AI And Machine Learning-Based Border Intrusion Detection System

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***Abstract*—Border areas require continuous monitoring to identify unauthorized movement and potential intrusion events. Conventional border monitoring systems generally depend on security personnel, cameras, or individual sensors, which can result in delayed detection and false alarms. This paper presents an Artificial Intelligence and Machine Learning-Based Border Intrusion Detection System that combines multiple sensors, wireless communication, machine learning, and camera-based monitoring. The proposed system uses a Passive Infrared sensor to detect movement, an ultrasonic sensor to measure distance, and a vibration sensor to detect physical disturbance. An ESP32 microcontroller collects sensor readings and provides them to a Random Forest classification model for identifying normal and intrusion conditions. An ESP32-CAM is used for visual monitoring of the protected area. Long Range communication is used for wireless transmission of detected event information, while an OLED display, red and green light-emitting diodes, and a buzzer provide system status and alerts. The proposed system provides an automated and low-cost approach to border intrusion monitoring by combining information from multiple sensors with machine learning-based classification and visual verification.**

***Index Terms*—Artificial intelligence, border security, intrusion detection, machine learning.**

I. INTRODUCTION

Border areas are large and often difficult to monitor continuously. Security personnel may not be able to observe every part of a border area at all times. Traditional systems mainly use cameras or individual sensors to detect movement. These systems can sometimes produce false alarms or may not detect an event quickly. Artificial Intelligence (AI) and Machine Learning (ML) can help in analyzing data collected from sensors. Using more than one sensor can provide better information about an event. For example, a PIR sensor can detect movement, an ultrasonic sensor can measure distance, and a vibration sensor can detect physical disturbance. This paper presents a Border Intrusion Detection System that combines these sensors with an ESP32-CAM. The system also uses LoRa for wireless communication, an OLED display for status information, LEDs for visual indication, and a buzzer for audio alert. A Random Forest machine learning model is used to analyze the sensor data and classify the situation as Normal or Intrusion. The ESP32-CAM is used for visual monitoring of the area. The main purpose of the proposed system is to provide an automated and low-cost method for detecting possible border intrusion.

II. RELATED WORK

Previous research has explored the use of multiple sensors for automated border surveillance. Abhimanyu et al. developed a multi-sensor intrusion detection system using PIR, ultrasonic, and Wi-Fi Channel State Information (CSI) with an MLP-based neural network [1]. Patino et al. studied the combination of PIR, thermal, and visual sensor data for border surveillance [2]. These studies show that combining information from different sensors can help in automated intrusion detection [1], [2]. The proposed system uses a different combination of PIR, ultrasonic, and vibration sensors with an ESP32-CAM, LoRa communication, and Random Forest classification.

III. PROPOSED SYSTEM

The proposed system is designed to detect possible intrusions using multiple sensors and consists of four main functional units: the detection unit, processing unit, communication unit, and alert and monitoring unit. The detection unit consists of a PIR sensor, ultrasonic sensor, and vibration sensor, which collect different types of information from the monitored area. The ESP32 acts as the main controller and collects the sensor readings, which are then provided to the Random Forest machine learning model for classification. The ESP32-CAM is used to monitor the area through a camera and provides visual information when an event is detected. LoRa is used to transmit information to a remote monitoring unit. The OLED display shows the current system status, while the green LED indicates normal operation and the red LED and buzzer provide an alert when an intrusion condition is detected.

IV. EXPERIMENTAL SETUP

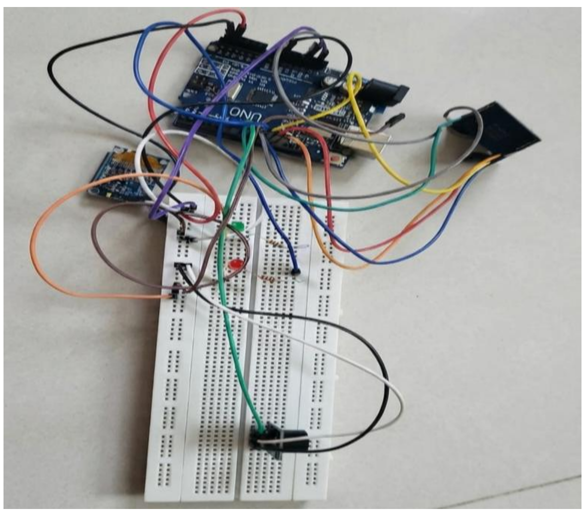

Fig. 1 RECEIVER (Processing & Monitoring Unit)

