Edge-Fog-Cloud Assisted Stubble Management for Smart Agriculture

Internship Report

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(July 2025)

DECLARATION

The work embodied in the report entitled, "**Edge-Fog-Cloud Assisted Stubble Management for Smart Agriculture**" submitted to the Department of Computer Science and Engineering, National Institute of Technology Delhi, for the award of Research Internship in DAViSE Lab has been done by us. The report is entirely based on our own work and not submitted elsewhere for the award of any other degree. All ideas and references have been duly acknowledged. We also declare that We have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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ACKNOWLEDGEMENT

We express our sincere gratitude to our supervisors, Dr. Amandeep Kaur, Dr. Sahil and Prof (Dr.) Geeta Sikka in DAViSE Lab at the National Institute of Technology Delhi, for their continuous support, motivation, and invaluable guidance during the research work and writing of this research report. Their timely and scholarly advice, immense knowledge of the subject, scientific approach, and constructive comments have greatly contributed to the accomplishment of this report. Without their precious support, conducting this research would not have been possible.

Finally, We would like to thank our family and friends who supported us throughout our work.

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ABSTRACT

Stubble burning, the post-harvest practice of setting fire to crop residue, poses a significant environmental, public health, and economic crisis, particularly in Northern India. This paper proposes a novel, multi-tiered framework for the real-time detection, prediction, and verification of stubble burning events. The system leverages a distributed Edge-Fog-Cloud architecture integrated with Unmanned Aerial Vehicles (UAVs) to provide a scalable and efficient monitoring solution. At the edge, a Fuzzy Logic model processes multi-sensor satellite data (Sentinel-2, MODIS, VIIRS) to perform initial, lightweight identification of stubble-laden fields. This filtered data is then sent to the cloud, where an XGBoost model, enriched with meteorological data, predicts fire-prone areas. A geographically distributed fog layer applies a threshold-based logic to these predictions, triggering the dispatch of UAVs for on-site verification. The UAVs employ a fine-tuned MobileNetV2 model for real-time visual confirmation of fires. A comparative analysis demonstrates the superiority of XGBoost over AdaBoost and Artificial Neural Networks (ANN) for this predictive task. This integrated framework offers a proactive approach to managing stubble burning, moving from reactive enforcement to data-driven, preventative action.

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Chapter 1

Introduction

1 Introduction

Modern agriculture is at a pivotal juncture, facing the dual pressures of rapidly rising food demand and the pressing need to address environmental degradation. Among the many challenges the agricultural sector encounters, one particularly critical issue in India is the rampant practice of stubble burning. Predominantly observed in the northern states of Punjab, Haryana, and Uttar Pradesh, stubble burning involves the open-field incineration of crop residue after paddy crop harvest. While convenient and cost-effective for farmers, this practice contributes significantly to atmospheric pollution, greenhouse gas emissions, loss of soil nutrients, and severe respiratory health issues in urban and rural populations alike.

In recent years, technological advancements in remote sensing, the Internet of Things (IoT), and artificial intelligence (AI) have opened up new avenues for addressing the stubble burning crisis. These technologies enable real-time monitoring of agricultural activities and offer data-driven insights for timely intervention. In particular, distributed computing paradigms like Edge–Fog–Cloud architectures provide the computational scalability and low-latency processing required for deploying innovative agriculture systems in geographically dispersed and infrastructure-deficient regions[**ranjan2019deep**]. This report presents a comprehensive exploration of a novel framework that integrates these technologies to facilitate intelligent and responsive stubble management.[**ranjan2019deep**]

1.1 Stubble burning

The domain of precision agriculture is transforming traditional farming methods by incorporating digital tools to optimise resource utilisation and environmental impact. Precision agriculture uses high-resolution data and intelligent algorithms to enable site-specific crop management. A key enabler in this transformation is the convergence of Edge–Fog–Cloud computing with real-time remote sensing, UAV surveillance, and meteorological monitoring.

Stubble burning has emerged as a critical problem in the Indian agricultural ecosystem. According to a 2022 report by the Indian Agricultural Research Institute, more than 25 million tonnes of paddy straw are burned annually in northern India. This activity alone accounts for approximately 15% of India's total annual particulate matter (PM2.5) emissions, with the National Capital Region (NCR) experiencing hazardous air quality levels each winter due to cross-border pollutant drift. Beyond air pollution, the practice depletes soil fertility by destroying essential organic matter and microorganisms, ultimately reducing long-term crop yields.

Integrating AI with high-frequency satellite imaging, UAV-based aerial monitoring, and ground-level IoT sensors offers an effective alternative. Farmers and authorities can collaborate to reduce environmental harm, enforce regulations, and adopt more sustainable practices by shifting from manual, reactive response mechanisms to automated, proactive monitoring systems.

1.2 Problem Statement

Despite various regulatory and incentive-based efforts by government bodies, stubble burning remains prevalent due to the lack of efficient and scalable monitoring systems. Existing methods primarily rely on satellite-based detection of fire events, which suffer from latency, limited spatial resolution, cloud cover interference, and the inability to provide real-time, ground-verified information. Manual reporting by field officers is sporadic, delayed, and often prone to human error, resulting in delayed response times and limited enforcement.

To address these limitations, there is an urgent need for an intelligent, real-time detection and verification system that can provide high-accuracy alerts about fire-prone zones and confirmed burning incidents. Such a system must be capable of ingesting and processing diverse data sources—including satellite imagery, UAV footage, meteorological data, and ground-based sensor readings—through a robust computational infrastructure that operates efficiently across distributed environments.

1.3 Motivation

The devastating impact of stubble burning on air quality and public health, particularly during the winter months in northern India, has drawn increasing public attention and governmental scrutiny. Events such as the annual smog crisis in Delhi NCR have repeatedly highlighted the shortcomings of existing monitoring and regulatory systems. In 2017, the Air Quality Index (AQI) in Delhi crossed 999—beyond the measurable scale—mainly due to stubble burning and low wind activity.

