ANIMAL INTRUSION ALERT SYSTEM USING CNN

Report by

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1. Problem Statement

Human-animal conflicts have intensified, especially in regions where agricultural lands are close to wildlife habitats. Farmers experience financial losses due to crop damage, livestock predation, and increased risks to human safety. Traditional surveillance and manual monitoring systems are inefficient, requiring significant resources and lacking real-time response capabilities. This project proposes an innovative Animal Intrusion Alert System, which leverages Convolutional Neural Networks (CNN) and Internet of Things (IoT) technology to monitor wildlife activity. By capturing images through strategically placed cameras, processing them with a CNN model, and sending instant alerts, the system enables timely intervention. This solution aims to reduce human-wildlife conflicts, safeguard resources, and promote coexistence.

2. Business Need Assessment

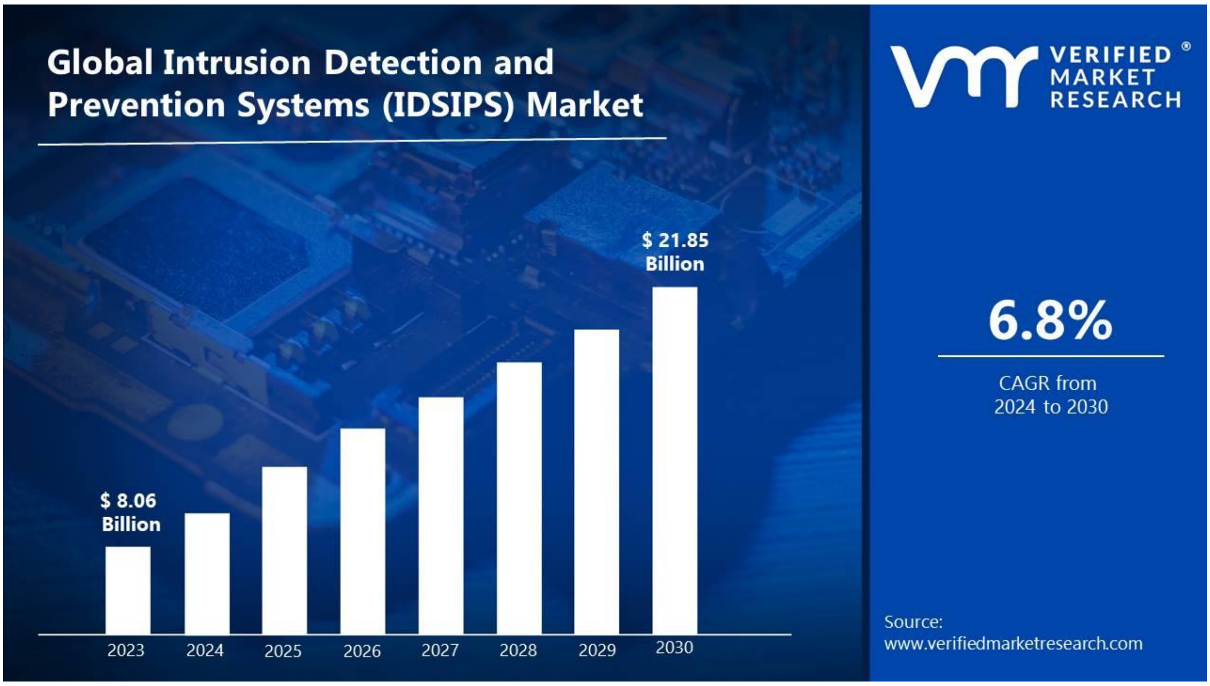
- **Market Need**: The agriculture sector in wildlife-adjacent rural areas frequently suffers from animal intrusions, leading to significant crop and livestock losses. The economic impact is coupled with increased safety risks for farmers, especially in areas where dangerous wildlife is prevalent.
- **Customer Challenges**:
    - **Crop and Livestock Damage**: Crop destruction and livestock deaths impose substantial financial burdens on farmers.
    - **Human Safety Risks**: Encounters with wildlife in farming areas, particularly at night or in remote locations, present serious safety concerns.
    - **Inefficient Monitoring**: Existing animal monitoring methods are labor-intensive, slow, and unable to provide real-time alerts, leading to delayed responses.

The Animal Intrusion Alert System addresses these issues by providing a fast, automated solution that reduces the need for constant human oversight while enhancing protection for farmers and supporting wildlife conservation.