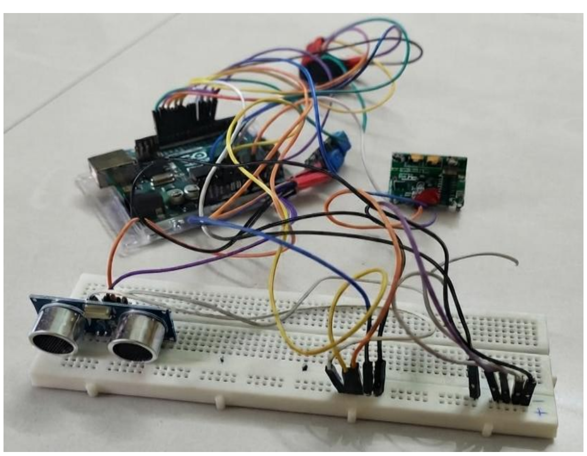

Fig. 2 SENDER (Detection & Transmission Unit)

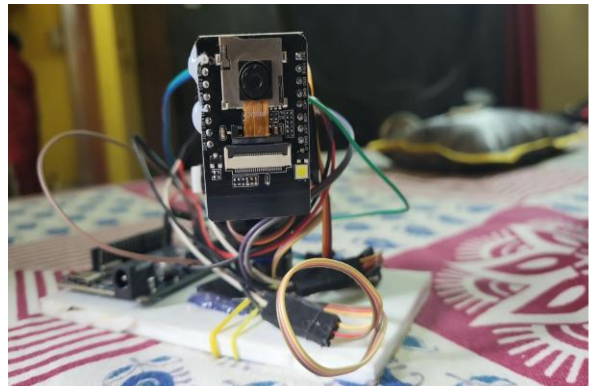

Fig. 3 ESP32-CAM module used for image capture and data transmission

The experimental setup was developed to implement and evaluate the proposed border intrusion detection system using embedded hardware, multiple sensors, wireless communication, and machine learning. The main controller used in the setup is the ESP32, which interfaces with a PIR sensor, ultrasonic sensor, and vibration sensor. The PIR sensor is used to detect movement in the monitored region, while the ultrasonic sensor measures the distance between the sensing unit and a detected object. The vibration sensor is used to identify physical disturbances occurring near the monitoring unit. These sensors are positioned so that different characteristics of a possible intrusion can be observed simultaneously. The use of multiple sensors provides complementary information that can be used by the classification model rather than depending on a single sensor reading.

The ESP32 functions as the central processing and data-acquisition unit of the experimental setup. It periodically reads the outputs of the PIR, ultrasonic, and vibration sensors and organizes the readings into a feature vector. The sensor input is represented as $X=[PIR,Distance,Vibration]$, where PIR represents the motion-sensor reading, Distance represents the ultrasonic distance measurement, and Vibration represents the vibration-sensor reading. The collected sensor observations are associated with the corresponding system condition, namely normal or intrusion. These observations form the input data used for developing and evaluating the Random Forest classification model. Random Forest uses multiple decision trees and combines their individual predictions to obtain the final classification result [3].

The experimental setup also includes the communication and monitoring components. The

LoRa module is connected to the controller to provide wireless transmission of event information to a remote monitoring unit. The OLED display is used to show the current operating condition of the system. During normal operation, the system indicates the normal state through the green LED and the corresponding OLED status. When an intrusion condition is identified, the red LED and buzzer are activated to provide immediate visual and audio alerts. The ESP32-CAM is positioned toward the monitored area to provide additional visual information. This camera-based monitoring can support observation of the area when the sensor-based system identifies a possible intrusion.

