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A Study on Wild and Domestic Animal Detection for Farm Protection by using Computer Vision

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Abstract

Crop protection against wild animal intrusion has become a pressing challenge with significant social and economic implications, particularly in agricultural-dependent nations like India. In response, an innovative AI-driven surveillance system is designed to detect and determine potential threats from animals to farm environments. The system accurately identifies and classifies animals in farm images by leveraging advanced computer vision techniques and machine learning algorithms, including Support Vector Machines, K-Means clustering, Random Forest, Decision Trees, and Logistic Regression. The model generalizes effectively by analyzing a diverse dataset comprising various animal species. Key features such as accuracy, precision, recall, F1-score, and confusion matrices are employed to assess model performance comprehensively. The results showcase high accuracy across multiple algorithms. The proposed system offers a promising solution to protect crops, minimize losses, and foster harmonious coexistence between farming and wildlife. The results demonstrate good accuracy for various algorithms: 92.75% for Logistic Regression, 86.47% for Decision Trees, 95.65% for Random Forests, and 94.20% for Support Vector Machines. This highlights how reliable the system is in classifying animals, providing a viable way to safeguard crops, reduce losses, and promote peaceful cohabitation between agriculture and wildlife.

Keywords: Animal Detection, Farm Protection, SIFT, Animal Intrusion, K Means

1. Introduction

This paper introduces a novel and cost-efficient approach to mitigate human-wildlife conflicts within the agricultural landscape of India. It advocates for the implementation of a photo-based animal detection system, complemented by targeted deterrents, as an effective strategy to safeguard crops and livestock while promoting coexistence between farmers and wildlife. India is heavily dependent on its agricultural sector. Agriculture is a major source of income for the majority of the population. Two-thirds of the population in India relies on agriculture for a living. The Gross Domestic Product (GDP) rate for agriculture in 2022–2023 was 18.3 percent, and in the first quarter of 2023, it generated Rupees 6071.31 INR billion. Despite the significant contribution of agriculture to the Indian economy, human-wildlife conflicts threaten farmer livelihoods and food security. Current methods for mitigating these conflicts, such as crop insurance and forest department interventions, have been insufficient in adequately protecting farmers. In their search for food, wild animals frequently come into contact with territory rich in crops. Some of these animals damage the crops, while others prey on the farmers' livestock, increase in human-wildlife conflicts.

Contrary to most other countries, farmers in India are remarkably tolerant when it comes to harming animals, yet because of the country's large population and the deaths that result from both sides, the conflict and loss concerns are among the worst in the world right now. According to some media sources, wildlife assaults cause crop losses totaling Rs.4000 Crore annually throughout India, resulting in a 40% decline in farmer income. However, the damages incurred due to such attacks have not been adequately compensated for by the insurance companies or the relevant forest departments, forcing the farmers to take desperate measures to defend their cattle and crops. Conflicts between people and animals have frequently resulted in incidents in the past; crops suffered significant damage, which led to the devastation of the economy and farmer life including pets in India. Elephant-human conflict is on the rise since they are one of the wildlife species that are most prone to it, especially in India. An innovative and economically effective strategy for animal security in agriculture is offered in this paper. A method for detecting animals from camera-acquired images is discussed here. When an animal is discovered, the sound of a specific siren is aimed at the animal in an attempt to scare it away.