3. Target Specifications and Characterization

This system is designed for small to medium-scale farmers and wildlife management authorities who need an affordable, easy-to-operate solution. Key characteristics include:

- **Usability**: The system is intuitive, with a simple interface that doesn't require advanced technical skills to operate or maintain.
- **Cost-Effectiveness**: The system's design minimizes upfront and operational costs, making it accessible to budget-conscious users, particularly small-scale farmers.
- **Scalability**: The system can adapt to varying farm sizes and terrains, allowing expansion by adding cameras and extending coverage as needed.



4. External Search (Information Sources/References)

The development of this system is informed by extensive research on existing technologies, frameworks, and regulatory guidelines:

4.1 Industry Reports:

4.1.1 Global Wildlife Monitoring Technologies Report 2023: Highlights advancements in IoT and AI-driven wildlife monitoring, emphasizing the growing demand for real-time animal detection solutions.

https://www.worldbank.org/en/programs/global-wildlife-program

4.1.2 Monitoring the Movements of Wild Animals and Alert System using Deep Learning Algorithm" by Y. A. Roopashree, M. Bhoomika, R. Priyanka, K. Nisarga, and Sagarika Behera
https://www.semanticscholar.org/paper/Monitoring-the-Movements-of-Wild-Animals-and-Alert-Roopashree-Bhoomika/9e83155298365dae319be12a33281403d5756913

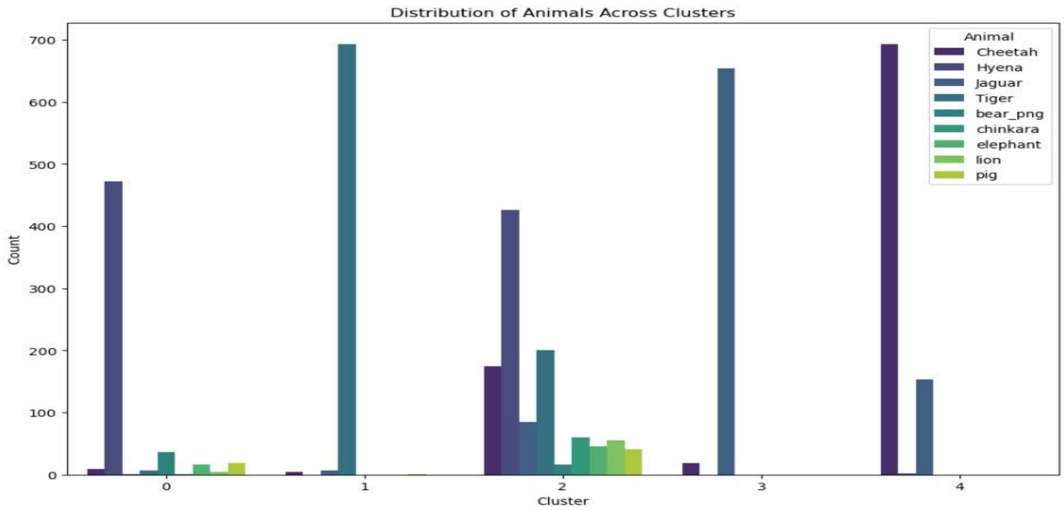
4.2 DATASETS:

4.2.1 Animals Detection Images Dataset

https://www.kaggle.com/datasets/antoreepjana/animals-detection-images-dataset

4.2.2 wild animal detection and alerting system

https://www.kaggle.com/datasets/arbethi/wild-animal-detection-and-alerting-system



The graph “Distribution of Animals Across Clusters” visualizes how the images of animals are grouped into different clusters after applying the K-Means clustering algorithm. Each bar represents a cluster, with its height indicating the number of images assigned to that cluster. This helps in understanding the effectiveness of the clustering process and the distribution of animal images across the clusters.

5. Benchmarking Alternate Products

Various wildlife monitoring solutions are available, though they typically lack real-time detection capabilities or are prohibitively expensive for small farms. Common systems include:

- **Traditional CCTV Systems**: Offer basic, continuous surveillance but lack real-time alerts and species differentiation.
- **Motion Sensor Cameras**: Provide energy efficiency and basic alerts but can be prone to false positives from non-animal movements.
- **High-End Drones**: Cover large areas but are costly and require specialized training.

The proposed Animal Intrusion Alert System differentiates itself by using CNN to identify animals accurately, thereby providing actionable insights in real-time and allowing for cost-effective, automated monitoring.

6. Applicable Patents

To ensure legal compliance and avoid patent infringement, a thorough patent search was conducted:

- **AI-Driven Animal Detection**: Focus on patents related to CNN-based animal recognition and classification models, verifying that open-source or non-restricted methods are used.
- **IoT Surveillance Systems**: Ensures adherence to existing patents covering wireless connectivity between sensors and cloud platforms.
- **Automated Alerting**: Identifies and respects existing intellectual property in automated alert generation methods based on real-time video or image processing.