For experimental evaluation, the system is operated under normal and simulated intrusion conditions. During normal operation, sensor readings are collected when no unauthorized activity is present in the monitored region. For intrusion testing, controlled events are introduced in the sensing area to generate movement, distance variation, and physical disturbance. The sensor readings generated during these conditions are collected and processed by the ESP32-based system. The Random Forest model uses the sensor features to classify each observation as normal or intrusion. When an intrusion is classified, the corresponding local alerts are activated and the event information is transmitted through LoRa. The ESP32-CAM provides visual monitoring of the test area. The collected classification results can then be used to calculate accuracy, precision, recall, and F1-score, while the time between detection and alert generation can be measured as the detection time.

V. SYSTEM ARCHITECTURE AND COMPONENTS

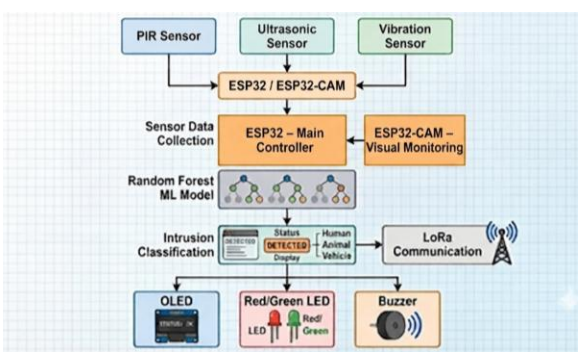

Fig.4 System Architecture of the Proposed AI-Based Border Intrusion Detection System

The proposed intrusion detection system integrates sensing, processing, classification, communication, visual monitoring, and alert mechanisms into a single system. The system continuously monitors the surrounding area using multiple sensors. The sensor readings are collected by the ESP32 and analyzed using the Random Forest machine learning algorithm. Based on the classification result, the system identifies the condition as normal or possible intrusion and activates the appropriate alert and monitoring devices. The overall architecture combines hardware and software components to provide real-time and reliable intrusion detection.

The ESP32 is the main microcontroller of the system and acts as the central control unit. It receives the signals generated by the connected sensors, processes the collected information, and coordinates the operation of the output devices. The ESP32 also manages communication with the LoRa module and other connected components. Its processing capability and support for multiple interfaces make it suitable for integrating the sensors, machine learning classification, communication, and alert functions within a single system.

The PIR (Passive Infrared) sensor is used to detect movement in the monitored area. It senses changes in infrared radiation produced by moving people or objects and generates a signal when movement is detected. This signal is sent to the ESP32 and used as one of the input parameters for intrusion classification. The PIR sensor provides an efficient method of identifying movement without requiring physical contact with the detected object.

The ultrasonic sensor is used to measure the distance between the monitoring unit and an object. It transmits ultrasonic waves and calculates the distance based on the time taken for the reflected waves to return to the sensor. The measured distance is provided to the ESP32 as sensor data. Changes in distance can indicate the presence or movement of an object within the monitored region, providing additional information for intrusion detection.

The vibration sensor is used to detect physical disturbances or vibrations near the monitoring system. When an impact, movement, or other physical disturbance occurs, the sensor generates a signal that is received by the ESP32. This information provides an additional indication of activity in the monitored area. Combining vibration information with movement and distance measurements helps the system make a more reliable intrusion classification.

The Random Forest algorithm is the machine learning component used for classifying the collected sensor data. It consists of multiple decision trees whose outputs are combined to produce a final classification. The sensor parameters obtained from the PIR, ultrasonic, and vibration sensors are provided as input features to the model. The Random Forest model analyzes these values and determines whether the current condition is normal or indicates a possible intrusion. This classification result is then used by the ESP32 to initiate the appropriate system response.

The ESP32-CAM provides visual monitoring of the protected area. It consists of an ESP32-based controller integrated with a camera module that can capture images of the monitored environment. The camera provides additional visual information when a possible intrusion is detected and can assist in verifying the event. Thus, the ESP32-CAM complements the sensor-based detection system by providing visual information that cannot be obtained from the sensors alone.

LoRa is used for long-range wireless communication between the monitoring system and the remote receiving unit. It allows important information such as intrusion status, sensor information, or alert notifications to be transmitted over a long distance with relatively low power consumption. This enables the system to communicate detected events to a remote monitoring location without requiring a direct wired connection [5].