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Animal detection and alarm systems to keep wild animals out of the farm fields were developed with the aim of minimizing the harm to the environment (Kommineni et al., 2022). Computer vision techniques were used to recognize animals, which helps to detect and identify the animal that try to enter the field. A loud sound was generated using the alarm system to drive the animals away. The system uses cameras positioned at potential animal entry points (Enathur et al., 2023), and the camera footage is processed using a pre-trained model of Mobile Net SSD. When an animal is detected, a siren is activated to alert the farmer. The system aims to detect wild animals before they enter crop fields (Ferrante et al., 2023) and implement appropriate scare-away mechanisms in real-time. The models process the captured images, and if the presence of an animal is detected, sudden flashes of light, ultrasound, and bee sounds are produced to scare away the animals. The literature discussed how accidents happen on the highway when the animal comes between the car and the driver is unable to control the speed (Caballero and Beltrán et al., 2018). Algorithms and techniques were proposed to calculate the distance, convert pixel values into meters, and how a system would send an emergency alert to the driver in the car. This research presents an object detection technique based on a Deep convolutional neural network that not only identifies but also classifies the observed object in an image (El Abbadi and Alsaadi, 2020). These deep networks often integrate low/mid/high-level features and classifiers in a multilayer way, with the number of stacked layers reinforcing the feature levels. This system presents and compares a variety of animal-vehicle techniques. Furthermore, various prominent proposed systems are explored, and a comparison of their benefits and drawbacks is offered. The difficulties in developing a reliable animal recognition system were summarized, and a proposed model for a camel-vehicle accident-avoidance system was offered. The system proposed a smart farm protection system that uses Raspberry Pi, PIR sensors, and CNN Network to detect and classify animals that intrude on farmland (Lekhaa and Sumathi, 2022). The system captured images of the intruded animals using a Pi camera and classified them as wild or domestic using CNN. The system then generated sounds to ward off the creature and send an SMS to the landowner in case of wild animal intrusion. The system is effective in driving animals off the fields and precisely detects the animals in the fields. The impact of illumination on object detection was investigated, and a Night Vision Detector (NVD) specifically designed for low-illumination scenarios was presented (Xiao et al., 2020). The proposed NVD incorporated Feature Pyramid Fusion Network (FPN) and Context Fusion (CF) Net to enhance the detection performance, especially for small objects. The experiments demonstrated that the NVD outperforms the basic RFB-Net, achieving 0.5% to 2.8% higher precision on COCO evaluation metrics. The system implemented an object recognition algorithm for night scenes using a combination of DCGAN and Faster R-CNN (Wang and Liu, 2020). The DCGAN is employed to generate virtual samples by establishing a spatial distribution relationship between nighttime and daytime scenes. These virtual samples were then used to train the Faster R-CNN model. The project aimed to identify animals that damage crops and to monitor them more efficiently (Rey et al., 2017). The algorithm classified animals based on their images. The proposed system used the YOLOv3 algorithm to detect real-time objects, including model weights, a prediction, and loss function. The article aimed to prevent wild animals from entering farm fields and causing damage to property and crops (Sowmya et al., 2022). System architecture with four modules: object detection, feature extraction, SVM classifier, and an Android application was described for alerting farmers about the intruder. The article discussed the process of finding key points, assigning orientation to each key point, and generating SIFT features. The article concluded by stating that the proposed system can help farmers take necessary actions to prevent damage caused by wild animals. An acoustic-repellant device based on machine learning for safeguarding crops against wild animal attacks was developed (Ranparia et al., 2020). An animal sound-based detection system was developed to keep animals away from crops. The device was developed to detect animal sounds and respond with a sound that is unpleasant to the animal using machine learning methods. The study also analyzes the system's performance in field tests. The article described an intelligent deep learning-based animal detection system that used a DarkNet deep learning model to classify animals and detect their presence in their natural habitat (Petso et al., 2022). The system was aimed to prevent animal-vehicle accidents and animals from destroying agricultural lands. The proposed system included an Arduino controller and a GSM module to alert the animal presence to the people. The system can be installed in dangerous spots to prevent animal intrusion near forest borders and agricultural land, and it can work automatically without human intervention. Highway accidents due to animals crossing the roads were avoided by detection and warning systems (Nowosielski et al., 2020). The system employs object sensors, sound generating devices interfaced with an Arduino module to identify animal trespass in agriculture fields. The crop field nodes are outfitted with sensors that detect animal ingress at the farm barrier and report it to the central base station. When these nodes receive this information, they activate deterrent devices and direct the animal away from the field. The system includes a Zigbee application that can communicate with a several co-located sensors, each detecting one of several possible warning situations. Farmers will benefit from the proposed method in terms of field protection and cost savings. The attacker model, ROC curve, and system architecture are also covered in the literature. A deep learning-based system was developed to detect animals in farm areas to prevent crop damage without harming the animals (Ananth et al., 2024). By monitoring the farm through cameras and using machine learning techniques like convolutional neural networks, the system aims to detect animals entering the farm and play sounds to deter them. This innovative approach addresses the significant issue of animal intrusion in agricultural lands, providing a cost-effective and proactive solution for farmers to protect their crops. The study emphasizes the importance of using technology to mitigate human-wildlife conflicts and safeguard agricultural yields while ensuring animal welfare. The paper highlights the shift towards non-intrusive methods like camera traps. It explores the challenges of learning from noisy labels in deep neural networks and presents two methods to address this issue. The paper delves into animal classification systems, focusing on animal breed classification using benchmark datasets like Columbia Dogs with Parts. It also covers animal detection systems based on visible images, showcasing various techniques and models used for animal detection and classification (Battu and Lakshmi, 2023).

