	22.7	18.369	120.39
15.	40.66	28.34	325.63
16.	58.21	46.545	906.32
17.	39.101	25.36	314.25
18.	51.535	36.25	716.36
19.	36.556	14.235	112.32
20.	36.06	35.366	256.46
21.	55.4	47.55	399.63
22.	78.746	50.3	780.69
23.	65.55	44.556	144.112
24.	64.103	29.9	600.2
25.	39.12	45.336	456.36
26.	54.369	45.25	745.35
27.	68.968	45.298	663.325
28.	32.233	17.225	545.6
29.	82.65	50.36	567.514
30.	29.564	12.744	252.22

Density, Temperature, and flame, has been employed. Fig. 7 shows the fuzzy membership functions used in the proposed model. The output variable of the fuzzy set is the presence or absence of fire at a particular location based on whether the Smoke Density (whether it is Low, Medium, or High), Temperature (whether it is Hot, Medium, Cold), and Flame (whether it is Near, Far or Not near).

The various variables of the fuzzy system use a set of rules given in Table 2 based on which the module predicts a value for the intensity of the fire. The interference engine deduces the rules of interference and fuzzy control action to make decisions like humans. In defuzzification, fuzzy control values are converted back to crisp quantities. The output of this fuzzy system is then again fused with the CNN system's output for better results and to avoid false alerts.

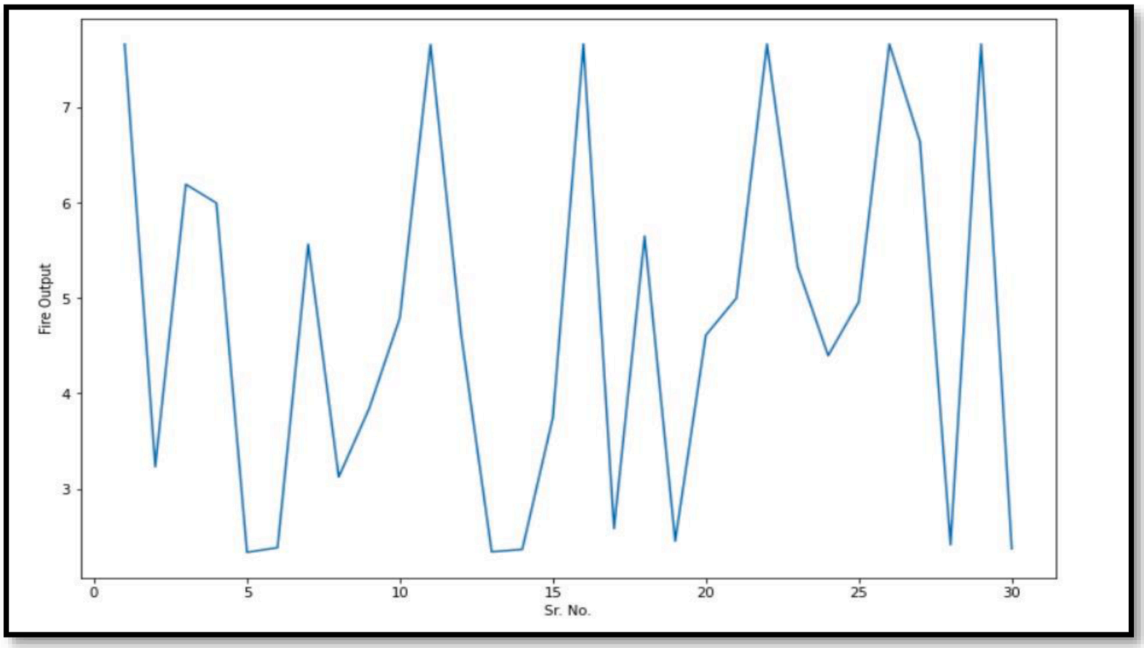
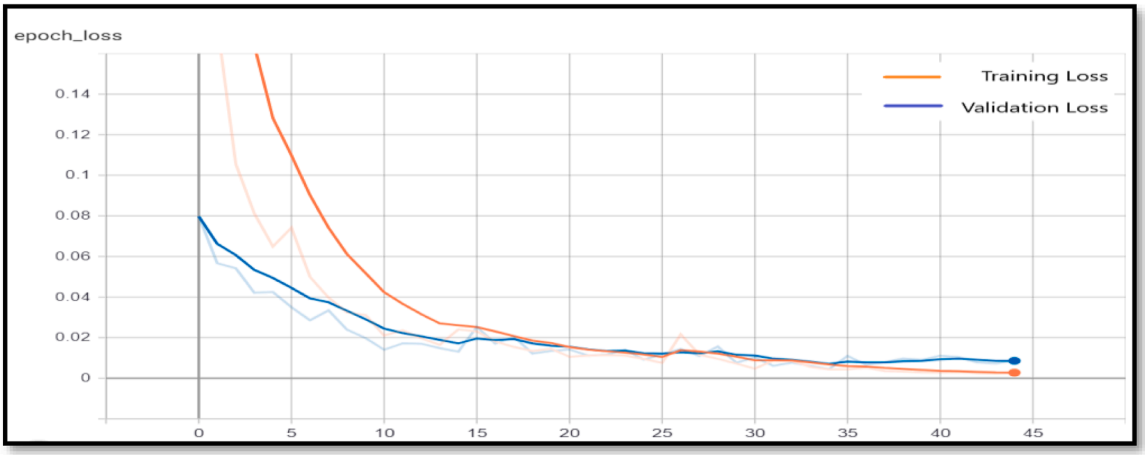


