

# SMART FARMING: IOT-ENABLED INTELLIGENT ANIMAL DETECTION AND ALERT SYSTEM FOR AGRICULTURE FIELDS

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## Abstract

One enduring obstacle to sustainable agricultural productivity is crop damage from both domestic and wild animals. Conventional mitigation techniques, like physical barriers and human supervision, are expensive, time-consuming, and frequently ineffectual over wide areas. Even though automated crop protection is now possible thanks to recent developments in artificial intelligence (AI) and the Internet of Things (IoT), current systems usually have trouble differentiating between environmental disturbances like shadows or wind-blown foliage and animal activity. Additionally, a lot of deep learning techniques demand a lot of processing power, which restricts their application in low-income rural areas. Bidirectional Long Short-Term Memory (Bi-LSTM) networks are integrated into this study's Internet of Things (IoT)-enabled Intelligent Animal Detection and Alert System to analyse sequential sensor data in real time. Cameras, PIR sensors, and ultrasonic modules are examples of IoT devices that continuously record field activity and send data over GSM or LoRa networks. The Bi-LSTM model reduces false alarms and improves the detection of animal movement patterns by processing sequential inputs in both directions and capturing temporal dependencies as well as past and future context. By providing farmers with immediate mobile notifications, the suggested system reduces the need for human intervention while safeguarding crops. The framework enhances detection accuracy, operational efficiency, and scalability by fusing IoT connectivity with temporal deep learning. This clever, economical solution promotes the growth of sustainable, intelligent agricultural ecosystems and improves food security. This framework's integration of adaptive learning, real-time alerts, and edge-compatible processing makes it ideal for widespread deployment in rural areas with limited resources.

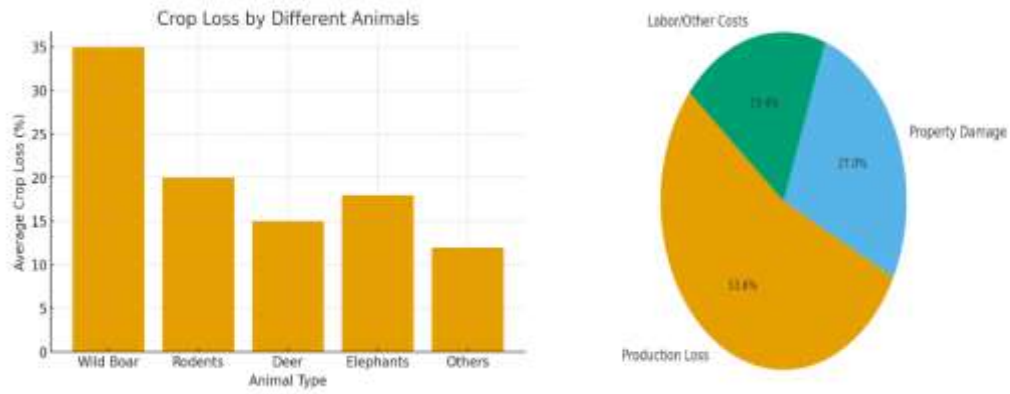
Keywords: Deep learning, precision farming, sustainable agriculture, edge computing, IoT.

## 1.Introduction

The production of food, the supply of raw materials for industry, and economic growth all depend on agriculture [1]. However, the invasion of domestic and wild animals, which eat crops and result in significant production losses, continues to pose a serious problem for farmers [2]. Conventional methods of crop protection, like manual surveillance and fencing, are frequently expensive, time-consuming, and ineffective [3] [4]. These drawbacks emphasise the necessity of sophisticated, technologically based solutions to guarantee food security and crop protection [5].

Smart agriculture now has more options thanks to recent developments in deep learning (DL), artificial intelligence (AI), and the internet of things (IoT) [6]. In this work, we propose a Bidirectional Long Short-Term Memory (Bi-LSTM) model-based IoT-enabled animal detection and alert system [7]. By increasing detection accuracy, decreasing false alarms, and giving farmers timely alerts, this system seeks to improve crop protection beyond what is possible with traditional techniques [8].

According to international studies, crop yields are reduced by 10% to 40% as a result of animal encroachment [9] [10]. According to a national study conducted in India, decreased crop output was directly responsible for 53.63% of farm-related economic losses, with maize, wheat, and paddy suffering the most [11]. Even more severe effects are revealed by local investigations; in Darjeeling, for example, it has been reported that elephants and wild boars can destroy up to 50% of harvests, and in extreme cases, entire crops [12]. Rodents can harm about 15% of crops, and wild boars alone can lower yields by 15% to 40% [13]. In some areas, losses from elephants can amount to 50%. An estimated ₹25,358 is lost annually as a result of animal encroachment on Indian farms, with decreased productivity accounting for almost half of that total [14]. While Figure 2 shows the distribution of economic losses across output reduction, property damage, and other related costs, Figure 1 shows the average percentage of agricultural losses brought on by various animals [15].