7. Applicable Regulations

Ensuring regulatory compliance is essential for the system's legal deployment. Key regulations include:

- **Data Privacy Regulations**: GDPR and similar laws govern the collection, processing, and storage of data, ensuring user rights and data protection.
- **Wildlife Protection Regulations**: Compliance with the **Endangered Species Act (ESA)** and similar international guidelines ensures non-invasive and non-lethal animal monitoring.
- **Environmental Regulations**: Aligns with sustainability initiatives to promote eco-friendly agricultural practices and resource conservation.

8. Applicable Constraints

The system design accounts for constraints faced by target users:

- **Space Constraints**: Hardware components are compact, durable, and suitable for outdoor deployment.
- **Budget Constraints**: Open-source frameworks and cloud-based storage reduce costs, ensuring affordability for small farmers.
- **Technical Expertise**: A user-friendly interface and plug-and-play setup minimize the need for technical expertise.
- **Power Supply**: Energy-efficient hardware and optional solar power ensure continuous operation in rural areas with limited electricity access.

9. Business Model

The Animal Intrusion Alert System operates on a subscription model with three tiers:

- **Basic Tier**: Low-cost option for essential animal detection and real-time alerts.
- **Premium Tier**: Adds multi-animal detection and IoT hardware integration for medium-sized farms.
- **Enterprise Tier**: Customizable features with advanced analytics for large-scale farms or conservation areas.

Additionally, a **freemium model** offers basic functionalities to attract users who can upgrade for advanced features.

10. Concept Generation

The concept development phase identified the following core solutions:

- **CNN-Based Animal Recognition**: Enables accurate, real-time detection and prioritization of animal species.
- **IoT Integration for Continuous Monitoring**: Provides 24/7 coverage with real-time data transmission.
- **Automated Alerts and Data Logging**: Sends real-time alerts to users and stores data for future analysis and improved animal movement predictions.

11. Concept Development

The architecture of the Animal Intrusion Alert System includes:

- **Data Collection Layer**: IoT-enabled cameras capture real-time images, sending data to the AI processing unit.
- **AI Engine**: The CNN model processes incoming images, classifying animals by species and assessing threat levels.
- **Cloud-Based Storage**: Data is stored on a cloud platform, enabling scalability and secure access.
- **User Interface**: A mobile and web dashboard provides real-time footage, alert logs, and historical data for user analysis.

12. CODE IMPLEMENTATION:

GitHub link :

https://github.com/hishu-kmd04/Animal_Intrusion_alert_system_using_CNN

12.1 System Testing:

Table 12.1: Unit test cases

Test Case No.	Input	Expected Animal	Observed Animal	Status P=Pass F=Fail
1	 The input image contains a bear	Bear	Bear	P
2	 The input image contains tiger	Tiger	Tiger	P
3	 The input image contains lion	Lion	Lion	P
4	 The input image contains an	Elephant	Elephant	P