Fig. 11. Sample outputs of fuzzy module

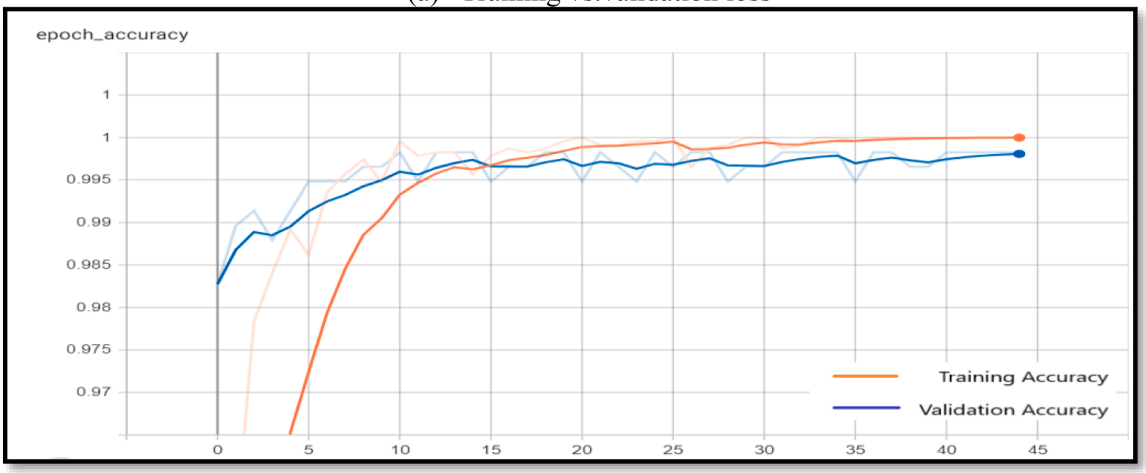
Fig. 12. Category-wise sample pictures in the proposed dataset

3.2. Data Processing and Analytics Module

The details of the data processing and analytics module are shown in Fig. 8; it allows for appropriate storage of all active fire locations, various villages, blocks, districts, diverse personal staff employed all over a state. The software periodically receives NASA FIRMS fire products notifications for extracting regions with possible fire in the form of longitude and latitude. The system then finds village name, district name, and employees on duty for the location. The corresponding details regarding the field and the farmer stored during the registration process of the field are fetched from the revenue department and are automatically allotted to the respective officers of that particular area. The data processing and analytics module helps in effective storage of all these details and ensures the availability of information in the desired form. The module also allows data analytics over it for reports and other stuff.