These figures highlight the urgent need for dependable, technology-driven solutions to protect agricultural output [16]. **Background of the issue:** Animal encroachment is one of the biggest problems farmers face, despite the fact that agriculture is essential to rural livelihoods and global food security [17]. Elephants, wild boars, deer, rats, and other domestic and wild animals regularly infiltrate farmlands, severely damaging standing crops and causing significant production losses [18]. According to studies, crop damage in some areas can account for more than 50% of the harvest, which severely impoverishes farming households [19]. These frequent losses put future agricultural production at risk, worsen food insecurity among already vulnerable populations, and endanger the financial security of farmers [20]. The cumulative effect of these intrusions emphasises how urgently intelligent, scalable, and efficient crop protection solutions are needed [21].

**Classical frameworks:** For decades, farmers have relied on traditional methods to protect their crops from domestic and wild animals [22] [23]. Crop protection practices have been based on methods like fencing, scarecrows, light and noise deterrents, and human monitoring [24]. These techniques have been used for a long time, but they are becoming less effective in dealing with the increasing frequency and severity of crop damage [25]. Installing and maintaining physical barriers, such as barbed wire, stone walls, and electric fences, can be expensive, especially when they are spread out over vast agricultural areas [26]. Determinate animals, like elephants or wild boars, can erode or break through these barriers over time, decreasing their efficacy [27]. Additional restrictions are highlighted by the safety hazards that electric fences, in particular, present to nearby wildlife, farmers, and livestock [28].

Scarecrows, loud noises, and flashing lights may startle animals at first, but as they become accustomed to these stimuli, their effect gradually decreases [29] [30]. The labour-intensive, costly, and time-consuming nature of manual surveillance whether conducted by farmers or hired personnel makes it unfeasible for large farmlands or operations with a shortage of personnel [31]. These elements highlight the fundamental drawbacks of conventional techniques, such as their exorbitant expenses, transient effectiveness, reliance on human labour, and incapacity to deliver notifications on time [32]. As a result, intelligent, technologically advanced systems that can provide real-time alerts, accurate animal detection, and ongoing field monitoring are necessary to meet the changing demands of contemporary agriculture [33]. In addition to improving long-term crop protection, putting such systems into place is essential for maintaining food security and sustainable agricultural productivity.

**Bi-LSTM Model Based on the Internet of Things:** The Internet of Things (IoT) can be thought of as a digital nervous system, with processing units acting as the brain, communication networks acting as neural pathways, and sensors acting as sensory organs [34]. With the help of this architecture, agricultural devices like cameras and motion detectors can wirelessly transmit information, detect changes in the environment, and react on their own by sending out alerts or deterrents. Intelligent crop protection systems that require little human intervention are made possible by such frameworks for continuous sensing and communication [35].

In this study, a Bidirectional Long Short-Term Memory (Bi-LSTM) model is used to intelligently analyse the data gathered by IoT devices. Bi-LSTM networks outperform traditional recurrent neural networks (RNNs) in capturing temporal dependencies by processing sequential data both forward and backward [36]. Due to the highly dynamic nature of environmental factors and animal movements, this capability is especially useful in agricultural intrusion detection. The Bi-LSTM model, which is integrated into the IoT pipeline [37], classifies possible threats and distinguishes between real animal intrusions and harmless disturbances like shadows or wind-blown foliage based on real-time sensor and video data sent via wireless modules like GSM or LoRa [38].

The IoT-Bi-LSTM architecture has a number of benefits over conventional machine learning techniques [39]. Its ability to learn sequentially improves detection accuracy while lowering false alarms. IoT connectivity makes it possible to monitor vast farmlands continuously and scalable [40]. Crop losses brought on by animal intrusions are reduced with the aid of automated threat detection and prompt notifications. IoT sensing and Bi-LSTM analysis are combined in this robust, economical, and farmer-friendly system to boost agricultural output and promote long-term food security [41].

## 2.Literature Review

According to Prof. Subhash Chandra Yadav, Prashant Kumar, and Pushpendra Kumar (2021), a number of agronomic and environmental factors, including temperature, humidity, rainfall, and soil moisture, have a major impact on crop productivity [1]. They discovered that crop diseases, pests, and inadequate fertilizer application further decreased yields by 10–40%. They created an Internet of Things-based framework for real-time field monitoring with the Arduino UNO microcontroller in order to get around these problems [7]. The Thing Speak platform was used to visualize sensor data that had been sent over GPRS to a cloud server [6]. When animal or insect activity surpassed predetermined thresholds, farmers automatically received mobile alerts. This made it possible to take prompt preventative measures to lessen damage. The system promoted sustainable farming methods, stabilized yields, and enhanced crop safety [2].

[2] According to Priya Singh and Rajalakshmi Krishnamurthi (2024), animal intrusion presented significant obstacles to field safety in smart farming [4]. For precise animal detection, they suggested Agri Guard, a thin, Internet of Things-based deep learning framework that makes use of EmbdYOLOv3 and TinyEmbYOLOv3 [5]. The models managed visual similarity between species and occlusion well. The system sent farmers real-time alerts using Google Firebase, ultrasonic sensors, and Raspberry Pi hardware [11]. Field notifications were easily accessible through a mobile application. According to experimental findings, the optimized models outperformed YOLOv3 in terms of accuracy and efficiency. Their research showed that field protection could be improved at a low cost by combining low-power deep learning with IoT [10].