	elephant			
5	 The input image contains Hyena	Hyena	Cheetah	F

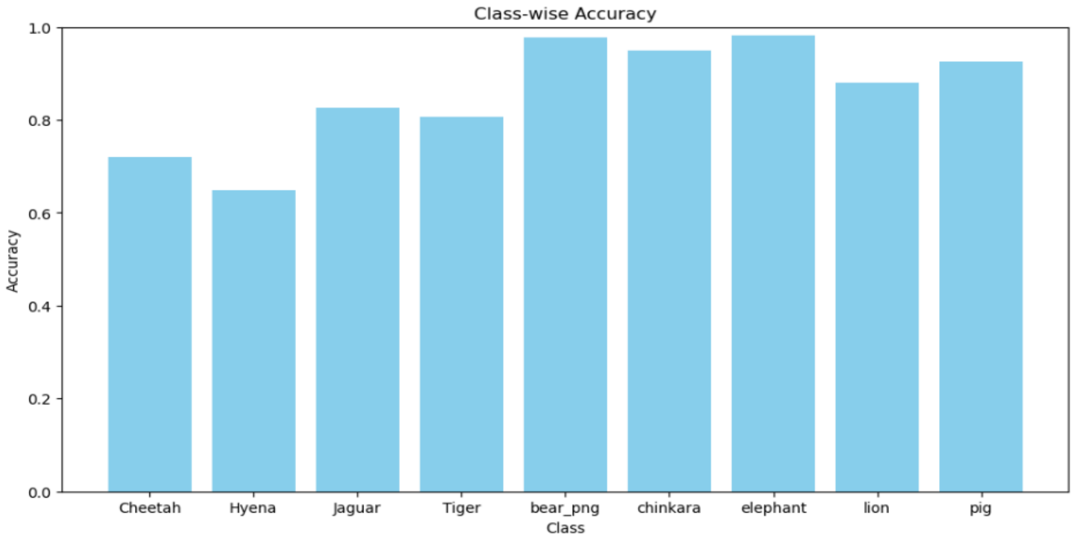


Figure 12.1: Analysis of the Class-wise Accuracy

Figure 12.1 shows the **Class-wise Accuracy** bar graph represents the precision (accuracy) of the model for each class. The X-axis denotes different classes in the dataset, while the Y-axis shows precision for each class, ranging from 0 to 1. This graph illustrates how accurately the model identifies each class, with higher bars indicating better performance for the corresponding class.

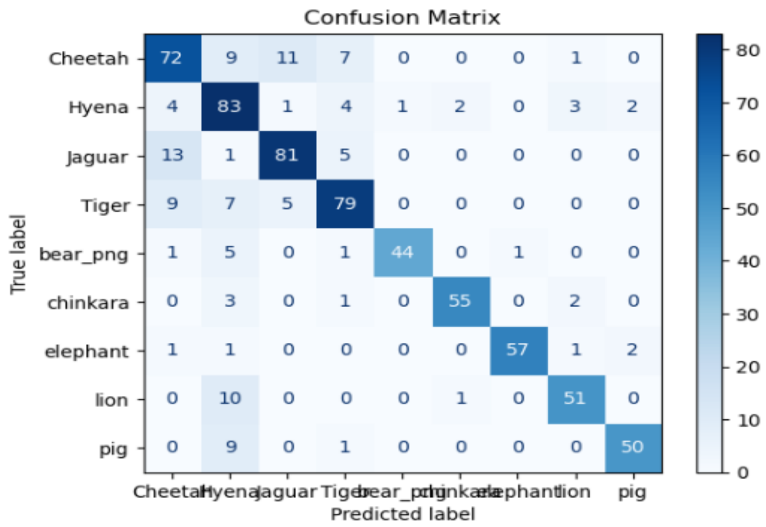


Figure 7.2: Confusion matrix

Figure 12.2 shows the **Confusion Matrix** graph visualizes the performance of the classification model by displaying the actual versus predicted class labels. In this matrix, rows represent actual classes, and columns represent predicted classes. Diagonal elements show the number of correct predictions for each class, while off-diagonal elements indicate misclassifications. Ideally, a perfect classifier would have non-zero values only on the diagonal, indicating perfect predictions.

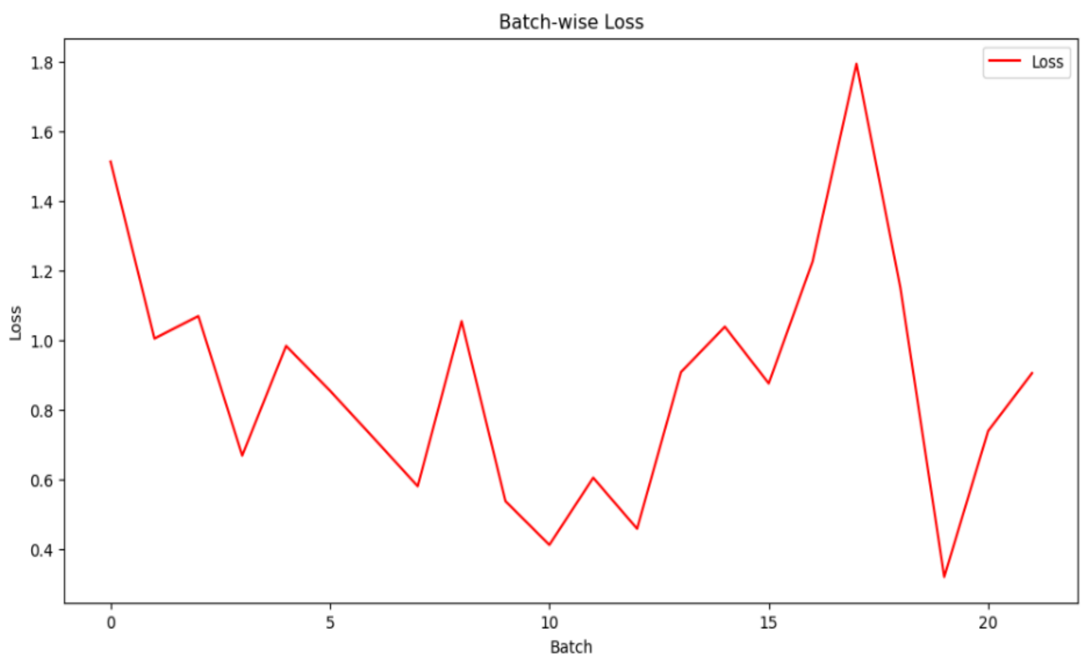


Figure 12.3: Batch-wise Loss

Figure 12.3 shows the **Batch-wise Loss** line graph shows the loss of the model for each batch in the test dataset. The X-axis represents the batch number, and the Y-axis shows the loss value for each batch. The line depicts how the loss changes as the model evaluates different batches, providing insight into the model's performance consistency across the dataset