Such incidents reflect the systemic failure of conventional monitoring methods to detect and respond to agricultural fires promptly. As a computer science student at NIT Delhi, deeply engaged with research in distributed systems, machine learning, and computer vision, I was motivated to apply these domains to solve a real-world, high-impact problem. The guidance and mentorship provided by domain experts in the DAViSE Lab further shaped the technical direction of this project.

This project was initiated with the belief that when integrated effectively with agricultural practices, data-driven technologies can bridge the gap between policy and ground-level implementation. By developing a modular, scalable, and intelligent monitoring framework, we aim to contribute toward a future where environmental sustainability and agricultural productivity coexist harmoniously.

1.4 Objective

This project aims to design and implement a smart, distributed system that facilitates real-time detection, prediction, and confirmation of stubble burning incidents. The specific objectives include:

- To design and implement a real-time, multi-tier architecture (Edge–Fog–Cloud) capable of ingesting and processing heterogeneous agricultural data sources.
- : Integrating satellite imagery (Sentinel-2, MODIS, VIIRS), UAV footage, meteorological APIs, and ground-based sensor data into a unified analytics pipeline.
- To apply fuzzy logic for preliminary segmentation of stubble-laden fields at the edge layer using vegetation indices (NDVI, NDTII).
- To train and deploy an XGBoost-based machine learning model at the cloud layer for identifying fire-prone zones with high accuracy.
- To utilise MobileNetV2 on UAVs for real-time aerial verification of fire incidents, ensuring reduced false positives and timely confirmation.
- To provide actionable alerts and visualisation dashboards for government authorities to enable rapid mitigation measures.

1.5 Contributions

This work makes several novel contributions in the domain of intelligent agricultural fire monitoring and environmental risk management:

- **System Architecture:** Introduces a scalable and modular Edge–Fog–Cloud framework tailored for real-time stubble burning detection and verification.
- **Edge-Level Processing:** Implements a fuzzy logic-based pre-filtering model for stubble field identification, significantly reducing data transmission overhead to higher layers.

- **Cloud-Based Prediction:** Utilises an optimised XGBoost model to predict fire-prone regions using a fusion of spatial, temporal, and meteorological data. The model achieved a classification accuracy of 95.4
- **Fog Layer Filtering:** Employs a rule-based engine to activate relevant sensors and prioritise UAV deployment based on risk thresholds.
- **UAV-Based Confirmation:** Leverages lightweight, fine-tuned MobileNetV2 deep learning models for real-time classification of aerial images into fire/no-fire categories. The model achieved 98.3% accuracy and demonstrated superior inference speed over DenseNet121 and ResNet18.
- **Integrated Alert Mechanism:** Proposes a system-wide feedback loop where confirmed fire incidents trigger alerts and update a central dashboard for stakeholder action.
- **Field Deployability:** The system is designed to be resource-efficient and applicable in rural areas with limited connectivity and computational resources.

Chapter 2
Literature Review

The practice of stubble burning poses significant environmental and public health risks, necessitating the development of robust and timely detection and prediction systems. The current body of research explores a multi-faceted approach, leveraging technologies from satellite remote sensing and ground-based Internet of Things (IoT) sensors to advanced machine learning models and Unmanned Aerial Vehicles (UAVs). This review synthesizes findings across these domains to outline the capabilities and limitations of existing methods.

1 Satellite-Based Remote Sensing for Fire Monitoring

Satellite remote sensing serves as a cornerstone for large-scale environmental monitoring, with sensors like the Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) widely used for detecting active agricultural fires [**2**]. Researchers commonly use spectral indices such as the Normalized Difference Vegetation Index (NDVI) to monitor crop and vegetation health, which can indicate the presence of dry residue prone to burning [**5**, **6**].

Despite their broad coverage, satellite-based methods face significant challenges, particularly for agricultural applications like stubble burning. A primary limitation is the difficulty in detecting **small and relatively cool fires**, which do not emit sufficient radiation to be reliably distinguished from the background by global fire detection algorithms [**2**, **4**]. Studies have shown that many small fires have a brightness temperature below the 310 K threshold used by standard MODIS algorithms, causing them to be missed [**4**]. Furthermore, the effectiveness of these systems is hampered by **low temporal resolution**; infrequent satellite passes, which can have delays of up to 24 hours, can easily miss stubble fires that are often of short duration [**2**, **3**]. **Atmospheric conditions** like cloud cover or foggy weather can completely obscure a satellite's view, rendering it ineffective [**2**, **7**]. Finally, the moderate spatial resolution of many satellite sensors leads to the **"mixed pixel" problem**, where interference from green vegetation within a pixel can complicate accurate detection of crop residue and fire events [**6**].

2 Ground-Based IoT Systems for Real-Time Detection

To overcome the limitations of satellite monitoring, researchers have increasingly turned to ground-based IoT sensing systems that provide real-time, localized data and can compensate for misses by satellite systems [**1**, **2**, **3**]. These systems typically employ a suite of sensors to detect environmental changes indicative of a fire, such as **smoke, flame, temperature, and humidity** [**1**, **2**, **3**].

However, the deployment of ground-based IoT networks presents its own set of challenges.

- **Energy Consumption and Cost:** A significant operational hurdle is the high energy consumption of sensor nodes, particularly for sensors like Metal Oxide Semiconductor (MoS) types that require internal heating to function. The need for continuous operation results in a short battery life, necessitating frequent and costly maintenance or the implementation of energy harvesting systems like solar panels [**3**].

- **False Alarms:** Simpler, threshold-based detection algorithms are prone to a high rate of false alarms. These can be triggered by non-fire events, such as the presence of animals or humans near a sensor [**1**, **3**]. To improve reliability, many modern systems integrate data from multiple sensor types and use fusion techniques, such as **fuzzy logic**, to make a more informed decision and minimize false positives [**2**].