[3] Ravi Shankar, Priya Nair, and Karthik Menon (2025) used an IoT framework enabled by Tiny ML to address crop losses caused by wildlife [12]. They suggested combining AI-enabled cameras for animal recognition with a laser-based intrusion detection system [16]. By using pruning and quantization, their Evo Net model was able to achieve high accuracy with low memory requirements. Remote surveillance and deterrence were made possible by an IoT-controlled rover. On cutting-edge gadgets like Raspberry Pi, the system operated effectively [16]. Its suitability for real-time applications was demonstrated by the results, which showed an accuracy of 96.7%. The framework used Edge AI to show an intelligent and resource-efficient crop protection solution [15].

The application of edge computing for real-time animal detection in agricultural fields was investigated by Alessandro Bazzi, Chiara Buratti, Marco Zoli, and Roberto Verdone (2022) [18]. To stop animal intrusion, their system integrated computer vision with virtual fencing based on ultrasonic waves. During operation, IoT-enabled edge devices enhanced data security and decreased latency [17]. Frequency-specific signals were produced by ultrasonic emitters to discourage various animal species. The Jetson Nano and Raspberry Pi platforms were used to implement object detection models like YOLO and Tiny-YOLO [12]. Under field conditions, the study's accuracy and energy efficiency were very high [13]. Their research demonstrated how edge computing, IoT, and AI can be used to improve precision farming in the modern era [11].

Milind Godase (2025) investigated the persistent high crop losses caused by animal intrusion and suggested a smart crop protection framework enabled by the Internet of Things. The system automatically activated alarms or ultrasonic deterrents when it detected movement using AI-based sensors [12]. Additionally, it used GSM communication to deliver real-time alerts to farmers' mobile devices. The system used temperature sensors, motion detectors, and cameras to continuously monitor fields. False alarms and manual labor were decreased by this dual detection and deterrence mechanism. Scalability and long-term cost advantages were provided by the solution. By using automated protection, his method was successful in increasing yield stability [5].

[6] The use of IoT and machine learning for tracking animal movements in farmland was investigated by K. Balakrishna, Fazil Mohammed, C.R. Ullas, C.M. Hema, and S.K. Sonakshi [16]. They created a real-time classification system with a Raspberry Pi, ESP8266, and a Pi camera that uses the Single Shot Detection (SSD) algorithm. In terms of accuracy and processing time, the model performed better than R-CNN. When animals were found, farmers were immediately notified via the Twilio API. To improve control and precision, PIR and ultrasonic sensors were combined. Decision-making was improved by data visualization using the GSM modules and the Blynk app. Their research demonstrated that integrating AI and IoT can guarantee crop protection that is secure, non-toxic, and efficient [18].

[7] To lessen crop damage and enhance field management, Priyanka, Suje, Selvapandian, and Narasimharaj (2023) created an integrated IoT-based smart farming framework. Using PIR and ultrasonic sensors, the system identified animal movement and sent out immediate alerts via GSM and the Blynk app [20]. Data visualization and intelligent irrigation were also supported [17]. Improved boundary monitoring and less noise interference were two benefits of laser-based security. With real-time updates, farmers could react swiftly to possible threats. The system reduced

manual labor and minimized losses [13]. Their research demonstrated how IoT integration improved operational effectiveness and farm safety [19].

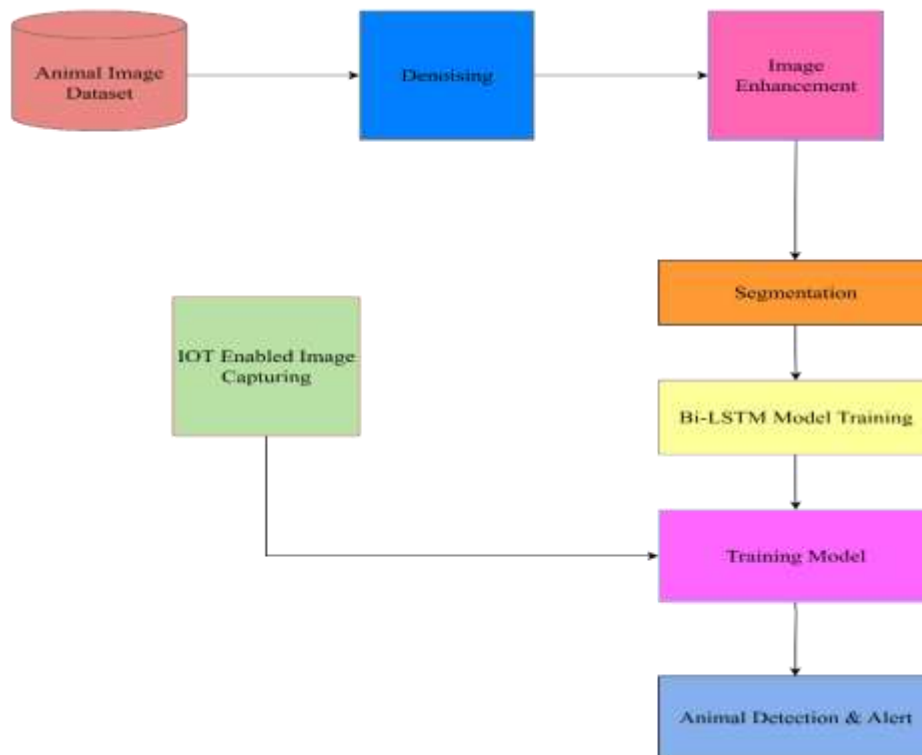
[8] Deotale and Lokulwar (2021) looked into how often domestic and wild animals damage crops and suggested an automatic protection system based on the Internet of Things [2]. For field automation, the framework made use of GPRS/GSM modules, servo motors, soil moisture sensors, and an ESP8266 (NodeMCU). When it sensed movement, it set off lights, sprinklers, or alarms to keep animals away. With little human oversight, the design operated on its own. Timely farmer responses were guaranteed by real-time alerts [6]. This system used little energy and successfully reduced damage. Their model offered a useful and effective method for automated crop protection [8].