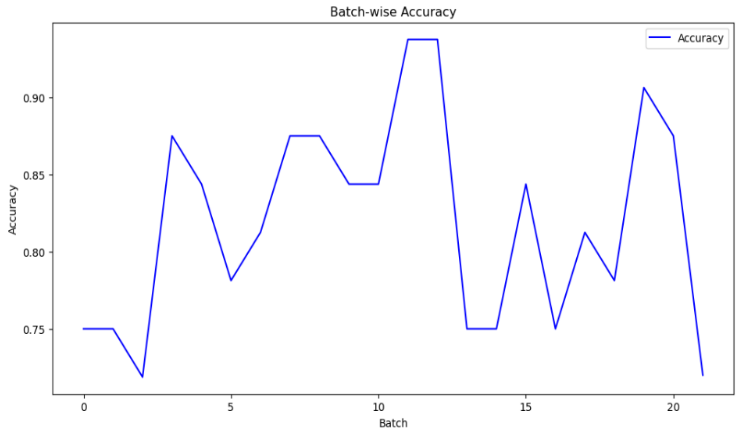
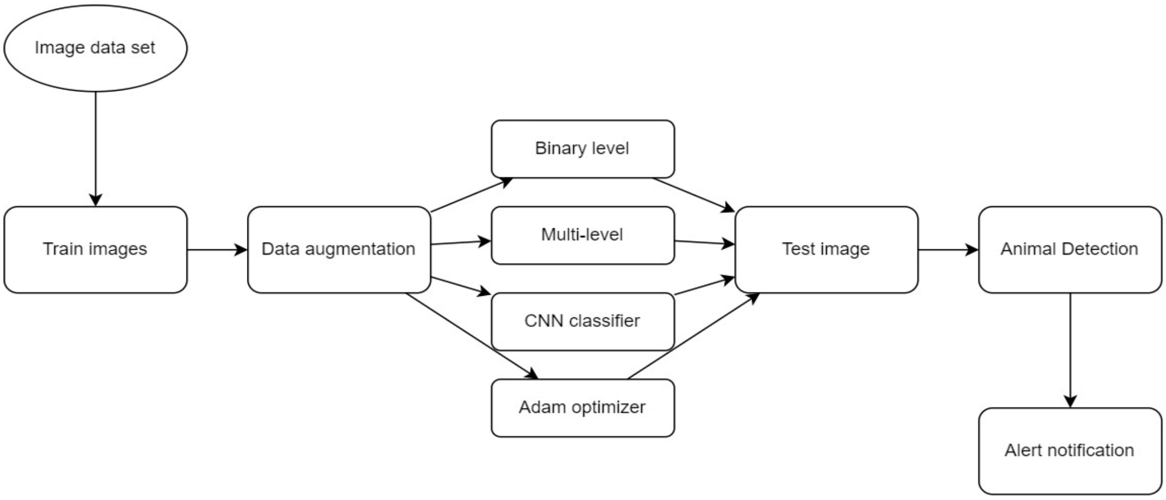


Figure 12.3 : Batch-wise Accuracy

13. Final Product Prototype

The final prototype of the Animal Intrusion Alert System includes:

1. **IoT Camera Network**: Strategically placed cameras that monitor animal movements continuously.
2. **AI Detection Module**: Processes images using CNNs, accurately identifying animal species and assessing threats.
3. **Cloud Storage and Processing**: Scalable cloud infrastructure for data management and real-time analysis.
4. **Automated Alert System**: Delivers notifications to users with detailed information on detected species and location.
5. **Mobile-Friendly Dashboard**: Allows users to monitor and manage alerts and settings from any device.