All the studies reviewed here provided data, observations, and answers to a variety of issues; however, there is a glaring research gap in animal detection. Previous work on computer vision-based animal detection for farm safety has significantly increased the effectiveness of monitoring and protecting agricultural assets. There are still a number of significant research gaps that need to be filled. First of all, there is a conspicuous dearth of standardized datasets that are especially suited to the wide variety of farm animals and climatic conditions. The application of established models to actual farm scenarios is constrained because existing datasets frequently concentrate on particular species or controlled environments. Second, there is a lack of studies on behavior recognition, crucial for spotting anomalies or signs of livestock distress. In contrast, many studies have concentrated on the detection of specific animals. As a result, small-scale and subsistence farmers have limited access to cost-effective and user-friendly animal detection technology. The resilience and dependability of computer vision models in various lighting, weather, and terrain conditions are further concerns that still need to be fully resolved. these research gaps must be filled to improve the efficiency and usability of animal detection systems for farm protection. This will ultimately help both the agriculture sector and animal welfare.

2. Materials and Methods

The proposed system methodology is built upon cutting-edge computer vision techniques, orchestrating an automated system meticulously designed to address the pressing issue of identifying and mitigating animal to agricultural farms. The approach leverages the formidable capabilities of machine learning algorithms, including Support Vector Machines (SVM), K-Means for clustering, Random Forest, Decision Tree, and Logistic Regression. The system diligently processes images acquired within the farm environment through a sophisticated interplay of these algorithms, rendering precise identification and classification of potential threats. In this work a technology-driven solution is proposed for farm protection. By integrating advanced computer vision with the robustness of machine learning, a level of automation is introduced that significantly enhances the ability of farmers to safeguard their agricultural assets. This proactive approach is intended to minimize the agricultural losses caused by wildlife intrusion. Through the strategic deployment of SVM, the model excels in classification tasks. It differentiates between friend and foe in the form of animals that may harm the farm. K-means clustering facilitates the grouping of similar patterns within the data, which aids in identifying recurring behaviors or animal types. Random Forest and Decision Tree algorithms offer ensemble support in making complex decisions, while Logistic Regression provides a probabilistic insight into the likelihood of specific events. The system's ultimate goal is to empower farmers with the means to protect their farms efficiently and intelligently. The proposed system enables early intervention and strategic decision-making by automating threat detection and classification. This holistic approach not only minimizes potential losses but also fosters sustainable coexistence between farming and wildlife, making it a pivotal step forward in modern agriculture. This research utilizes a processing system equipped with a 64-bit Windows Operating System, an Intel Core i5 processor and 8GB RAM for computational tasks. Figure 1 provides an overview of the proposed AI-driven surveillance system. A comprehensive dataset is assembled featuring a variety of farm-threatening animals. This dataset is the foundation of the proposed system, enabling precise intruder detection and positioning. Consequently, it is a pivotal asset in safeguarding farms against potential threats. The preprocessing techniques, such as image scaling, feature extraction, and object recognition, are vital to the system's ability to monitor and protect farms against potential attacks. Visual data representation is used to create insightful graphs and charts to improve the project's analytics and findings, making it a powerful tool for efficiently communicating outcomes and insights. A wide range of mathematical and statistical processes makes the analysis jobs. The feature set is extracted and stored in CSV (Comma-Separated Values) files to store and exchange structured data. It is a standard format for saving and exchanging datasets, allowing for simple data storage and retrieval in tabular form. Data preprocessing, model selection, and evaluation are carried out. Classification, regression, clustering, and model evaluation are carried out using machine learning techniques.