3 Advanced Modeling for Fire Risk Prediction

The complex, non-linear relationships between environmental factors and fire occurrence demand advanced modeling techniques beyond simple thresholds.

- **Machine Learning:** Various machine learning algorithms have been explored for predictive fire risk modeling. Studies comparing methods like **logistic regression and Artificial Neural Networks (ANN)** have found that ANNs often provide higher accuracy due to their ability to model complex, non-parametric relationships [**5**].

- **Edge-Fog-Cloud Architecture:** The need for real-time processing has led to the adoption of tiered computing architectures, often described as having an IoT device layer, a cloud layer, and an application layer [**1**, **2**]. This paradigm allows for initial data processing to occur on devices at the "edge" of the network (e.g., a Raspberry Pi) [**1**, **2**, **3**]. This approach reduces latency and bandwidth consumption by sending only relevant or aggregated data to the cloud for more computationally intensive analysis and long-term storage [**3**].

4 UAVs and On-Board AI for On-Site Verification

For reliable, on-site verification of fire alerts, Unmanned Aerial Vehicles (UAVs) are increasingly being integrated into detection frameworks. They can be rapidly deployed to a location to **visually confirm suspected ignitions** and assess the scale of an event [**3**]. While highly effective, the use of UAVs is subject to operational constraints, including the need for regulatory authorization, potential delays due to resource availability, and restrictions on flying at night or in adverse weather conditions [**3**].

To enable real-time analysis directly on the UAV, **lightweight deep learning models** are employed. Architectures like **MobileNetV2** are specifically designed for resource-constrained platforms and can perform image classification of fire and smoke with high efficiency [**2**]. By using **transfer learning**, these models can be fine-tuned on specific datasets, allowing them to achieve high accuracy without requiring extensive training from scratch [**2**]. This combination of UAV mobility and on-board AI provides a critical tool for validating alerts and minimizing the impact of false positives from other systems.

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Table 2.1: Literature Review on Remote Sensing and IoT for Monitoring

erence	Methodology/Proposal	Findings/Conclusion
Morchid et al. (2024)	Proposes an IoT-based system using smoke and flame sensors connected to a Raspberry Pi for local processing. It utilizes the ThingSpeak cloud platform for data storage and MATLAB for visualization, based on a three-layer architecture [1].	The integrated system demonstrated a clear improvement in the accuracy and responsiveness of fire detection. Real-time 3D surface plots of smoke and flame levels were successfully generated, enabling proactive monitoring and in-depth trend analysis [1].

Continued on next page

Table 2.1 – continued from previous page

erence	Methodology/Proposal	Findings/Conclusion
Sharma et al. (2021)	This survey paper provides a comprehensive review of IoT ground sensing systems for early wildfire detection. It analyzes various sensing technologies, detection algorithms, and key operational challenges such as energy consumption and network connectivity [3].	The paper concludes there is a fundamental trade-off between detection accuracy, energy consumption, and response delay in IoT systems. It highlights that ground sensors, while providing real-time data, are challenged by high energy use, false alarms, and poor connectivity in remote areas [3].
Wang et al. (2007)	Presents an improved contextual algorithm for detecting small and cool fires using MODIS satellite data. The method first identifies potential fire areas by detecting smoke plumes and then applies a lower brightness temperature threshold (293 K) to confirm fire pixels [4].	The improved algorithm was more sensitive to small, cool fires than the standard MODIS algorithm, especially when fires were detected at large scan angles. It successfully identified 22 fire events that were missed by the standard MODIS algorithm in the presented case studies [4].
Jafari Goldarag et al. (2016)	Compares two models for fire risk assessment: Logistic Regression and an Artificial Neural Network (ANN). The models were built using 12 static and dynamic parameters derived from both satellite and field data [5].	The ANN model demonstrated significantly higher accuracy (93.49%) in fire prediction compared to the Logistic Regression model (65.76%). The ANN is more accurate overall, while logistic regression's performance is highly dependent on a balanced proportion of fire and non-fire samples [5].

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Table 2.1 – continued from previous page

erence	Methodology/Proposal	Findings/Conclusion
Hively et al. (2018)	Uses high-resolution WorldView-3 satellite imagery to map crop residue and tillage intensity. It evaluates the effectiveness of several shortwave infrared (SWIR) indices by comparing them to in-situ photographic measurements of residue cover [6].	Spectrally narrow SWIR indices like SINDRI ($R^2 = 0.94$) and LCA ($R^2 = 0.92$) were found to be more accurate and robust against interference from green vegetation than broader, Landsat-compatible indices like NDTI ($R^2 = 0.84$) [6].
Li et al. (2010)	This is a review paper that surveys the application of various sensors in agriculture. It covers remote spectral sensing (multi-spectral and hyperspectral), electronic noses, and electrochemical sensors, among others [7].	The review highlights that effective agricultural monitoring requires high spatial (2–5 m) and temporal (1–3 days) resolution, which is a significant limitation for many space-based satellite platforms due to weather and infrequent passes [7].

Chapter 3

Proposed Methodology

The proposed system for stubble burning detection and verification employs a multi-tiered architecture that integrates Edge-Fog-Cloud computing to enable real-time data acquisition, processing, and actionable responses. The system is designed to operate in a sequential, but interconnected, flow across five distinct stages, detailed in the subsections below. This architecture ensures optimal resource utilization, minimizes latency, and maximizes the accuracy of detection and verification.