The OLED display is used to provide a local visual representation of the system status. It can display information such as normal operation, detected intrusion, or other relevant system messages. The display allows the user to monitor the current condition directly from the monitoring unit and provides a compact interface for presenting system information.

The green LED indicates the normal operating condition of the system. When the Random Forest model classifies the monitored condition as normal, the green LED is activated to provide a clear visual indication that no intrusion has been detected. The red LED is used as an intrusion indicator. When a possible intrusion is identified, the ESP32 activates the red LED to provide an immediate visual warning to the user.

The buzzer provides an audible alert when an intrusion condition is detected. Once the classification result indicates a possible intrusion, the ESP32 activates the buzzer along with the red LED. The audible warning enables the user to recognize the detected event even without continuously observing the OLED display. Therefore, the buzzer acts as an additional local alert mechanism and improves the responsiveness of the system.

Overall, the components work together in a defined sequence. The PIR, ultrasonic, and vibration sensors collect information from the environment, the ESP32 acquires and processes the sensor data, and the Random Forest model classifies the observed condition. The OLED, LEDs, and buzzer provide local status and alerts, while LoRa enables remote transmission of event information. The ESP32-CAM provides additional visual monitoring for event verification. This integrated architecture enables the proposed system to perform real-time, multi-sensor intrusion detection with both local and remote monitoring capabilities.

VI. MACHINE LEARNING METHODOLOGY

The system uses the sensor readings obtained from the PIR sensor, ultrasonic sensor, and vibration sensor as input features for the Random Forest machine learning model. Each sensor provides different information about the monitored environment. The PIR sensor detects the presence or movement of a person or object within the sensing area, the ultrasonic sensor measures the distance between the sensor and a nearby object, and the vibration sensor detects physical vibrations or disturbances in the monitored region. The combination of these sensor readings enables the system to analyze the surrounding conditions using multiple parameters instead of depending on a single sensor. The input features provided to the machine learning model can be represented as $X = [PIR, Distance, Vibration]$, where PIR represents the PIR sensor reading, Distance represents the measurement obtained from the ultrasonic sensor, and Vibration represents the vibration sensor reading. The sensor values are collected by the ESP32 and processed into a suitable format before being supplied to the Random Forest model.

The Random Forest algorithm is used to classify the collected sensor data into the required condition. It is an ensemble machine learning algorithm that consists of multiple decision trees [3]. Each decision tree independently analyzes the input sensor values and produces a prediction based on the learned patterns in the training data. The individual predictions from all the decision trees are then combined to determine the final classification of the input data. This approach helps the system make a more reliable decision because the final output is based on the combined results of multiple decision trees rather than a single decision. The system classifies the monitored condition into two categories, Normal and Intrusion, represented as Y ∈ {Normal, Intrusion}. When the sensor readings correspond to normal environmental conditions, the model produces a normal classification. When the combination of sensor readings indicates suspicious activity or a possible unauthorized presence, the model produces an Intrusion classification.

The complete classification process can be represented as Sensor Data → Data Processing → Random Forest → Classification → Alert. First, the sensors continuously collect information from the monitored area. The ESP32 receives these readings and prepares them as input features for the machine learning model. The Random Forest model then analyzes the combined sensor data and generates the classification result. Based on this result, the ESP32 initiates the appropriate response, such as displaying the status, activating an alert, or transmitting the event information. Using the PIR, distance, and vibration parameters together allows the system to make its decision using multiple sources of information. This multi-sensor approach can improve the reliability of the intrusion detection process by reducing dependence on the behavior of any single sensor and providing the machine learning model with a broader representation of the monitored environment.