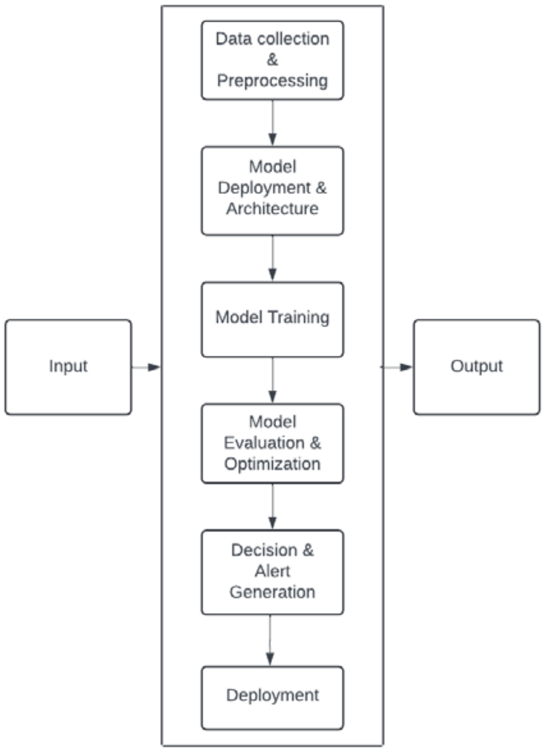

Figure 1. Procedural flow

Table 1 presents a breakdown of the dataset, illustrating the quantity of images contained within each folder. The dataset encompasses a wide variety of animal images. The animal species generally categorized as distractors of agricultural yield are selected. This deliberate diversity is a strategic advantage as it contributes significantly to the overall effectiveness, adaptability, and resilience of the machine learning model. The images were included from diverse sources and categories, to ensure that the model is exposed to a rich blend of visual information. This exposure enables the model to generalize better, accurately processing and classifying images it has not encountered during its training phase.

Table 1. Dataset information

Animal	**Total Number of Images**
Bull	45
Cattle	70
Elephant	155
Horse	400
Leopard	125
Monkey	770
Pig	190
Rabbit	215
Ship	100
Total Number of Images	**2070**

The enhanced generalization and robustness are pivotal when applying the model to real-world scenarios where the appearance of objects or animals may vary significantly. This diversity of animal images within the dataset serves as a crucial asset, empowering the machine learning model to perform effectively and reliably across a wide range of applications, including but not limited to species identification, object recognition, and environmental monitoring.

Resizing all the images is carried out. Resizing involves interpolating the pixel values to fit the new size. Shrinking an image may result in a loss of fine details, while enlarging an image may cause a loss of sharpness and introduce interpolation artifacts. Then, the images need to be blurred using smoothing and noise reduction techniques. It involves applying a filter or convolution operation to the image's pixels. This process averages or smoothens adjacent pixel values, reducing high-frequency components (details) in the image. Figure 2 (a) and (b) exhibit the effect on the images when they are blurred in original form.

Figure 2. a) Original Image b) Blurred Image

Figure 3 shows the images of different animals which were blurred, resized and detected edges or boundaries of it which was done using Canny Edge Detection technique. Edges play an important role in object recognition and shape analysis.

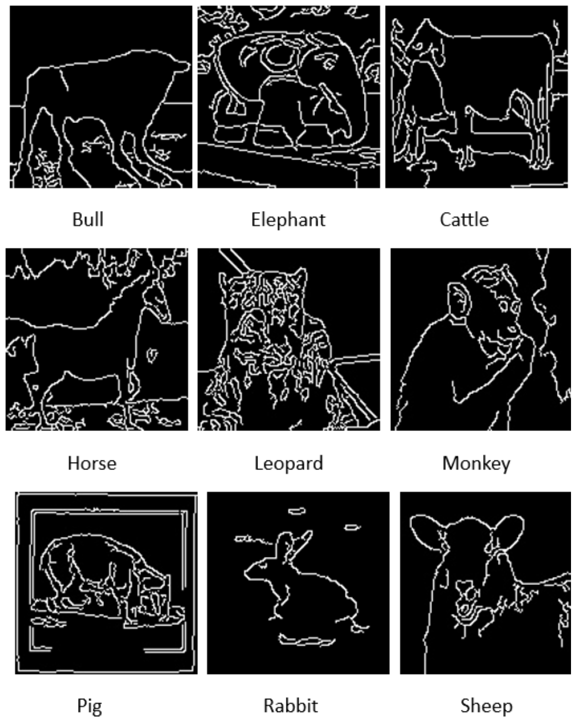

Figure 3. Canny edge detected images

Edge detection can assist in identifying and distinguishing objects within a picture. Edges aid in the extraction of essential features from an image. They are often used to show substantial changes in intensity or color. Edge detection through the Canny Edge Detection technique is an important step in the process of object recognition and shape analysis, as it contributes to the system's ability to detect and classify animals within the farm environment accurately. Figure 4 shows the feature-extracted images with key points marked using the Scale Invariant Feature Transform (SIFT) extraction technique. This plays an important part in extracting distinguishing elements from animal photos, which are then utilized for classification or recognition, such as identifying different animal species based on their animal traits. Using SIFT, the key points are detected, and descriptors are computed. These descriptors are essentially arrays of numbers that record the image's distinctive qualities, such as important feature locations, orientations, and scales. SIFT is a technique for extracting unique and resilient features from images. These are typically based on the portions of an image and are not affected due to changes in scale, rotation, or illumination. This feature primarily aids animal detection in various ambient conditions throughout the day and night. SIFT characteristics are well-known for their robustness.