13.1 Result Analysis:

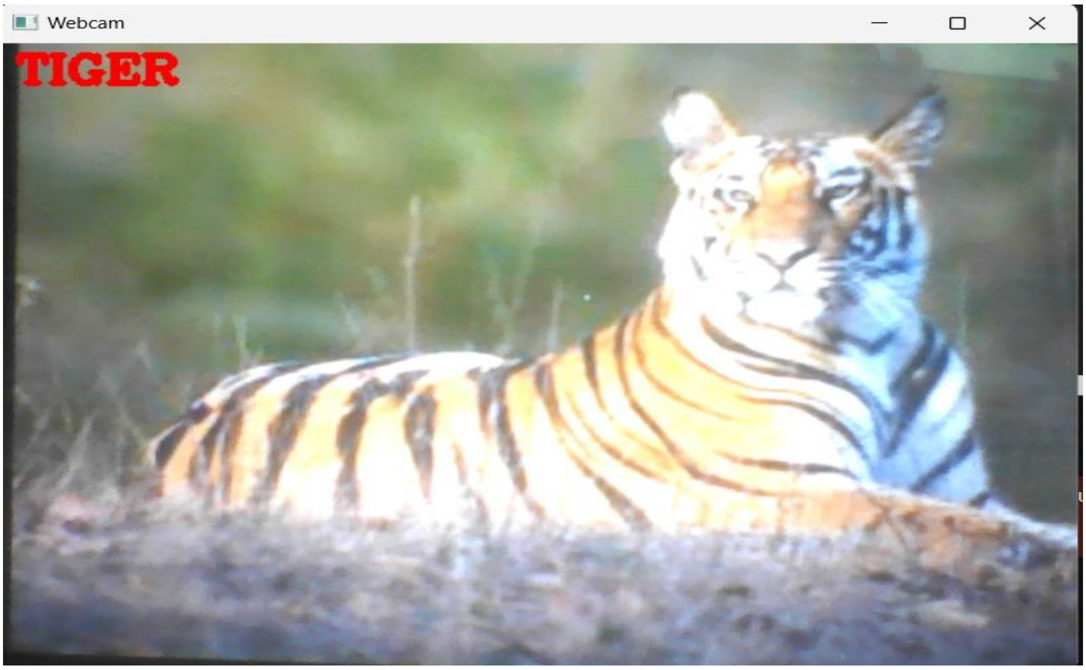


Figure 13.1: Captured image through webcam

The webcam captures video frames in real-time and processes each frame by resizing and normalizing it. The processed image is then fed into a pre-trained deep learning model to predict the class of the detected animal. The predicted class label is displayed on the video feed. If a wild animal is detected, the system saves the frame and triggers an email alert with the detection details.

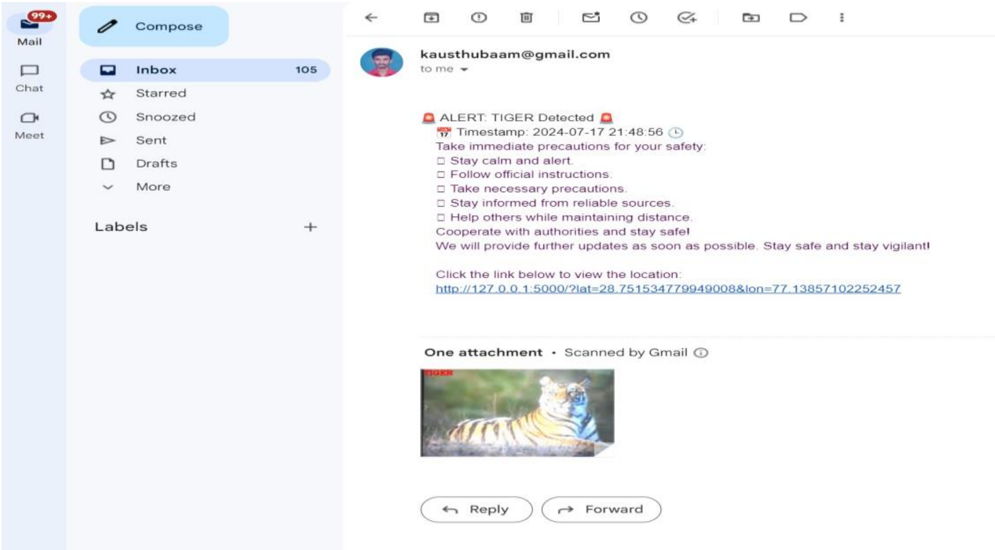


Figure 13.2: Email alert

When a wild animal is detected, the system sends an email alert with the subject "ALERT: TIGER Detected". The email contains the timestamp of the detection and a list of safety precautions to take. It also includes a link to view the animal's location on a map. An attachment of the captured image from the webcam is included in the email. This notification ensures immediate awareness and prompts necessary actions for safety.