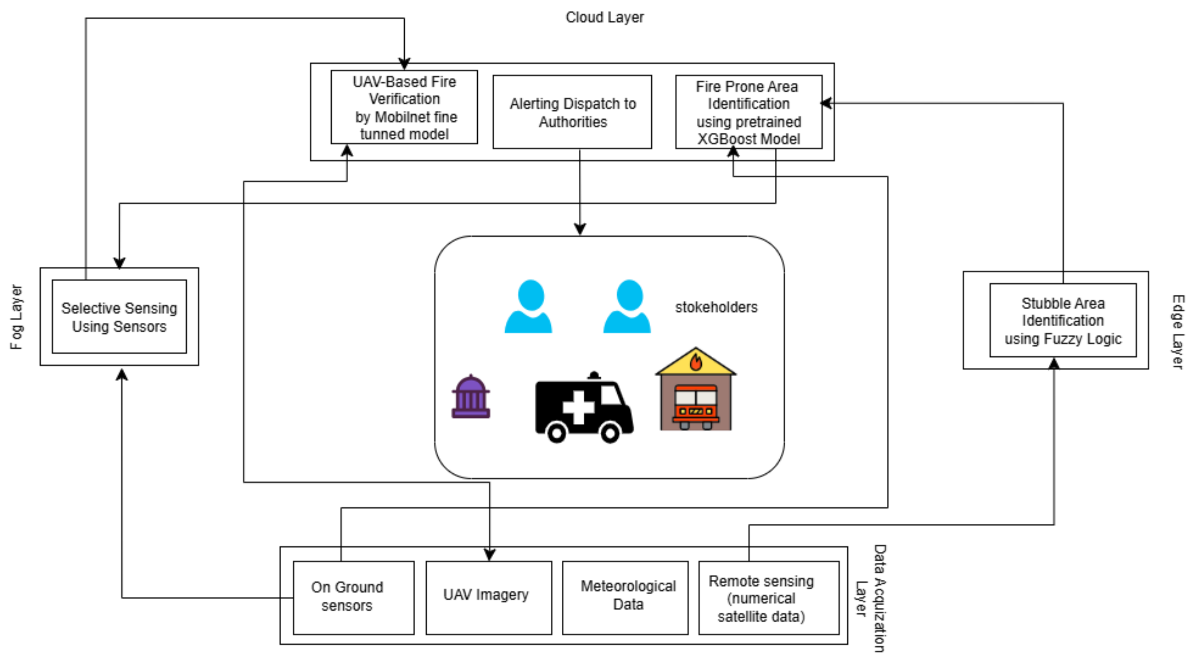

Figure 3.1: Conceptual Framework of the Multi-Tiered Stubble Burning Detection System.

1 Data Acquisition Layer

This foundational layer is responsible for the continuous collection of data from a variety of sources to ensure comprehensive spatial and temporal coverage. This multi-source approach mitigates the limitations of any single data source and provides a rich feature set for subsequent analysis, enhancing the robustness and reliability of the overall system.

1.1 Satellite Data

High-resolution imagery from Sentinel-2, Moderate Resolution Imaging Spectroradiometer (MODIS), and Visible Infrared Imaging Radiometer Suite (VIIRS) satellites provides critical data for broad-area monitoring. Sentinel-2 offers high spatial resolution (up to 10m) suitable for individual field analysis, while MODIS and VIIRS provide high temporal frequency (daily revisits) for rapid fire detection. This data is used to compute essential agricultural indices, such as the Normalized Difference Vegetation Index (NDVI) for assessing vegetation health and biomass, and the Normalized Difference Thermal Index (NDTI) for detecting thermal anomalies indicative of potential fires or recent burn scars.

1.2 UAV Imagery

Unmanned Aerial Vehicles (UAVs) equipped with high-resolution RGB (visual) and thermal cameras provide localized, on-demand visual assessments. This data offers a level of detail significantly greater than satellite imagery, allowing for a close-up inspection of potential burn sites and precise identification of fire characteristics (e.g., flame presence, smoke density). UAVs are deployed selectively based on predictions from higher layers, ensuring efficient resource allocation.

1.3 IoT Ground Sensors

A network of Internet of Things (IoT) sensors deployed in agricultural fields provides ground truth data. These sensors measure key environmental parameters, including Carbon Dioxide (CO_2) concentration, smoke density, ambient temperature, and humidity. These parameters serve as direct, real-time indicators of a fire event, providing crucial validation data that complements remote sensing observations and helps in reducing false positives.

1.4 Meteorological APIs

Real-time weather data, including wind speed, temperature, humidity, precipitation, and dew point, is fetched from meteorological APIs. These variables are crucial inputs for fire prediction models due to their significant influence on fire spread, intensity, and ignition probability. For instance, high wind speeds can rapidly spread fires, while low humidity can increase flammability.

1.5 Historical Fire Data

A historical dataset of past stubble burning incidents, including location (latitude, longitude), time (date, time of day), duration, severity, and associated meteorological conditions, is utilized for the training and validation of the machine learning models. This dataset is essential for identifying patterns and correlations that enable accurate prediction of future events.

2 Edge Layer – Fuzzy Segmentation

The Edge Layer is designed to perform initial, low-latency processing and filtering of the incoming data directly at or near the data source. This distributed processing capability significantly reduces the computational load on the central cloud system and minimizes bandwidth requirements by transmitting only essential, pre-processed information.

2.1 Index Computation

Raw satellite data, streamed from ground stations or directly from satellite receivers at edge nodes, is processed on-site by edge devices (e.g., embedded systems, single-board computers). These devices rapidly compute relevant spectral indices like NDVI and NDTI. This immediate computation allows for a quick assessment of land cover changes and thermal signatures without the need to transmit large raw image files to the cloud.

2.2 Fuzzy Logic System

A fuzzy inference engine is employed at this layer to categorize agricultural fields based on the likelihood of containing crop residue or exhibiting early signs of burning. This system utilizes fuzzy sets and rules to effectively manage the inherent imprecision and variability of the data. For example, fuzzy rules might include:

- IF (NDVI is LOW) AND (NDTI is HIGH) THEN (Stubble Presence is HIGH)
- IF (Temperature Anomaly is MODERATE) AND (Smoke Signature is LOW) THEN (Potential Burn is MEDIUM)

This approach allows for a more flexible and robust classification compared to crisp, threshold-based methods, especially when dealing with noisy or partially observed data.