(a) Training vs.validation loss



(b) Training vs.validation accuracy

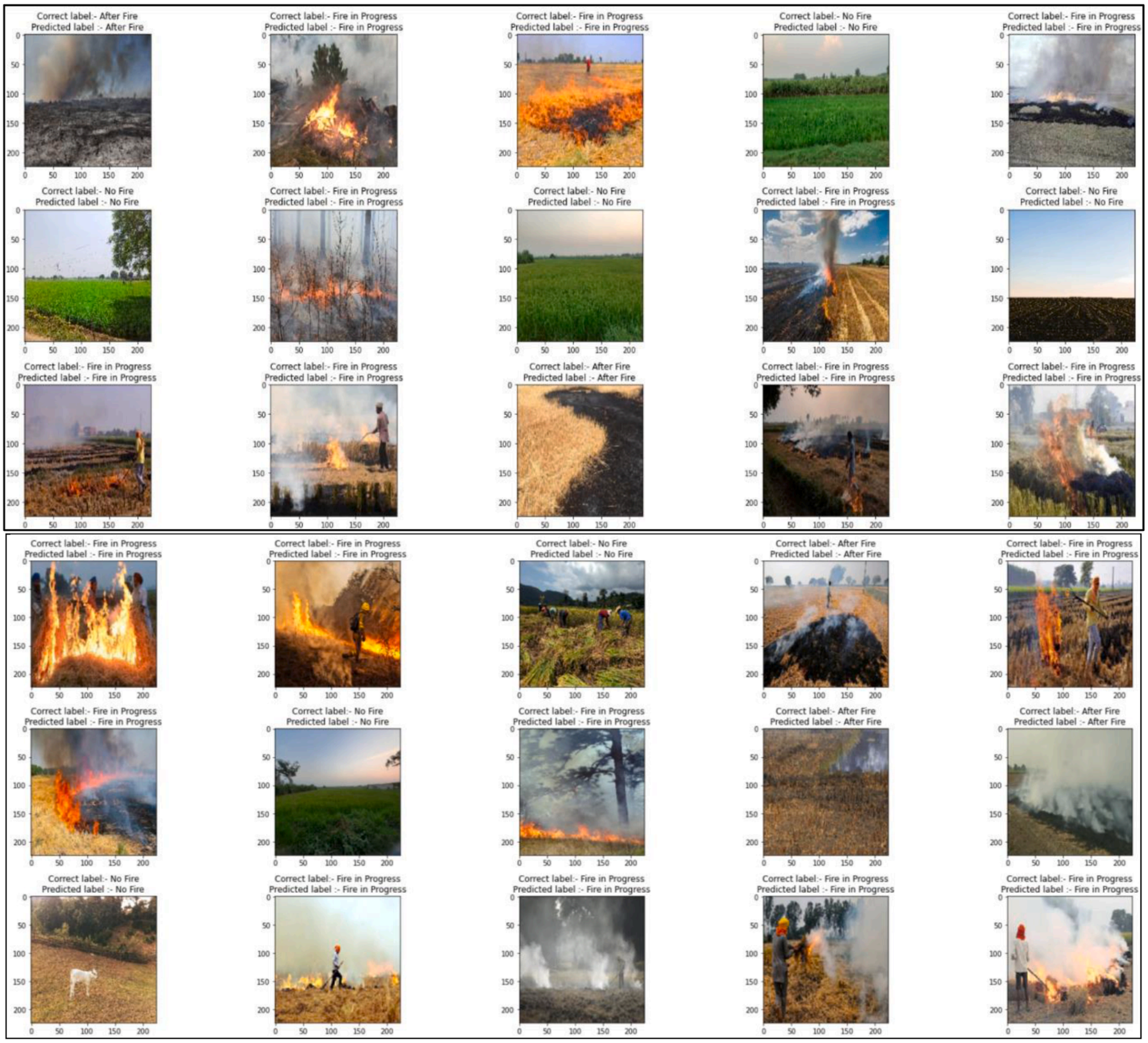
Fig. 13. Tensorboard plots for training vs validation for proposed model (a) Loss (b) Accuracy