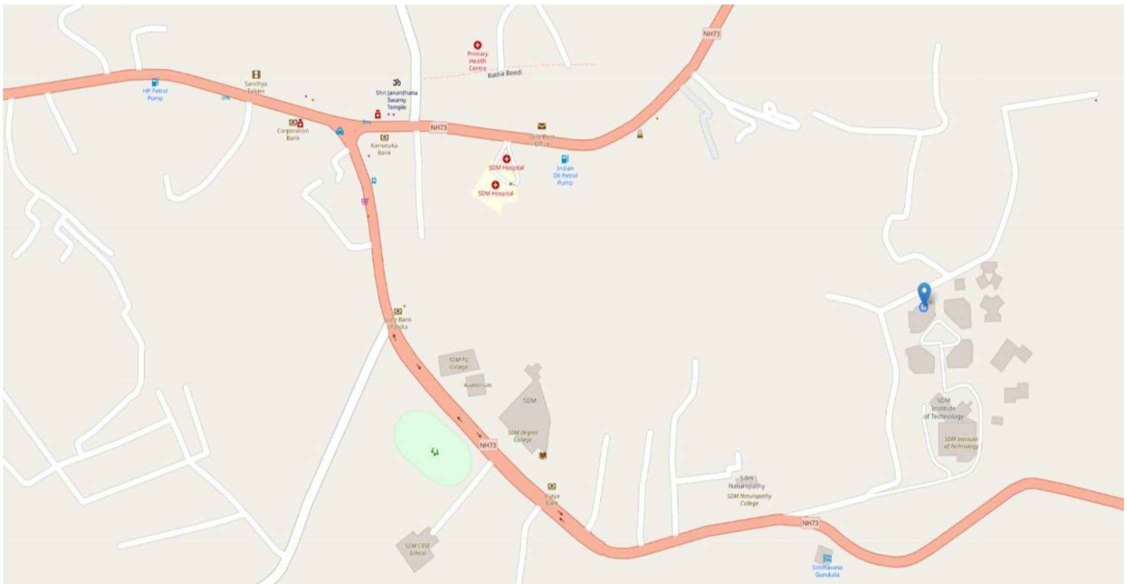


Figure 13.3: Location of detected animal

Figure 13.3 shows the precise location where the animal was detected. In the project, when the link in the email is clicked, it directs the recipient to the Flask web application, which displays this map image. This functionality ensures that recipients can easily view and understand the geographical context of the animal detection, providing a clear visual representation of the detection site

14. Product Specifications

- **System Operation**:
    - **Data Collection**: Cameras capture images triggered by motion or animal proximity.
    - **Real-Time Processing**: The CNN model processes images, identifying animals and determining risk levels.
    - **Alerts**: Alerts are sent directly to users' devices, detailing the species, location, and time of detection.
- **Core Technologies**:
    - **Algorithms**: CNN for animal detection, with predictive analytics for movement pattern recognition.
    - **Frameworks**: TensorFlow/Keras for machine learning, OpenCV for image processing, and Flask for web deployment.
    - **Data Sources**: Wildlife datasets, camera feeds, and environmental factors for refined detection and prediction accuracy.

15. Conclusion

The Animal Intrusion Alert System offers a transformative solution to human-wildlife conflicts in agriculture, merging AI and IoT for reliable, real-time monitoring. This system not only protects crops and livestock but also fosters a balanced relationship with local wildlife. Future improvements will include expanding animal detection databases and integrating predictive analytics to enhance response strategies.

BUSINESS MODEL

In this part of the report, we examine the business model best suited for the Animal Intrusion Alert System. While there are multiple options, we have selected a **Subscription-Based Business Model** that balances accessibility, scalability, and long-term value for users. This model offers tailored plans to meet diverse client needs, ranging from small-scale farmers to larger conservation groups.

SUBSCRIPTION-BASED BUSINESS MODEL

The subscription-based model allows clients to access a range of service tiers, each designed to meet different levels of monitoring needs. This approach ensures affordability and scalability, making it accessible to small farms and adaptable to larger conservation projects.

This model is ideal because:

- **Customization**: Each farm or conservation area may have different requirements, which can be met by adjusting the tier of the subscription.
- **Ongoing Value**: Regular updates and support are provided, enhancing the customer experience and maintaining long-term engagement.
- **Scalability**: Clients can expand their service tier as their needs grow, making this model flexible and sustainable.

PRODUCT DESCRIPTION

The product combines advanced technology with a user-friendly interface, which is accessible through a subscription tailored to the user's requirements. Below is a step-by-step outline of the product's deployment and usage:

1. **Client Onboarding and Requirements Assessment**
   Each new client goes through an initial setup phase where the team assesses their needs. For example, are they focused on a specific set of animal threats, or do they require continuous, full-area monitoring? This phase also sets the service scope, such as the frequency and type of alerts, or additional data requirements for conservation analysis.