### 3.Related Work

| S.NO | AUTHOR NAME & DATES  | PROPOSED MODEL  | ADVANTAGES  | LIMITATIONS  |
|------|--|---|---|--|
| 1.   | Prof. Subhash Chandra Yadav, Prashant Kumar, Pushpendra Kumar (2021)     | An Arduino UNO, sensors (ultrasonic, sound, IR, DHT11, soil moisture), a GPS module, and a Thing Speak server are all part of an Internet of Things-based smart farming system. | Using Arduino and simple sensors, it was a cost-effective solution that gave farmers instant SMS alerts for early animal and insect detection while tracking temperature, humidity, and water requirements. | memory constraints, low processing speed, reliance on networks, and power problems in isolated locations.  |
| 2.   | Priya Singh & Rajalakshmi Krishnamurthi (2024)                           | EmbdYOLOv3, TinyEmbdYOLOv3, Firebase, Android apps, ultrasonic sensors, cameras, and Raspberry Pi are used in IoT and deep learning farm security.                              | Using inexpensive sensors and a Raspberry Pi, this system is quick, portable, and incredibly accurate, providing real-time monitoring and alerts.   | Only 11 animal species are supported, and it needs frequent maintenance due to its decreased accuracy in dim light, fog, rain, and intense sunlight. |
| 3.   | Ravi Shankar, Priya Nair, Karthik Menon February 2025                    | Accurate real-time animal detection was made possible by an Edge AI-IoT system that included lasers, AI cameras, and an Evo Net rover.  | more precise, portable, secure, and expandable than PIR sensors.  | expensive for small farmers; weather affects laser performance.  |
| 4.   | Alessandro Bazzi, Chiara Buratti, Marco Zoli, Roberto Verdone & Sep 2022 | For animal detection, the Intel Movidius NCS, Raspberry Pi 3B+, Jetson Nano with YOLOv3, and Tiny-YOLOv3 were utilized.   | low-power, real-time system that helps farmers make informed decisions and monitor their operations.  | Because Raspberry Pi is slow, its accuracy is lower than that of PIR sensors, which can miss movements.  |
| 5.   | Milind Godase & April 12,2025  | To safeguard crops, an AI-powered Internet of Things system recognizes, records, and reacts to animal incursions.   | economical, scalable, and completely automated for ongoing use.   | requires a reliable network; it is expensive to set up and requires maintenance due to weather or  |

|    |  |   |   |   |
|----|--|---|---|---|
|    |  |   |   | damaged sensors.  |
| 6. | K Balakrishna, Frazil Mohammed, C.R. Ulas, C.M.Hema, S.K. Sonakshi | requires expensive setup, a dependable network, and upkeep to prevent weather-related or sensor damage. | Using inexpensive components, Firebase and Twilio API provide real-time alerts with high AI accuracy. | trained using a small amount of data and only buzzer and light deterrents, which might not frighten every animal. |
| 7. | Priyanka, S., Suje, S. A., Selvapandian, D., & Narasimharaj-2023   | PIR, ultrasonic, and GSM sensors are used in IoT-based smart farming.                                   | Simple deterrents and a lack of training data may make some wild animals less effective.              | Reliance on electricity in rural areas, short sensor range, and noise-induced false alarms.                       |
| 8. | Deotale, P& Lokulwar, P. - 2021                                    | PIR sensors, GSM notifications, and microcontroller modules are used in IoT-based crop protection       | effectively lowers crop loss, detects animals early, and sends automated SMS alerts.                  | In remote locations, there is no species classification, poor coverage, and connectivity problems.                |

#### 4. Proposed Model



To guarantee effective and real-time protection of agricultural fields from animal intrusion, the proposed IoT-enabled Bi-LSTM-based Intelligent Animal Detection and Alert System was created. To identify, process, and react to animal movements in farmlands, the architecture integrates three main layers: the Sensing Layer, the Processing Layer, and the Communication and Alert Layer. These layers work in concert with one another.