Table 4
Performance of proposed system on various parameters

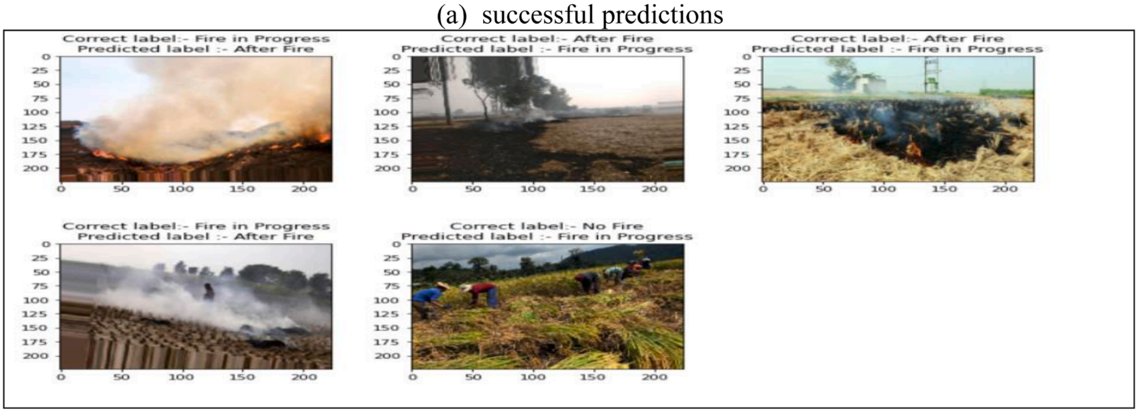
	Precision	Recall	F1-Score	MSE	RMSE	Accuracy	MAE
After Fire	0.99	0.99	0.99	0.005	0.071	0.998	0.005
Fire in Progress	1.00	1.00	1.00	0.001	0.03	0.998	0.001
No Fire	1.00	1.00	1.00	0.002	0.044	0.998	0.002
Macro average	1.00	1.00	1.00	0.0026	0.048	0.998	0.0026
Weighted average	1.00	1.00	1.00	0.0017	0.042	0.998	0.0017

3.3. Software Module

The software module is available both as an app and web interface and compatible with any android smartphone. The flawless user interface helps the users navigate through the software quite seamlessly. There are two levels of working (apart from the admin user), as shown in the use case diagram in Fig. 9 with the details of the roles assigned to each user. The system is structured to pull in the location of the AFL region from a centralized data storage location and output nodal location from the hardware system. In addition to this, the software can fetch the details of the field owner where the fire has been detected. (See appendix A for more information). All these details are submitted to various field officers(ADO) via email or message and trigger the first stage of software, i.e., pending stage. The field officer has to take around and inspect the location provided in his/her login. The software makes sure that the officer visits the site physically as it will not allow report filing until he visits. See appendix for more details. Once all the field officers across a district submit their reports along with all necessary proofs, these get reflected in the accounts of a district-level officer(DDA). After the submission of the report to the district level officer, the report is studied thoroughly, and if the fire is detected, strict actions are to be



(a) successful predictions



(b) unsuccessful predictions

Fig. 14. Sample results of various test images tested on the network

Table 5
Comparison with relevant studies

Paper / Study	Precision	Recall	F1-Score	Accuracy	MAE	R2 Score
Proposed System	1	1	1	0.998	0.0017	0.994
Wang et al. [26]	0.988	0.986	0.987	-	-	-
Jadon et al. [27]	0.97	0.94	0.95	0.93	0.609	-
Ram et al. [28]	0.95	0.95	0.95	0.946	0.054	-

taken against the owner such as FIR, penalty, or forfeit of subsidy availed by the farmer; otherwise, no fire detected will be reported, and the process ends. To encourage citizen participation, a provision for reporting fire has been provided where citizens can report about the active fire location by clicking and uploading pictures on the app portal, and it automatically detects the citizen's location. (Fig. b in Appendix A elaborates this point)