SIFT descriptors are vectors with 128 features. Working with high-dimensional data can be computationally costly, resulting in overfitting in machine learning models. K-means clustering is applied to deal with the large dimensionality of the descriptors. It attempts to categorize these descriptors into a set number of clusters. The centroids obtained by k-means clustering reflect the clusters. In this work, 17 clusters are found to be suitable. The descriptors for each image are then assigned to the closest centroid, significantly lowering the dimensionality of the descriptors. This simplified representation is significantly more compact and computationally efficient. This reduced dimensionality vector of 17 values is used to train the machine learning model. Because of the lower dimensionality, training and prediction times are faster, which improves the model's generalization performance.

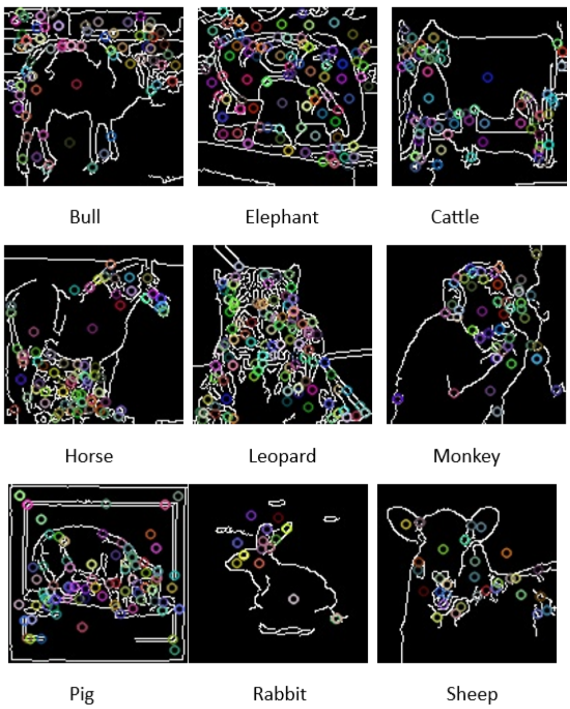

Figure 4. SIFT extracted key points

After extracting the SIFT features the high-dimensional data is reduced to low-dimensional data using k-means clustering. The clustered features of the data are formed through K-means clustering. These clusters form the basis for getting feature values of the images. These feature values are used to train machine learning algorithms. Logistic Regression, Decision Tree, Random Forest, and Support Vector Machines (SVM) were employed to classify animals accurately. The model's performance is assessed using a battery of critical metrics. Metrics like accuracy, precision, recall, and F1-score are used for model assessment. These metrics play a pivotal role in gauging the model's overall quality, allowing us to make informed decisions regarding model selection. Moreover, model optimization is carried out to achieve peak performance. This comprehensive evaluation process makes a reliable, and effective animal classification system. Figure 5 shows the system flowchart, which outlines the essential steps for building and evaluating machine-learning models for farm security and animal detection. It begins with data preprocessing, including image import, blurring, grayscale conversion, thresholding, and Canny edge detection.

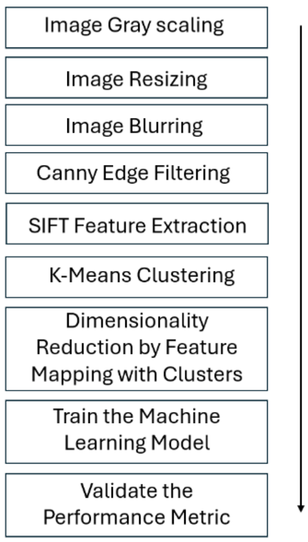

Figure 5. System block diagram for classifier training

Next, it performs feature extraction using SIFT and applies k-means clustering. Then, the data is split into training and testing the model. The study explores diverse algorithms such as SVM, Logistic Regression, Random Forest, and Decision Trees. Evaluation metrics, including accuracy, recall, precision, F1 scores, and confusion matrices are used to explain model performance. The final step involves selecting the most suitable model based on the evaluation results, offering insights into improving farm security and animal detection systems.