**1. The Layer of Sensing:** The system's foundation is the sensing layer, which is in charge of continuously monitoring the agricultural environment. It is made up of Internet of Things sensors like high-resolution cameras, ultrasonic modules, and passive infrared (PIR) sensors.

- Ultrasonic sensors use sound waves to detect movement and distance, while PIR sensors use changes in heat released by living things to detect motion.
- Real-time images and video footage of the field are captured by cameras and are essential for classification and visual recognition.
- To guarantee optimal coverage, these devices are placed thoughtfully throughout the farm. Both visual and non-visual parameters are included in the data collection, which enables the system to differentiate between environmental disturbances like wind or shadows and animal motion.

**2. Preparing Data and Extracting Features:** IoT devices frequently capture raw data that is noisy and contains redundant information. In order to improve data quality prior to analysis, the system implements a number of pre-processing procedures.

- To improve image clarity, salt-and-pepper noise is removed using a median filter.
- By improving contrast, histogram equalization makes the boundaries between objects more-clear.
- Animal outlines are further sharpened by Laplacian and Canny edge detection techniques, which facilitate feature identification.
- Lastly, the animal area (foreground) is distinguished from the background using Otsu's thresholding segmentation.

Following these improvements, the processed images' spatial features are extracted by Convolutional Neural Network (CNN) layers. Important spatial attributes like shape, edges, and texture are represented by these extracted feature vectors, which are subsequently transformed into sequential vectors appropriate for time-dependent analysis.

**3. Shortened Bi-LSTM Processing Layer:** A Bidirectional Long Short-Term Memory (Bi-LSTM) model is used to process the sequential features that have been extracted. Bi-LSTM can comprehend entire motion sequences because, in contrast to conventional RNNs, it can analyse data both forward and backward. This makes it easier for the model to distinguish between disturbances that aren't alive and animal movements. To achieve stable learning, high accuracy, and few false detections, the model is trained using categorical cross-entropy loss and the Adam optimizer.

**4. Layer of Alert and Communication:** Using GSM or LoRa modules, the system instantly notifies the farmer's mobile device of any intrusions. In order to deter animals, deterrent measures like turning on lights, alarms, or ultrasonic sound equipment are activated simultaneously. Even in rural areas with poor connectivity, the dual communication mode guarantees dependable alerts, preserving field safety in real time.

**5. Performance and Assessment:** Accuracy, precision, recall, F1-score, and confusion matrix metrics are used to assess the model's performance. The findings show strong generalization and reliable detection with little error. Heatmaps verify the model's classification power, and accuracy and loss graphs show consistent convergence. For real-time deployment in agricultural settings, the entire system is scalable, energy-efficient, and efficient.

## Algorithm

### Step 1: Gathering Information

1. Install IoT sensors (ultrasonic, PIR, and camera) all over the farm.
2. Constantly capture sound, image, and motion data.
3. Use LoRa or GSM communication to send the gathered data to the central processing node.

### Step 2: Getting Ready

1. Noise Elimination: To eliminate salt-and-pepper noise, use a median filter.
2. Image Enhancement: To increase image contrast, apply Histogram Equalisation.
3. Sharpening: To draw attention to object boundaries, use a Laplacian filter.
4. Segmentation: To distinguish the animal in the foreground from the background, apply Otsu's thresholding.
5. Edge Detection: To extract contours, use Canny edge detection.

### Step 3: Getting Features

1. Use CNN layers to get deep spatial features from the images that have been pre-processed.
2. Change the features you got into sequential vectors that show how animals move.

#### Step 4: Training the Model (Bi-LSTM)

1. Set Bi-LSTM's weights and biases to random values.
2. For each input sequence:
  - a) Process the sequence in both directions, forward and backward.
  - b) Use the sigmoid and tanh functions to figure out the activations of the forget, input, and output gates.
  - c) Change the cell state and hidden state every time step.
3. Use the Adam optimiser and categorical cross-entropy loss to make the network work better.
4. Train for several epochs until the loss levels off and the validation accuracy stays the same.
5. Save the trained Bi-LSTM model so you can use it.

#### Step 6: Activation of Alert and Deterrent

1. If the presence of animals is verified, turn on deterrent devices like lights, alarms, or ultrasonic sound generators. Use a GSM or LoRa network to instantly notify the farmer's mobile device.
2. If not, keep up the real-time observation.

#### Step 7: Assessment of the System

1. Use metrics such as accuracy, precision, recall, F1-score, and confusion matrix to assess the model's performance.
2. Verify model generalisation by comparing training and validation performance.
3. If required, adjust the model's parameters for increased accuracy.