4. System implementation and results

The proposed IoT node architecture consists of hardware and software components. The hardware components comprise flame, smoke, and temperature sensor integrated with the IP camera on the microprocessor powered by solar panel (hardware component) to monitor the agriculture fields all day long continuously. It sends an alert to the server when it detects fire over the wireless network created using XBee modules, and its overall system architecture is depicted in Fig. 10. To detect fire, we tested the system on sample data collected by three sensors at different time intervals in a day at various field locations. We tested the system for the number of days scattered over almost a month, and table 3 shows some sample readings as observed by the IoT module taken at various time intervals, with Fig. 11 producing the predictions made by fuzzy logic.

For testing the deep learning-based fire detection unit, the dataset was web-scrapped and collected manually by visiting fields for desired images. The collected images were organized into three different categories as under:-

(1) After fire
(2) Fire in progress
(3) No fire

The categories are carefully chosen so that the system can actively detect and communicate fire status in almost real-time. Fig. 12 shows some sample pictures of the various types of images under the three proposed categories.

The images were later pre-processed with operations like re-sizing (224, 224, 3), normalizing in range of (0-1) and data augmentation. Since the images collected were of various sizes, therefore data augmentation using ImageDataGenerator library of keras was applied with parameters width_shift_range=0.1, rotation_range10, height_shift_range=0.1, fill_mode='nearest', horizontal_flip=True, zoom_range=0.2.

The training process was implemented with Adam optimizer employing a learning rate of 0.0001 without any decay, batch size of 32, beta_1=0.9, beta_2=0.999, epsilon=1e-07, amsgrad=False. We trained the model till convergence and observed its behavior in the tensorboard library of Google.

Fig. 13 shows the tensorboard plots of the results obtained by the model, and Table 4 shows the values of precision, recall, f1-score, mean score error(MSE), root mean square error(RMSE) and mean absolute error(MAE) for the proposed model. The proposed model inspired an accuracy of 99.83%, which is quite impressive, and the results were found to be stable. The precision and recall score for all the categories was found to be 1.00, indicating that the model has been successfully evaluating all the test images. The error values for various types were also observed to be significantly low for all category types.

For readers' understanding, we plotted successful and failure cases classified by the proposed system; Fig. 14(a) shows the results of images that were correctly classified by the model, and Fig. 14(b) shows the images that were incorrectly classified by the model. There are few images on which the model failed, and carefully looking at failure cases indicates the presence of smoke as the common factor in all the images; still, the system can be considered as widely successful.

To validate the performance of the proposed system, we had also compared it with some recent and relevant studies in literature, and table 5 compares the performance of our system with studies of Wang et al. [26], Jadon et al. [27], and Ram et al. [28]. The results indicate the superior behavior observed by the proposed method over previous studies.

5. Conclusion and Future Work

Reducing active farm fire instances require a single system capable of detecting and monitoring such locations. This paper has proposed an Internet of Things and deep learning-inspired multi-modal framework for monitoring active farm fire locations. The proposed system is state of the art since it considers multiple ways to tackle this problem that sets it apart from previous works. The proposed framework deploys an Internet of Things-based hardware driven by powers of fuzzy logic in conjunction with camera and sensor based nodes installed in sensitive areas. The camera-based detections are performed using MobilenetV2-based deep learning architecture that provides quick and correct decisions regarding the presence of fire. The framework provides a real-time stubble burning detection response since the decision-making is done at the node itself rather than collecting the data from fields and sending it back to the server. The paper has also proposed a software module for providing a mechanism for real-time monitoring and reporting of the fire location. The software can extract locations automatically and assign them to the respective functionaries of government and can also initiate citizen participation. The study's future work can be focused on scaling and testing the system to a larger level, collecting more data for some categories, and initiating talks with government agencies for its adoption.