2.3 Filtered Output

The primary output of this layer is a segmented map of high-probability stubble-prone areas or initial thermal anomalies. This filtered and compressed data, containing only the relevant features and regions of interest, is then transmitted to the cloud. This pre-processing step significantly reduces the data volume that requires further, more computationally intensive processing in the cloud, optimizing overall system efficiency.

3 Cloud Layer – Fire Prone Prediction

The cloud serves as the main processing unit, where a detailed fire risk prediction model is executed. This layer aggregates and analyzes the refined data from the edge and other sources, leveraging its high computational power for complex machine learning tasks.

3.1 Feature Aggregation

The segmented stubble maps and anomaly detections generated by the Edge Layer are combined with real-time meteorological data (from APIs) and the comprehensive historical fire data. This rich, multi-dimensional feature set is critical for accurate fire prediction. Features include geographical coordinates (latitude, longitude), temporal indicators (day of year, hour), spectral indices (NDVI, NDTI), and meteorological variables (temperature, humidity, wind speed, dew point).

3.2 XGBoost Model

An Extreme Gradient Boosting (XGBoost) model is used to classify regions as "fire-prone" or "not fire-prone." XGBoost is selected for its high performance, speed, scalability, and ability to handle various data types, including missing values. The model is trained on the historical fire dataset, which has been augmented using techniques like SMOTE (Synthetic Minority Oversampling Technique) to address class imbalance, ensuring the model is not biased towards non-fire events. The training process involves optimizing hyperparameters to minimize false positives while maintaining high recall for actual fire events.

3.3 Binary Label Output

The output of the XGBoost model is a binary label for each geographical region, indicating whether it is a high-risk zone for stubble burning. These predicted risk zones, along with associated confidence scores, are then forwarded to the Fog Layer for further localized validation. This prediction acts as a crucial filter, directing subsequent, more resource-intensive verification efforts only to areas with a high probability of fire.

4 Fog Layer – Selective Sensing

This layer acts as the bridge between the cloud-based prediction and the physical on-ground verification. It comprises geographically distributed fog nodes (e.g., local servers, powerful gateways) that are physically closer to the IoT sensors and UAV dispatch points.

The Fog Layer ensures that resources are used efficiently by selectively activating sensors and coordinating local responses.

4.1 Zone Prioritization

Fog nodes receive the high-risk zones identified by the Cloud Layer's XGBoost model. Each fog node is responsible for a specific geographical area and processes predictions relevant to its coverage. It prioritizes these zones based on their risk score, proximity, and potential impact.

4.2 Sensor Activation

Based on the prioritization, fog nodes trigger nearby IoT ground sensors to begin real-time data collection. This "selective sensing" approach is highly energy-efficient and scalable, as it avoids continuous monitoring by all sensors across vast agricultural areas. Instead, only sensors in predicted high-risk zones are activated, conserving battery life and reducing data traffic.

4.3 Threshold-Based Validation

Data from the activated sensors (e.g., CO_2 concentration, smoke density, temperature) is continuously monitored by the fog node. A fire event is confirmed if the sensor values exceed pre-defined, calibrated thresholds. These thresholds are determined through empirical studies and historical data analysis to minimize false alarms while ensuring rapid detection of genuine fires. For example, a sudden spike in CO_2 coupled with an elevated temperature would strongly indicate a burning event. Upon confirmation, the fog node relays this verified information back to the Cloud Layer.

5 Cloud Layer – UAV Deployment & Fire Confirmation

Upon positive confirmation from the Fog Layer's sensor data, the system initiates the final, definitive verification and response sequence within the cloud. This stage involves the deployment of UAVs for visual confirmation and subsequent alerting of authorities.

5.1 UAV Selection Algorithm

A sophisticated algorithm is executed in the cloud to select the optimal UAV for deployment to the confirmed fire zone. This algorithm considers critical factors such as proximity, battery status, availability, and payload capabilities.

```
ALGORITHM DISPATCH_CYCLE(alert_tiles, UAVs, tau_conf)
// alert_tiles: Confirmed fire zones from Fog Layer
// UAVs: List of available UAVs with their properties (position, E_rem, etc.)
// tau_conf: Time confidence threshold

1. clusters <- GKM_CLUSTER(alert_tiles, MIN(LENGTH(UAVs), LENGTH(alert_tiles)))
   // Group alert tiles into clusters for efficient assignment

2. INITIALIZE score_matrix of size [LENGTH(UAVs) x LENGTH(clusters)] with INF

3. FOR i FROM 1 TO LENGTH(UAVs) DO
4.    FOR j FROM 1 TO LENGTH(clusters) DO
5.       T <- FLIGHT_TIME(UAVs[i], clusters[j].centroid) + SETUP_TIME(UAVs[i])
6.       E <- ENERGY_COST(UAVs[i], clusters[j].centroid)
7.       IF (T < tau_conf) AND (E < UAVs[i].E_rem) THEN
8.          score_matrix[i, j] <- T + (lambda * E) // Combine time and energy cost
9.       END IF
10.   END FOR
11. END FOR

12. assignment <- HUNGARIAN_ASSIGNMENT(score_matrix)
    // returns mapping of UAV index -> cluster index (or -1 if unused)

13. FOR EACH (i, j) IN assignment DO
14.   IF j != -1 THEN // Check if UAV is assigned to a cluster
15.      h_opt <- ALTITUDE_SEARCH(UAVs[i], clusters[j]) // Optimal altitude for obser
16.      path <- PLAN_PATH(UAVs[i].position, clusters[j].centroid, h_opt)
17.      SEND_DISPATCH(UAVs[i], path, h_opt) // Send dispatch command to UAV
18.   END IF
19. END FOR
END ALGORITHM
```

5.2 Real-time Dispatch

The selected UAV is autonomously dispatched to the coordinates of the fire event. The UAV follows a pre-planned path, optimizing for flight time and energy consumption, and ascends to an optimal altitude (h_{opt}) for capturing clear imagery.