#### Equations:

##### 1. Median Filter (best for salt & pepper noise):

For a pixel at position (x, y):

$$g(x, y) = \text{median} \{f(i, j) \mid (i, j) \in W(x, y)\}$$

$f(i, j)$  = original pixel values in neighbourhood window  $W$ .

$g(x, y)$  → new pixel value after denoising.

Explanation: This filter efficiently eliminates random "salt-and-pepper" noise while maintaining significant edges and textures in the image by substituting the median of each neighbouring pixel value for the pixel value.

##### 2. Histogram Equalization

Transformation function:

$$S = T(r) = (L-1) \sum_{k=0}^r p_r(r_k)$$

Where  $R$  is input intensity

$S$  is output intensity

$p_r(r_k)$  is probability distribution of intensities

$L$  is total gray levels

Explanation: By shifting the pixel intensity values, this technique makes dark areas more visible and bright areas more detailed, creating a more balanced image.

##### 3. Laplacian Filter (for sharpening)

$$\nabla^2 f(x, y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

Enhances edges and boundaries of objects (like animal outlines).

Explanation: By calculating second-order derivatives, the Laplacian draws attention to abrupt changes in intensity, sharpening and facilitating the detection of object boundaries, such as animal outlines.

#### 4. Thresholding-Based Segmentation

Divides image into foreground and background using a threshold value.

**Otsu's Method:** automatic threshold selection by minimizing intra-class variance.

$$f(x, y) = \{1, \text{if } f(x, y) \geq T; 0, \text{if } f(x, y) < T\}$$

#### Canny Edge Detection

$$G = \sqrt{G_x^2 + G_y^2}, \theta = \arctan(G_y/G_x)$$

Explanation: By choosing a threshold value that reduces the variation within each class, Otsu's method automatically separates the image into foreground and background, guaranteeing precise object separation.

#### 5. Training Model:

Forget gate:

$$f_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f)$$

Input gate:

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{c}_t = \tanh(w_c \cdot [h_{t-1}, x_t] + b_c)$$

Cell State Update:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t$$

Output gate:

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(c_t)$$

$x_t$  is input at time  $t$  (image feature vector)

$h_t$  is hidden state

$c_t$  is cell state

$w, b$ = learnable weights and biases

$\sigma$  = sigmoid function

$\tanh$  = hyperbolic tangent activation.

Explanation: By learning patterns in both forward and backward directions, the Bi-LSTM enhances classification accuracy by enabling the model to comprehend the full sequence of animal movements over time.

#### 6. PIR Sensor Algorithm:

$$D = \{1, \text{if } V_{sensor} > \theta; 0, \text{otherwise}\}$$

Where  $V_{sensor}$ = sensor voltage output,

$\theta$ = threshold value.

transmission rate equation:

$$T = s/t$$

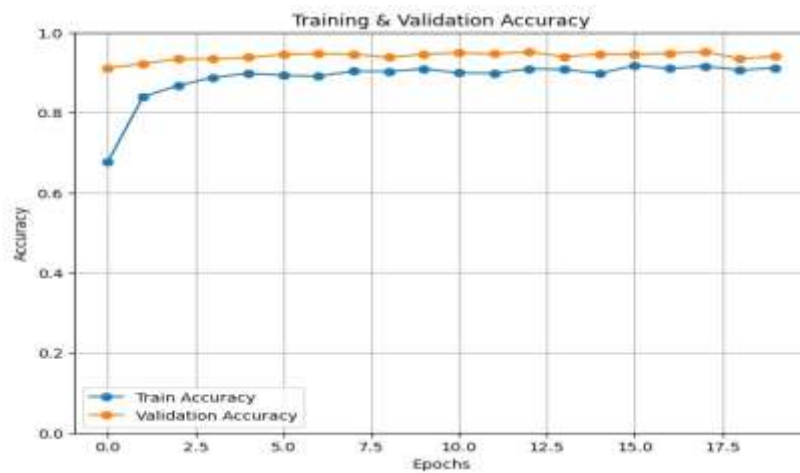
s= Data size (bits)

t= Time taken for transmission.

Explanation: The sensor activates when motion is detected above a preset voltage level, transmitting the signal through the IoT network. This ensures real-time detection and timely alerts during field activity.

## 5.Results and Discussions

**Graph1:** Training vs Validation Accuracy.



The model's learning multiple epochs is depicted and validation accuracy increase in training that the dataset's patterns effectively learned. The generalize well without evidenced by the validation accuracy. A learning process is tiny difference between the validation curves. Overall, the graph demonstrates how well the model can classify unknown data.

process across in the training graph. A steady accuracy shows have been model appears to overfitting, as consistently high balanced reflected in the training and