Declaration of competing interest

None

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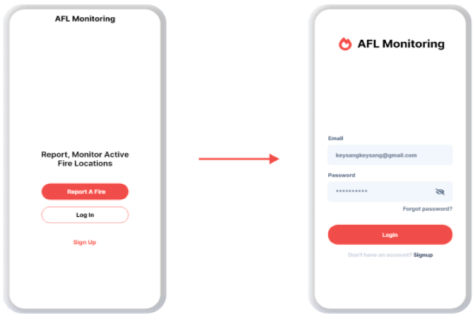
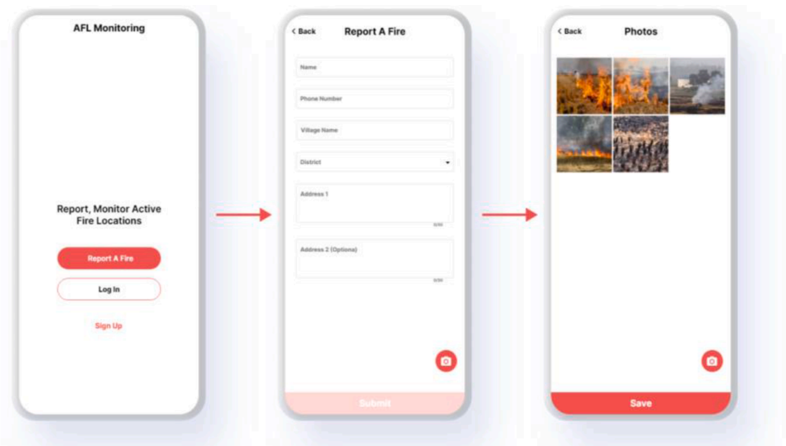
Appendix A:-. Screenshots for working of the software system