The mathematical equations are given in Eq. 1 to Eq. 5 present the performance metric of model training, and evaluation. These are critical for interpreting data and creating measures for the farm security and animal detection systems.

$$Real\ width = \frac{bounding\ box\ width}{image\ width\ in\ pixels} real\ image\ width \quad (1)$$

$$Real\ height = \frac{bounding\ box\ width}{image\ width\ in\ pixels}\ real\ image\ height \quad (2)$$

Logistic Regression Equation:

$$p\left(y = \frac{1}{x}\right) = \frac{1}{1+e^{-(b0+b1*x1+b2*x2+\cdots)}} \quad (3)$$

$$Accuracy = \frac{(Correct\ Predictions)}{Total\ Predictions} \quad (4)$$

Distance Calculation using Camera Parameters:

$$Distance = \frac{focal\ length*object\ height}{image\ height\ in\ pixels} \quad (5)$$

Logistic Regression is an interpretable machine learning approach that uses the feature vector of 17 features from each image of the training dataset for training. It is an excellent tool for binary classification tasks. This work has been modified for multiclass classification. Decision Trees are used for feature selection and classification. It aids in the classification of animals in images based on extracted traits. It divides the data into branches at each node, making decisions depending on the values of the characteristics. Random Forest is an ensemble of Decision Trees. It integrates predictions from many trees to increase accuracy and prevent overfitting. Combining Decision Tree outputs improves classification performance, making it more resilient and accurate for image classification applications. SVM seeks the hyperplane with the most significant margin between classes. This hyperplane effectively divides data points into classes. It facilitates discriminating between animals and non-animals, as well as between different animal species. It can handle non-linearly separable data by transferring it into a higher-dimensional space with kernel functions. It recognizes data outliers or anomalies, which can assist a farm security system detect unusual or unexpected intruders.

3. Results and Discussion

In this section, a comprehensive exploration of the outcomes is carried out. The machine learning model performance is studied. The evaluation extends across of diverse algorithms, including Logistic Regression, Decision Tree, Random Forest, and SVM. This assessment identifies the strengths of each model's performance. Table 2 shows the performance of machine learning algorithms. The metrics utilized in the analysis include accuracy, precision, recall, and F1 Score, providing a multifaceted view of each algorithm's efficiency in the classification of animals. The proposed system aims to identify the superior-performing model and to find the process that contributes to its excellence. This in-depth examination attempts to improve the animal detection system's precision and overall effectiveness.

Table 2. Classifier performance metric (%)

	Accuracy	Precision	Recall	F1 Score
Logistic Regression	92.75	93.25	92.75	92.89
Decision Tree	86.47	87.19	86.47	86.36
Random Forest	95.65	96.33	95.65	95.81
Support Vector Machine	94.20	94.51	94.02	94.19

Figure 6 compares accuracy scores with and without Canny edge detection. It is seen that the Canny edge detection process significantly improves the classification performance of models. This technique enhances the models' ability to identify and classify animals in farm images, as reflected in the higher accuracy scores across all algorithms. Like accuracy, other metrics parameters, including precision, recall, and F1 score, were also seen to have improvement with canny edge detection as preprocessing technique. The utilization of Canny edge detection considerably enhances the accuracy and robustness of the proposed system, leading to notable improvements in these performance metrics compared to the results obtained without Canny edge detection.

Figure 7 presents a comprehensive visual representation of the performance of machine learning models with Canny Edge Detection. The bar chart illustrates the significant improvements achieved with Canny Edge Detection across multiple key metrics, including precision, recall, and F1 score.