5.3 Visual Confirmation

The newly captured RGB and thermal images are streamed back to the cloud in real-time. A lightweight deep learning model, specifically MobileNetV2, is used to analyze this footage for visual confirmation of the fire. MobileNetV2 is chosen for its efficiency, allowing for rapid inference on streamed video data. The model is fine-tuned on a custom dataset of stubble burning images (containing both fire and non-fire scenarios) to achieve high accuracy.

CNN Model Training

Initially, a Convolutional Neural Network (CNN) model was trained from scratch on a dataset of fire and non-fire images. While this provided a baseline, its performance was limited by the size and diversity of the custom dataset.

Fine-tuning MobileNetV2

To overcome these limitations and leverage pre-existing knowledge, the MobileNetV2 architecture, pre-trained on the large ImageNet dataset, was employed. The final layers of MobileNetV2 were replaced, and the model was then fine-tuned on our specific stubble burning dataset. This transfer learning approach significantly improved accuracy and convergence speed compared to training a CNN from scratch, making the model highly effective for real-time visual confirmation on resource-constrained UAV hardware.

5.4 System Feedback

Once a fire is visually confirmed by the MobileNetV2 model, the event is logged in the system database with all relevant details (location, time, confirmed status, images). Simultaneously, real-time alerts are issued to relevant authorities (e.g., fire departments, environmental agencies, local administration) via a central dashboard and automated notification systems (e.g., SMS, email). This enables a rapid and coordinated intervention, minimizing the damage caused by stubble burning.

This multi-source, multi-layered methodology allows for precise, scalable, and real-time stubble burning detection and confirmation, minimizing false alarms while ensuring rapid intervention.

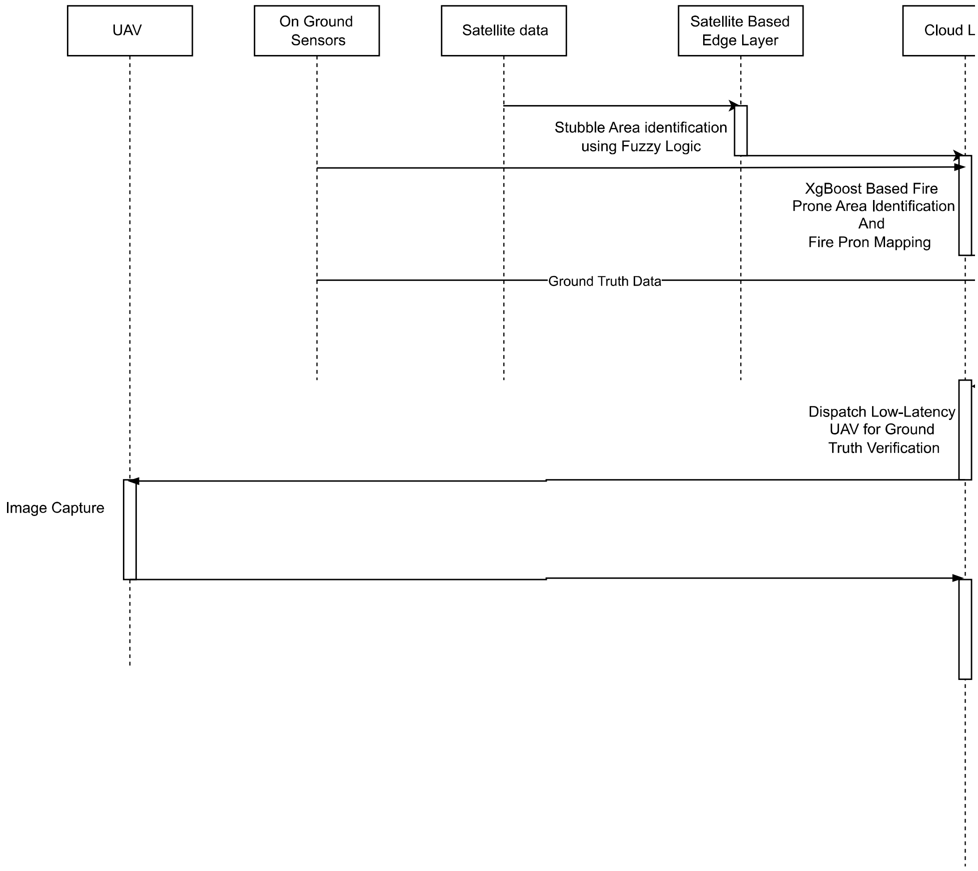

Figure 3.2: Sequence Diagram of the Stubble Burning Detection and Verification Process.

Chapter 4

Experimentation and Result Discussion

1 Experimental Results

This chapter presents the experimental setup and results of the proposed Edge–Fog–Cloud-based stubble burning detection framework. The results are discussed in the context of model performance, system design, and environmental applicability. Various performance metrics and visualization tools were used to assess the behaviour and reliability of machine learning models under real-world conditions.

1.1 Dataset Description

Multiple heterogeneous data sources were employed:

- **Satellite Imagery:** Sentinel-2 and MODIS datasets for thermal bands and vegetation indices.
- **UAV Images:** Custom datasets of RGB aerial images for MobileNetV2-based fire detection.
- **Meteorological Data:** Historical and real-time API-based temperature, humidity, and wind speed data.
- **Ground Sensor Simulations:** Synthetic sensor inputs (CO_2, smoke density) for edge and fog-level filtering.