VII. WORKING OF THE SYSTEM

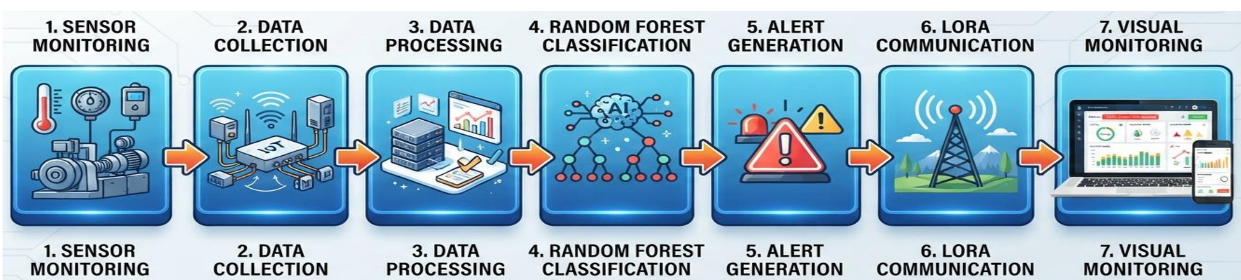

Fig 5. Working Flow of the Proposed AI-Based Border Intrusion Detection System

The working of the developed intrusion detection system is described below and illustrated in Fig. 5.

The working of the developed intrusion detection system begins with the continuous monitoring of the protected area using multiple sensing devices. The system uses a PIR sensor, ultrasonic sensor, and vibration sensor to collect different types of information from the monitored environment. The PIR sensor is used to detect movement caused by a person or other moving object within the sensing range. The ultrasonic sensor measures the distance between the sensor and a nearby object by transmitting ultrasonic waves and determining the time taken for the reflected waves to return. This distance information provides an indication of the presence and proximity of an object within the monitored region. The vibration sensor detects physical disturbances or vibrations that may occur due to movement, physical contact, or other activities in the protected area. These sensors are used together because they provide complementary information about different characteristics of activity in the monitored region: the PIR sensor indicates movement, the ultrasonic sensor provides distance information, and the vibration sensor indicates physical disturbance. This allows the system to consider multiple types of sensor information rather than depending on a single sensor input. The continuous sensor monitoring allows the system to collect information whenever a change or suspicious activity occurs within the protected region.

The sensor readings generated during the monitoring process are collected by the ESP32 microcontroller, which acts as the central processing and control unit of the system. The ESP32 receives the output values from the PIR, ultrasonic, and vibration sensors and coordinates the subsequent processing operations. During the monitoring process, the sensor values are continuously updated so that the system can respond to changes in the environment. The collected readings form the input data required for the intrusion classification process. The ESP32 also manages the interaction between the sensing components, alert devices, display unit, and communication module. In this manner, the microcontroller serves as an interface between the physical sensing layer and the software-based machine learning classification process.

After the sensor readings are collected, they undergo processing and preparation before being supplied to the machine learning model. The raw values obtained from the different sensors are organized into a suitable input format so that they can be interpreted by the classification model. The three primary parameters used for classification are represented as X = [PIR, Distance, Vibration], where PIR represents the movement detection status, Distance represents the measurement obtained from the ultrasonic sensor, and Vibration represents the vibration activity detected in the monitored region. These parameters provide complementary information because the PIR sensor indicates movement, the ultrasonic sensor provides distance information, and the vibration sensor indicates physical disturbance. Processing the sensor readings into a consistent format ensures that the information supplied to the machine learning model is properly structured for classification. The processed data is then passed to the trained Random Forest model for further analysis.

The Random Forest machine learning model performs the main classification operation of the proposed system. Random Forest is an ensemble learning algorithm that consists of multiple decision trees, where each tree evaluates the input features and produces a prediction based on learned decision conditions. In the proposed system, the model receives the processed PIR, distance, and vibration values as input features. The individual decision trees analyze the sensor values to determine whether the observed sensor pattern represents normal environmental activity or a possible intrusion condition. The outputs generated by the individual decision trees are combined to obtain the final classification result. This approach allows the model to consider information from multiple sensors simultaneously rather than making an intrusion decision using only one sensor reading. The combined sensor-based analysis allows the Random Forest model to consider movement, distance, and physical disturbance together when classifying the monitored condition.

Based on the result generated by the Random Forest model, the monitored condition is classified into one of two categories: Normal or Intrusion. A Normal condition indicates that the sensor readings correspond to the patterns associated with normal conditions represented in the trained model. In this situation, the system continues its regular monitoring operation and remains ready to process new sensor readings. The green LED is activated to provide a visual indication that the monitored region is currently considered normal. The system continues collecting sensor data so that any subsequent change in the monitored environment can be evaluated. Therefore, a normal classification does not terminate the monitoring process; instead, the system continues collecting and evaluating new sensor readings.