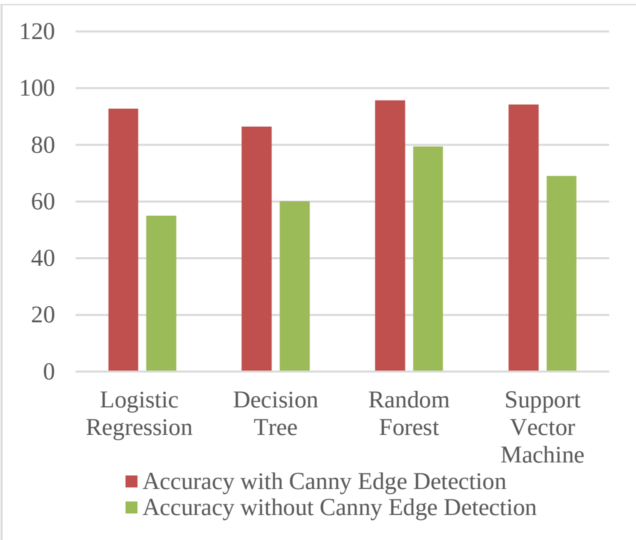

Figure 6. Accuracy of classifiers

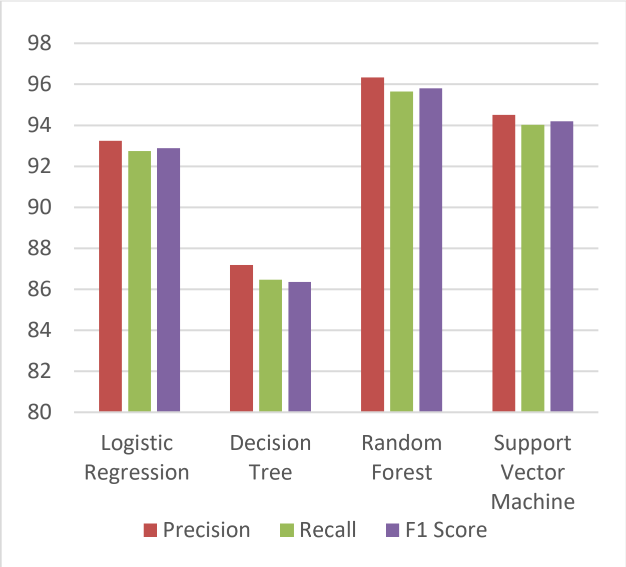

Figure 7. Classification performance of images preprocessed by Canny Edge Detection

Figure 8 displays the results of predictive models in the pickle file format. The outcomes appear as our predictive models identify the animal. The collective intelligence of the models is seen in the first image, which is a pig. Together, the models strongly identify the animal correctly as a pig. Such broad agreement demonstrates the models' robustness in classifying well-known subjects. However, the second picture, which shows an elephant, gives the story a fascinating new turn. While the other models disagree, classifying the image as a pig, the Decision Tree and Logistic Regression models correctly identify the image as an elephant. Even within the context of data-driven artificial intelligence, this forecasts discrepancy highlights how exciting and occasionally unanticipated machine learning results can be. The comparison of these photographs with their model-driven predictions in Figure 8 prompts us to consider the complex relationship between algorithms, data, and the quest for knowledge. It provides evidence of the complexity of predictive modelling. Additionally, using Canny edge detection emerges as a crucial enhancement strategy. Figure 6 visually represents the impact of Canny edge detection on accuracy scores.

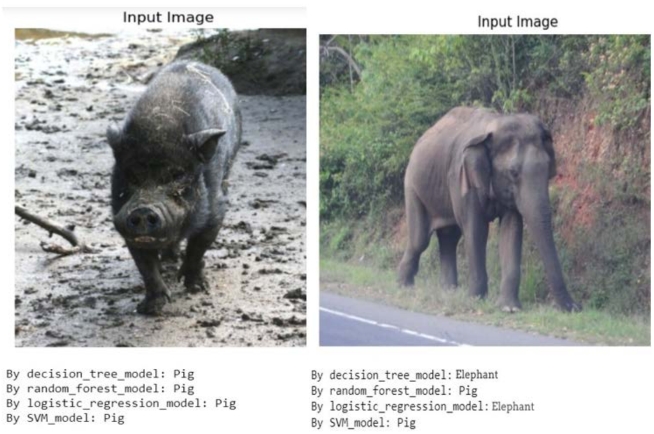

Figure 8. Image prediction

The proposed system showcases significant advancements in animal detection. The algorithms employed demonstrate notable accuracy and efficiency in classifying farm animals. The comparative analysis of classifiers accuracy and state-of-the-art comparison affirm the efficacy of proposed system, underscoring its potential for advancing animal detection systems in farm environments.

4. Conclusions

Crop damage caused by wild animals has emerged as a pressing societal concern demanding immediate intervention and practical solutions. The initiative is dedicated to mitigating this issue, carrying profound social implications. By developing this system, an effective mechanism is devised to take immediate measures to stop animals from invading fields. The proposed system is highly precise in pinpointing the presence of animals within the agricultural plots. This innovative approach ensures the protection of valuable crops on farms. Its potential benefits far surpass those of traditional methods, making it a promising alternative for agricultural purposes. In the comprehensive exploration of outcomes and analysis of machine learning models' performance in this work, it is evident that the Random Forest algorithm is the top performer, boasting impressive accuracy, precision, recall, and F1 scores. This model showcased effectiveness in classifying farm animals, offering promising advancements in animal detection systems for the farm environment. By harnessing the power of technology, crop protection strategies can be revolutionized, and economic losses caused by wildlife intrusion can be reduced significantly. In terms of other potential innovations, the following can be implemented. When intruders are spotted, implement automatic alert systems that can send messages or notifications to farmers. These notifications can be delivered via SMS, email, or IoT messaging networks. Data analytics can give farmers information on intruder patterns, farm activity, and potential risks. Also, when large animals are detected on farms, the siren can be activated, which will scare the animal.