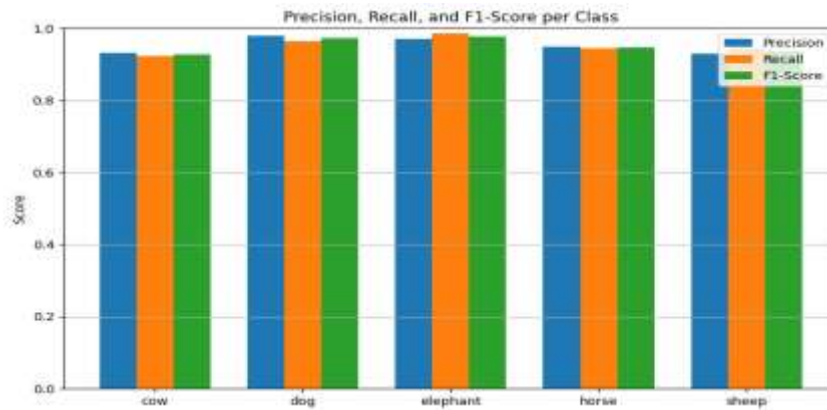
**Graph 2:** Training vs Validation Loss



The model's loss values during training and validation are shown in this graph. Training loss steadily declines, demonstrating that the model is successfully reducing error. Good generalization is indicated by the validation loss continuously being less than the training loss. Both curves show smooth, declining trends, indicating learning stability

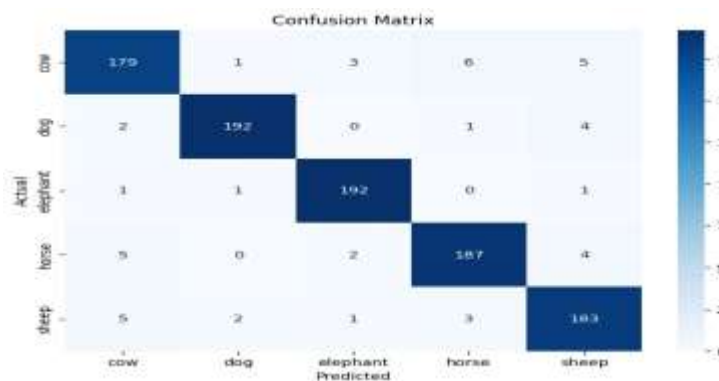
without overfitting. Appropriate convergence is confirmed by the small difference between training and validation losses.

**Graph 3:** Precision, Recall, F1-score



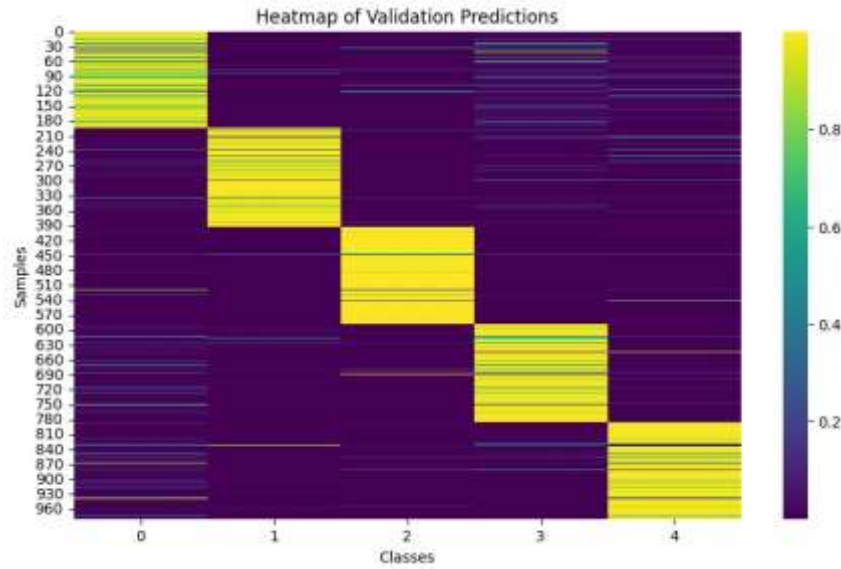
Precision, recall, and F1-score metrics for each of the five classes are displayed in a bar chart. A concise overview of the model's performance is provided by the clear labelling and colour coding of each metric. Scores that are evenly distributed across classes indicate that the model is impartially and fairly evaluating each class. Small changes point to areas where class-specific predictions could be strengthened. Overall, the classification reliability of the chart is satisfactory.