2.System Installation and Training

Once requirements are clear, an account is created for the client on the system's platform. The client can log in to customize their settings, view real-time monitoring data, and access support. If clients are unfamiliar with such technology, team members assist with setup and provide training on using the interface and managing alerts.

3.Model Deployment and Calibration

The machine learning model is deployed, calibrated based on the client's environment, and tested for accuracy in detecting species relevant to the area. This phase is critical, as it ensures that the system is optimized for the client's unique conditions.

4.Reporting and Visualization

Upon model setup and initial data collection, a report is generated on the client's personalized account. This report includes visualizations of intrusion patterns and potential threat areas, enabling the client to make informed decisions. Clients can also provide feedback, which is valuable for system improvement.

5.Periodic Review and Optimization

Regular review meetings with the client ensure that the system remains aligned with their evolving needs. These sessions allow for feature adjustments or upgrades to higher service tiers if necessary.

This five-step process forms the foundation of the subscription model and can be modified based on individual client needs.

MARKET ANALYSIS

Rural agricultural areas adjacent to wildlife habitats face a persistent challenge in managing animal intrusions. Despite the clear demand for efficient wildlife monitoring, accessible solutions remain limited. As AI and IoT technology are not yet widely adopted in these areas, the potential for early entry into this market is significant. By addressing this gap, the Animal Intrusion Alert System positions itself as a high-value solution in the agricultural and wildlife management markets.

OPERATING PLAN

A well-structured operational approach is critical to delivering effective solutions:

- **Team Structure**: The development and deployment team includes machine learning engineers, data scientists, and user interface specialists. Ideally, at least one team member has familiarity with rural and wildlife management practices.
- **Deployment Timeline**: The project timeline for each client is determined based on their needs. Initial installations generally take 1-2 weeks, followed by another 1-2 weeks for calibration and model fine-tuning.
- **Pricing Strategy**: The subscription is priced affordably for small to medium farms, with a flexible model that allows clients to scale up as their needs grow. This ensures accessibility and aligns with the financial capacities of the target market.

MARKETING PLAN

The marketing strategy targets rural communities, conservation organizations, and agriculture associations. Key steps include:

1. **Outreach**: Develop partnerships with agricultural cooperatives and wildlife authorities to promote the system.
2. **Demonstrations**: Arrange demos to showcase the system's functionality and cost-saving potential.
3. **Client Referrals**: As the user base grows, word-of-mouth and referral discounts are expected to contribute significantly to market expansion.

FINANCIAL EQUATION

The system's financial model is built on predictable, recurring subscription revenue. Costs primarily include the salaries of development team members and cloud infrastructure expenses.

1. Determine the Product Unit Price

The new pricing structure for the Animal Intrusion Alert System is as follows:

- **Basic Plan (for small farms)**: ₹40,000 per unit.
- **Premium Plan (for large farms or wildlife authorities)**: ₹60,000 per unit.

These prices reflect the inclusion of additional features like load alarms, high beam lights, and the overall enhanced value of the system.

2. Estimate Operational Costs

The monthly operational costs remain the same, covering:

- **Cloud infrastructure**: ₹20,000
- **Customer support and maintenance**: ₹60,000
- **Marketing efforts**: ₹40,000
- **Hardware upkeep**: ₹40,000

Total Monthly Operational Cost: ₹1,60,000

3. Estimate Sales

Sales projections for the first month:

- **Basic Plan**: 30 units.
- **Premium Plan**: 10 units.

4. Calculate Total Revenue

a. Revenue from the Basic Plan

- **Product unit price**: ₹40,000
- **Estimated sales**: 30 units

Revenue from Basic Plan = ₹40,000 × 30 = ₹12,00,000

b. Revenue from the Premium Plan

- **Product unit price**: ₹60,000
- **Estimated sales**: 10 units

Revenue from Premium Plan = ₹60,000 × 10 = ₹6,00,000

c. Total Revenue

The total revenue from both plans is:

Total Revenue = ₹12,00,000 + ₹6,00,000 = ₹18,00,000

5. Deduct Operational Costs

From the total revenue, the operational costs of ₹1,60,000 are subtracted:

Net Revenue = ₹18,00,000 − ₹1,60,000 = ₹16,40,000

6. Conclusion

After selling 30 units of the Basic Plan and 10 units of the Premium Plan in the first month, and accounting for ₹1,60,000 in operational costs, the **net revenue** amounts to **₹16,40,000**.

Component	Cost per Unit
Revenue from Basic Plan	₹12,00,000
Revenue from Premium Plan	₹6,00,000
Total Revenue	₹18,00,000
Operational Costs	₹1,60,000
Net Revenue	₹16,40,000