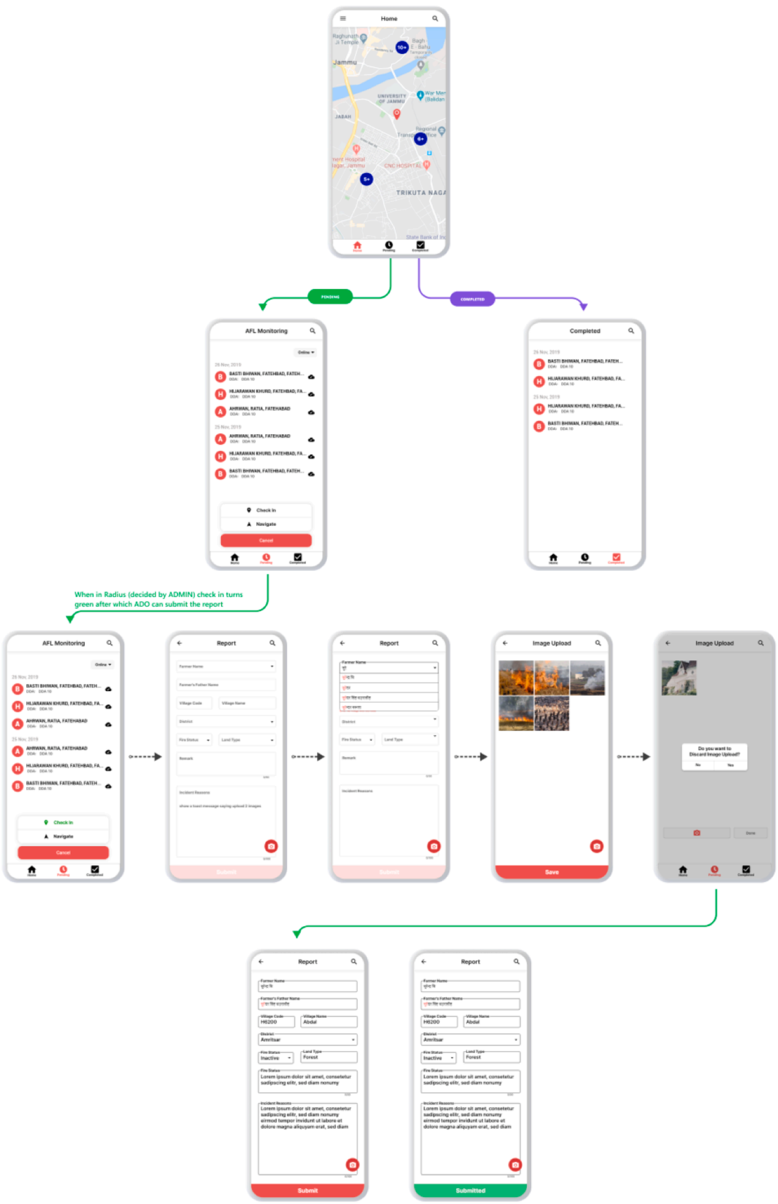


a) Login screen and AFL report available to any non-registered user

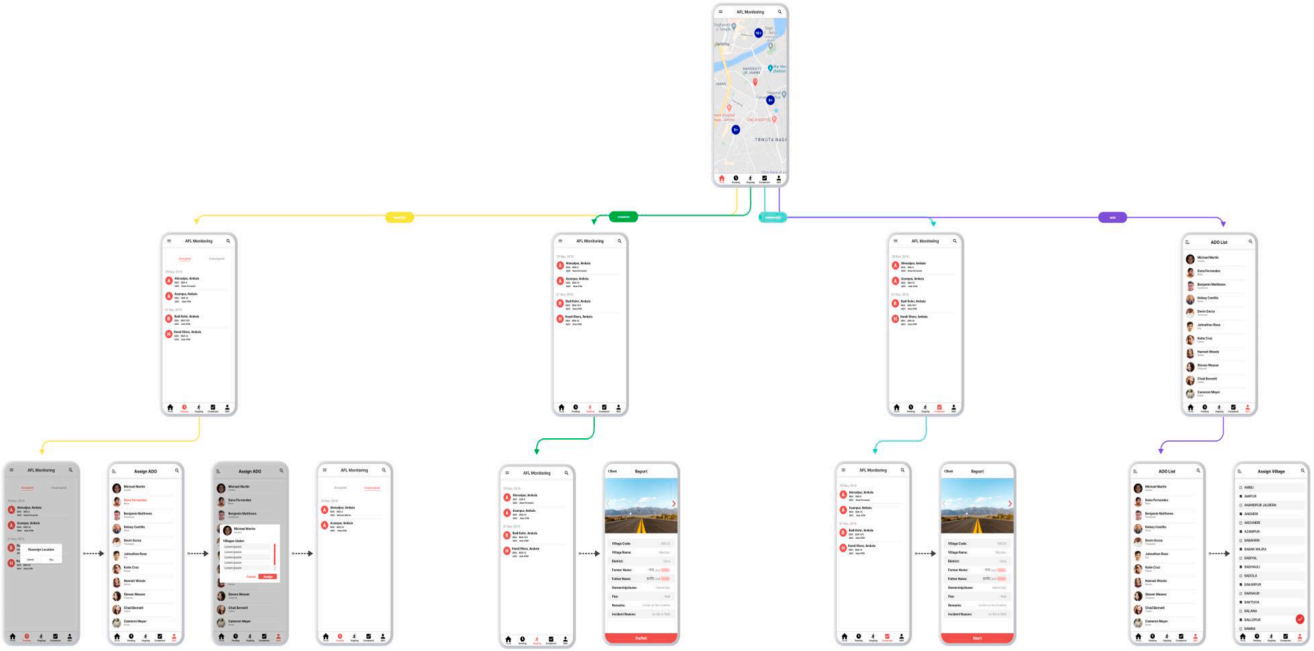


b) Citizen centric participation for report field fire in single click

c) Admin login details and flow: Admin can upload AFL locations, email to different government offices, download reports view current locations etc.



d) Field level officers(ADO) gets a location in his login, have to visit the site to enable report filing, have to upload pictures for successful report and can view their reports



e) District level user(DDA) : can view pending, ongoing and completed reports; assign various ADOs, locations

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