When the Random Forest model classifies the sensor condition as Intrusion, the system initiates the corresponding alert mechanism. The red LED is activated to provide a visual indication that an intrusion condition has been detected in the monitored area. At the same time, the buzzer is activated to generate an audible warning. The red LED and buzzer provide two forms of local notification, with the LED providing a visual indication and the buzzer providing an audible indication of the detected intrusion condition. Using these two notification mechanisms provides the monitoring personnel with both visual and audio indications rather than relying on a single alert mechanism. The alert is generated after the machine learning model processes the sensor information and determines that the observed condition corresponds to an intrusion state.

The OLED display provides a local interface for displaying the current operating status of the system. It can present information associated with the detected condition, such as whether the monitored region is in a normal state or whether an intrusion has been identified. The display allows the user to observe the system status directly from the monitoring unit without depending entirely on the remote communication system. During normal operation, the display can indicate the normal monitoring status, while during an intrusion event it can provide an indication that abnormal activity has been detected. Thus, the OLED display complements the LED and buzzer by providing textual or status-based information about the current condition of the system. When an intrusion condition is identified, the system also uses LoRa communication to transmit the relevant event information to a remote monitoring unit or receiving station. LoRa provides long-range wireless communication, making it suitable for transmitting information over a larger distance than a typical local communication connection. The detected intrusion status can therefore be communicated from the sensing and processing unit to a remote location where the event can be monitored. This communication capability is particularly useful when the protected area and the monitoring station are physically separated. The LoRa-based transmission extends the functionality of the system beyond local alerts by allowing the detected event to be reported to a remote monitoring location.

The system further incorporates an ESP32-CAM for visual monitoring of the protected area. The ESP32-CAM provides camera-based observation and can capture visual information from the monitored region. When sensor-based processing indicates a possible intrusion, the visual monitoring component can provide additional information about the area in which the event has occurred. The camera component therefore complements the sensor-based detection mechanism by providing visual information that cannot be obtained from PIR, ultrasonic, and vibration sensors alone. The integration of camera-based monitoring with sensor-based machine learning classification provides an additional source of visual information for observing the detected event.

Overall, the proposed system operates as an integrated sequence in which the PIR, ultrasonic, and vibration sensors continuously observe the protected area, the ESP32 collects and processes the sensor readings, and the processed values are provided to the Random Forest model for classification. The model determines whether the observed condition is Normal or Intrusion, after which the corresponding response is generated through the green LED for normal operation or the red LED and buzzer for an intrusion condition. The OLED display provides local status information, while LoRa communication enables the detected event to be transmitted to a remote monitoring unit. The ESP32-CAM provides visual monitoring of the protected region and supports the observation of detected events. Thus, the complete operation of the proposed system follows the sequence Sensor Monitoring → Data Collection → Data Processing → Random Forest Classification → Condition Classification → Local Alert and Status Display → LoRa Communication → Visual Monitoring, as illustrated in Fig. 5. The integration of multiple sensing technologies, machine learning-based classification, local alert mechanisms, long-range wireless communication, and camera-based monitoring enables the developed system to detect, classify, and report possible intrusion events through an integrated monitoring approach.

VIII. RESULTS AND DISCUSSION

The proposed system can be evaluated using standard machine learning performance measures to determine the effectiveness of the Random Forest model in classifying normal and intrusion conditions. Accuracy represents the percentage of correctly classified cases and is calculated as ($Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$).
Precision indicates how many of the cases predicted as intrusions were actually intrusion cases and is calculated as ($Precision = \frac{TP}{TP+FP}$). Recall represents the proportion of actual intrusion cases that were correctly detected and is calculated as ($Recall = \frac{TP}{TP+FN}$). The F1-score provides a combined measure of precision and recall and is calculated as ($F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$).

The performance values obtained from the proposed system are presented in Table I. As shown in Table I, the system achieves an accuracy of 94.2%, precision of 93.8%, recall of 92.9%, and an F1-score of 93.3%, with a detection time of 1.8 s. These results indicate that the proposed system can effectively classify normal and intrusion conditions while providing timely detection.