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References

Ananth, S., Radha, K., Raju, S. 2024. Animal Detection In Farms Using OpenCV In Deep Learning. *Advances in Science and Technology Research Journal*, 18(1):1. doi.org/10.12913/22998624/ 173123

Battu, T. and Lakshmi, D.S.R. 2023. Animal image identification and classification using deep neural networks techniques. Measurement: *Sensors*, 25: 100611. https://doi.org/10.1016/j.measen.2022.100611.

Caballero, C.U.B. and Beltrán, Z.Z. 2018. Detection of traffic panels in night scenes using cascade object detector. In 2018 International Conference on Mechatronics, Electronics and Automotive Engineering (ICMEAE) (pp. 32-37). IEEE. https://doi.org/10.1109/ICMEAE.2018.00013

El Abbadi, N.K. and Alsaadi, E.M.T.A. 2020. An automated vertebrate animals classification using deep convolution neural networks. In 2020 International Conference on Computer Science and Software Engineering (CSASE) (pp. 72-77). IEEE.

Enathur, K., Sankar, E., Reddy, Y.R.K., Bhaskar, D. 2023. *Animal Detection in Farms Using Opencv*. (7-5):1-7. https://doi.org/10.55041/ IJSREM21340

Ferrante, G.S., Rodrigues, F.M., Andrade, F.R.H., Goularte, R., Meneguette, R.I. 2021. Understanding the state of the Art in Animal detection and classification using computer vision technologies, 2021 IEEE International Conference on Big Data (Big Data), Orlando, FL, USA, pp. 3056-3065, 10.1109/BigData52589. 2021.9672049.

Kommineni, M., Lavanya, M., Vardhan, V.H. 2022. Agricultural farms utilizing computer vision (ai) and machine learning techniques for animal detection and alarm systems. *Journal of Pharmaceutical Negative Results*, 3292-3300. https://doi.org/10.47750/pnr.2022.13.S09.411

Lekhaa, T. R. and Sumathi, P. 2022. Airep: Ai And Iot Based Animal Recognition And Repelling System For Smart Farming. NVEO-Natural Volatiles & Essential Oils Journal|, (9-1):1873-1883.

Nowosielski, A., Małecki, K., Forczmański, P., Smoliński, A., Krzywicki, K. 2020. Embedded night-vision system for pedestrian detection. *IEEE Sensors Journal*, 20(16): 9293-9304. https://doi.org/10.1109/ JSEN.2020.298685

Petso, T., Jamisola Jr, R.S., Mpoeleng, D. 2022. Review on methods used for wildlife species and individual identification. *European Journal of Wildlife Research*, 68(1): 3. https://doi.org/10.1007/s10344-021-01549-4.

Ranparia, D., Singh, G., Rattan, A., Singh, H., Auluck, N. 2020. Machine learning-based acoustic repellent system for protecting crops against wild animal attacks. In 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS) (pp. 534-539). IEEE. https://doi.org/10.1109/ ICIIS51140.2020.9342713

Rey, N., Volpi, M., Joost, S., Tuia, D. 2017. Detecting animals in African Savanna with UAVs and the crowds. *Remote Sensing of Environment*, 200:341-351. https://doi.org/10.1016/j.rse.2017.08.026

Sowmya, M., Balasubramanian, M., Vaidehi, K. 2022. Classification of animals using mobilenet with svm classifier. In Computational Methods and Data Engineering: Proceedings of ICCMDE 2021 (pp. 347-358). Singapore: Springer Nature Singapore. doi: https://doi.org/10.1142/S0219519423400869

Wang, K. and Liu, M. Z. 2020. Object recognition at night scene based on DCGAN and faster R-CNN. IEEE Access, 8, 193168-193182. https://doi.org/ 10.1109/ACCESS.2020.3032981

Xiao, Y., Jiang, A., Ye, J., Wang, M.W. 2020. Making of night vision: Object detection under low-illumination. IEEE Access, 8, 123075-123086. 10.1109/ACCESS.2020.3007610.