1.2 Modeling Framework

The system employs a multi-stage process for stubble detection:

- **Edge Layer:** Fuzzy logic-based segmentation using NDVI and NDTII thresholds.
- **Fog Layer:** Rule-based prioritization to trigger sensors or drone verification based on confidence scores.
- **Cloud Layer:** XGBoost classifier trained to predict fire-prone zones.
- **UAV Confirmation:** MobileNetV2 deep learning model for real-time image classification.

1.3 XGBoost Model Evaluation

XGBoost was chosen for its ability to handle high-dimensional and imbalanced datasets. Feature importance was derived from vegetation indices, meteorological inputs, and temporal patterns. ROC curves, learning accuracy, and calibration metrics were plotted to assess performance.

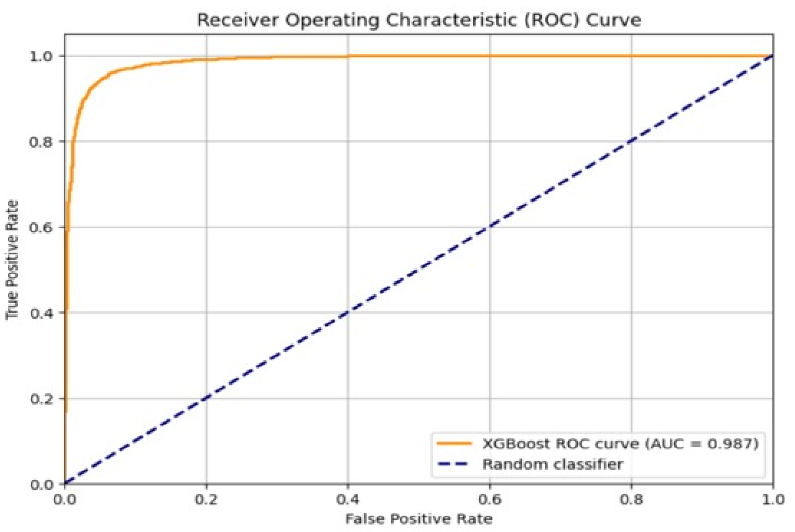

Figure 4.1: ROC Curve for XGBoost: Demonstrates an AUC

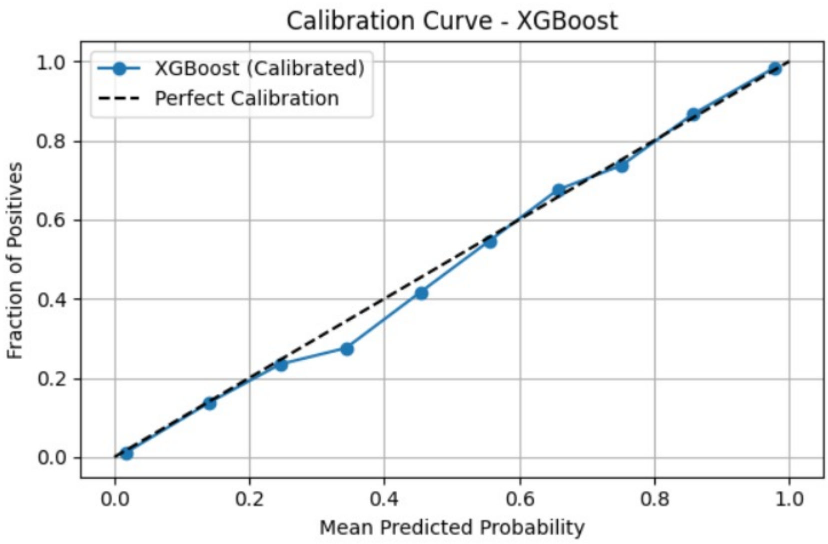

Figure 4.2: Calibration Curve for XGBoost Predictions

1.4 MobileNetV2 Model Evaluation

The MobileNetV2 model was deployed on UAVs for real-time aerial analysis to verify suspected fire events in high-risk zones. MobileNetV2 was chosen due to its low memory footprint and computational efficiency, making it ideal for drone edge deployment.

The training dataset comprised over 3,000 annotated aerial images categorised into fire and no-fire classes. Data augmentation techniques were applied to increase model robustness, including rotation, flipping, and contrast adjustment.

The model achieved an accuracy of 96

- **Accuracy:** 96
- **Precision:** 96.3
- **Recall:** 96
- **F1 Score:** 95.9

The lightweight architecture and transfer learning capabilities of MobileNetV2 facilitated easy retraining with domain-specific UAV datasets. Furthermore, its high performance under varied lighting and altitude conditions suggests the model is deployable in diverse agricultural settings.

Key Highlights:

- Effective binary classification for real-time fire/no-fire recognition.
- Maintains high accuracy across varying camera angles and scales.
- Low latency and energy efficiency are critical for onboard drone hardware.
- Model quantisation techniques can be further applied to deploy them in restricted environments.