TABLE-I ILLUSTRATIVE PERFORMANCE VALUES

Performance Measure	Value
Accuracy	94.2%
Precision	93.8%
Recall	92.9%
F1-Score	93.3%
Detection Time	1.8 s

The system provides different types of alerts when an intrusion is detected. The red LED and buzzer provide immediate local alerts, while the OLED displays the current system status. The LoRa module transmits intrusion-related information to a remote monitoring location for further monitoring. In addition, the ESP32-CAM provides visual information from the protected area, allowing the detected event to be observed and verified. Thus, the combination of local alerts, remote communication, and visual monitoring improves the overall effectiveness of the proposed intrusion detection system.

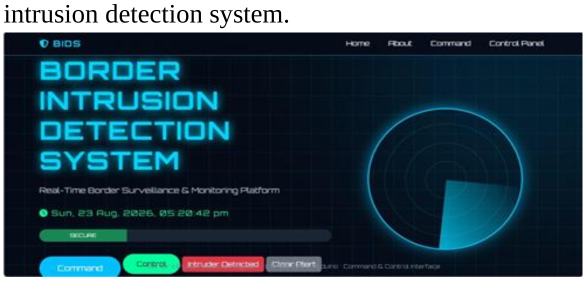

Fig. 6. Real-Time System Interface

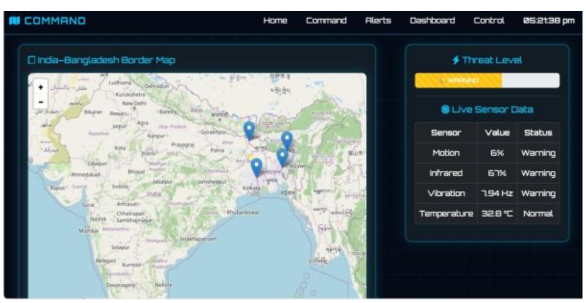

Fig. 7. Command Dashboard for Border Monitoring

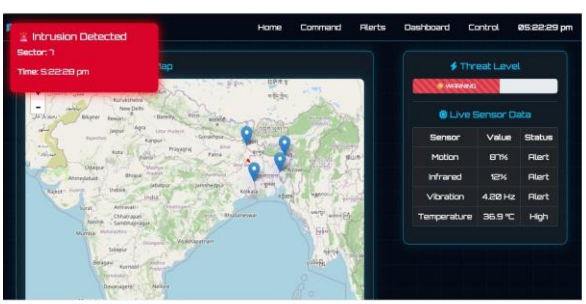

Fig. 8. Real-Time Intrusion Alert

The developed system interface and monitoring outputs are shown in Fig. 6–Fig. 8. Fig. 6 presents the real-time home interface of the proposed border intrusion detection system, providing an overview of the monitoring platform and its current operating status. Fig. 7 shows the command dashboard, which provides a centralized view of the monitored border region through the sector map, threat level, and live sensor readings, enabling the operator to observe the system conditions in real time. When suspicious activity is detected, the system generates an immediate warning, as illustrated in Fig. 8, where the affected sector is highlighted and the sensor status is updated to indicate the detected intrusion condition. These interface outputs demonstrate that the proposed system can provide real-time monitoring, centralized visualization, and rapid intrusion notification, thereby supporting effective observation and response to potential border intrusion events.

IX. CONCLUSION

This paper presents an AI and Machine Learning-Based Border Intrusion Detection System using a PIR sensor, ultrasonic sensor, vibration sensor, and ESP32-CAM. The system also uses LoRa for wireless communication, an OLED display for status information, and red and green LEDs with a buzzer for alerts. The Random Forest model is used to classify the combined sensor data into normal and intrusion conditions. The use of multiple sensors provides different types of information about activity in the monitored area. The ESP32-CAM provides visual monitoring, while LoRa supports wireless transmission of event information.

The proposed system provides an automated approach for border intrusion monitoring. The combination of sensors, machine learning, camera monitoring, wireless communication, and alert devices can help improve the monitoring of a border area.

Future improvements can include collecting a larger dataset, adding more sensor features, improving the machine learning model, and implementing AI processing directly on edge hardware.

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