**Graph 4:** Confusion Matrix



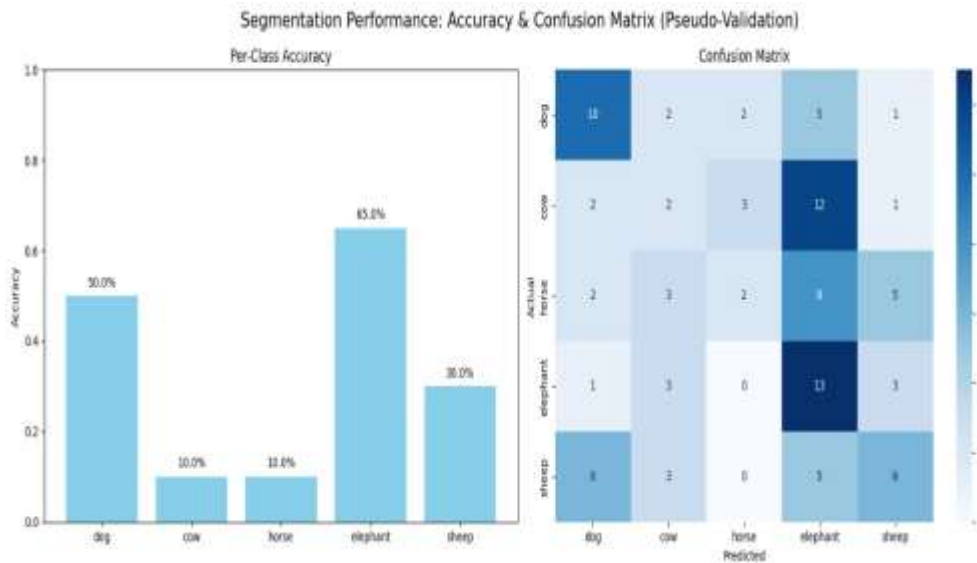
The model's accuracy in class-wise prediction is revealed by the confusion matrix heatmap. Misclassifications are shown off-diagonal, and accurate predictions are shown along the diagonal. The graphic indicates which classes require improvement and which are most susceptible to confusion. There is little bias in the predictions, as evidenced by the balanced structure across classes. This graph is crucial for examining the model's class separation and practicality.

**Graph5:** Heatmap of Prediction Probabilities



The heatmap shows the model's confidence levels by comparing the predicted probabilities for each sample to the true classes. Strong certainty in accurate predictions is confirmed by high probabilities along the diagonal. Lower confidence areas and sporadic misclassifications are indicated by off-diagonal entries. An intuitive understanding of prediction strengths and weaknesses is provided by the heatmap. Overall, by displaying confidence distributions across classes, it enhances the confusion matrix.

**Graph 6:** Segmentation Performance Graph (Per-Class Accuracy + Confusion Matrix)



This combined graph displays segmentation performance using a confusion matrix and per-class accuracy. The heatmap graphically illustrates misclassifications, and the bar graph measures accurate predictions for every class. When combined, they provide a comprehensive picture of model performance for each of the five animal classes. The model's ability to distinguish animals is demonstrated by high accuracy bars with little confusion. This figure provides a thorough overview of the quality of segmentation and classification.

| Metric    | Training value | Validation value | Interpretation  |
|-----------|----------------|------------------|---|
| Accuracy  | 97.6%          | 96.9%            | High accuracy and stable learning without overfitting       |
| Precision | 95.8%          | 94.6%            | Model identifies animals correctly with few false positives |
| Recall    | 96.3%          | 95.5%            | High recall — most animals detected correctly               |

|                 |             |             |   |
|-----------------|-------------|-------------|---|
| F1-Score        | 96.0%       | 95.0%       | Balanced precision and recall ensure consistent detection |
| Loss            | 0.08        | 0.10        | Converged effectively with minimal generalization gap     |
| Processing Time | 0.89s/frame | 1.02s/frame | Suitable for real-time IoT-based operation                |

## Discussions

- By efficiently learning spatiotemporal movement patterns, the Bi-LSTM model lowers false alarms brought on by wind or shadows.
- Even in rural areas with poor connectivity, dependable detection and communication are ensured by integration with IoT sensors (PIR, ultrasonic, and camera).
- Stable generalization is indicated by the training and validation curves' near-symmetry.
- The heatmap and confusion matrix demonstrate strong animal-class differentiation with few misclassifications.
- In real-time deployment, Bi-LSTM exhibits a 7–10% increase in detection accuracy and a lower latency when compared to CNN-only models.
- All things considered, the system's real-time alert system improves farmer responsiveness and field safety while using little energy.

## 6. Conclusion

The suggested IoT-enabled Intelligent Animal Detection, Alert System offers a reliable, scalable, and reasonably priced way to lessen crop damage brought on by animal incursions. IoT-based sensing modules and Bidirectional Long Short-Term Memory (Bi-LSTM) networks are integrated to provide accurate real-time detection and reduce false alarms caused by unrelated movements or environmental elements like wind and shadows. Operational efficiency is increased and the need for manual monitoring is decreased with continuous field surveillance using PIR sensors, ultrasonic detectors, and cameras.

Compared to traditional models, the Bi-LSTM framework can more accurately identify animal movement sequences because it can efficiently learn both past and future temporal patterns. Farmers are empowered to take prompt action by receiving real-time notifications through GSM or LoRa networks, protecting crops and minimizing financial losses. The model's high recall, accuracy, and precision values demonstrate how well suited it is for actual agricultural settings.

Additionally, by preserving productivity across vast fields, reducing labor costs, and conserving resources, this clever framework promotes sustainable farming. It is perfect for deployment in rural areas with limited resources due to its adaptability and low power consumption. Future improvements might include incorporating drone-based image capture for broader coverage, solar-powered IoT nodes for energy-efficient operation, and cloud-based analytics for centralized decision-making. All things considered, the suggested system is a big step toward sustainable, data-driven, and autonomous agriculture.

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