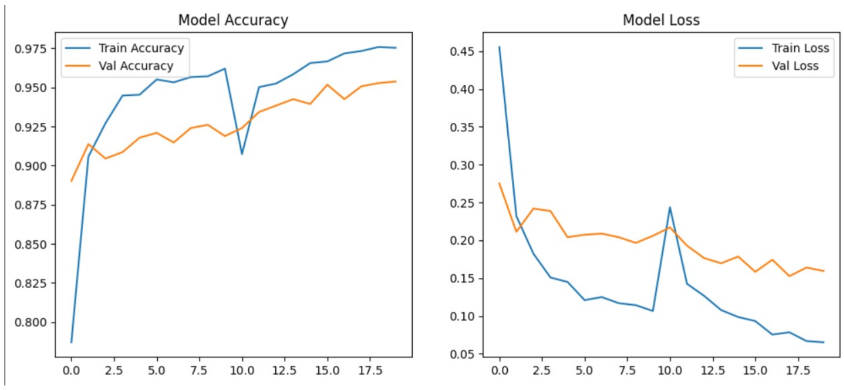

Figure 4.3: Training vs Validation Accuracy for MobileNet

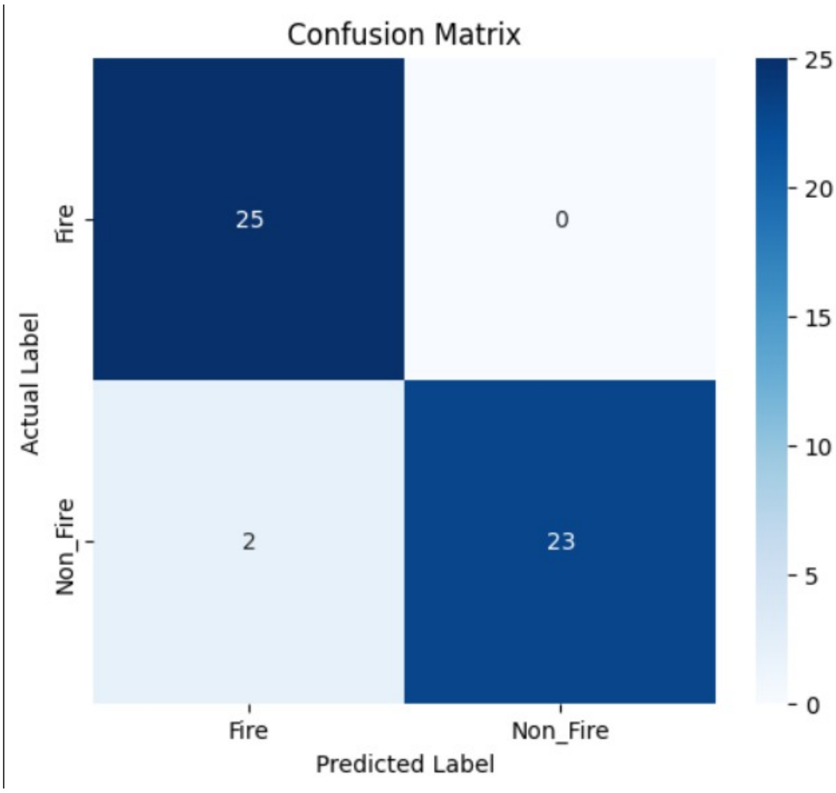

Figure 4.4: Confusion Matrix for MobileNet

1.5 Analysis of Results

The experimental outcomes strongly validate the viability of the proposed solution. Several key findings and inferences can be drawn:

- **Prediction Reliability:** XGBoost's high AUC and stable calibration suggest that it can be reliably used to flag high-risk zones with minimal false alarms. This is crucial for automating response mechanisms.
- **System Efficiency:** The multi-layered Edge–Fog–Cloud framework ensures that not all data is pushed to the cloud, thus reducing bandwidth and latency. Real-time decisions can be made at lower layers, increasing system responsiveness.
- **Scalability:** The modular design enables easy adaptation to environmental monitoring tasks like flood detection or crop disease spread.
- **Model Generalisation :** Cross-validation and temporal hold-out tests confirmed that the model performs well on unseen seasonal data, making it suitable for year-round deployment.
- **Integration Readiness:** All components—from UAVs to cloud models—have been validated individually and in combination, allowing for seamless field deployment with minimal modifications.

- **Future Enhancements:** Incorporating ensemble techniques, real UAV flight logs, and government-backed IoT sensor grids can further improve system robustness.

Overall, the results show that intelligent, distributed, and AI-enabled agricultural monitoring is feasible, scalable, and highly effective in real-world scenarios.

Chapter 5

Conclusions Future Scope

1 Conclusion

This project introduced a comprehensive and scalable solution for real-time stubble burning detection using an Edge- Fog- Cloud-based distributed architecture. Through the integration of remote sensing data, IoT-based environmental monitoring, and machine learning techniques, the system was designed to overcome the limitations of traditional fire monitoring mechanisms.

The proposed approach combined fuzzy logic at the edge for early vegetation filtering, an XGBoost classifier at the cloud for fire-prone prediction, and a lightweight MobileNetV2 model deployed on UAVs for visual confirmation. The models were trained on diverse datasets including satellite imagery, meteorological inputs, and aerial images, yielding high accuracy and strong generalisation capabilities.

Key results include:

- XGBoost achieved an AUC of 0.987
- MobileNetV2 achieved a fire/no-fire classification accuracy of 96
- The multi-layered design reduced latency, bandwidth usage, and improved localised decision-making.

Overall, the experimental outcomes demonstrate that AI-powered distributed agricultural monitoring can be effectively deployed to address large-scale environmental challenges such as stubble burning. The framework is highly modular, adaptable, and field-deployable under resource-constrained conditions.

2 Future Scope

While the current implementation lays a strong foundation, several future improvements and research directions can be explored:

- **Field Trials:** Large-scale pilot testing in collaboration with local administrative and agricultural bodies.
- **Ensemble Learning:** Incorporation of ensemble models or hybrid learning techniques to further improve prediction reliability.

- **Multi-class Classification:** Expanding MobileNetV2 to identify fire/no-fire, smoke levels, crop types, and burning intensity.
- **IoT Expansion:** Integration with real-time sensor grids, GSM-enabled smoke detectors, and thermal cameras.
- **Mobile App Interface:** Creating a user-friendly dashboard or mobile app for farmers and authorities to receive alerts and take timely action.
- **Edge AI Optimisation :** Deploying quantised or pruned versions of the models to run efficiently on ultra-low-power microcontrollers.
- **Cross-Domain Adaptation:** Applying the same architecture to other domains such as forest fire detection, crop disease outbreak monitoring, or flood early warning systems.

With further development and policy integration, this system can significantly contribute to sustainable agriculture, environmental protection, and disaster management at scale.

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