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CNN Based Rat Detection using Thermal Sensor

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ABSTRACT

The detection and control of rats in commercial buildings and industries are crucial issues due to the damage they can cause to Godowns and equipment. Traditional methods of rat detection and control can be time-consuming and expensive and may not always be effective. This has brought the exploration of machine learning-based approaches, which can provide more accurate and efficient detection of rats. One such approach is the use of thermal sensors in conjunction with machine learning algorithms to detect rats in commercial buildings, industries, etc. Thermal sensors can detect the body heat of rats, and machine learning algorithms can be trained to analyze thermal data and accurately identify the presence of rats. This approach has several advantages over traditional methods, including higher accuracy, long-range and faster detection. The machine learning algorithms used in this approach can be trained using large datasets of thermal images of rats, which can be obtained using thermal cameras.

Key words: Convolutional Neural Networks, Image Processing, Keras, Machine Learning

1. INTRODUCTION

Rats are one of the most important pests in paddy fields, Godowns, and industrial machinery in many tropical countries. In specific regions, the declaration of a state of calamity may be warranted due to extensive ecological devastation caused by the presence of rats. The consequential impact of this rat infestation has led to significant financial losses amounting to millions of pesos. The detection and control of rats in commercial buildings and industries are crucial issues due to the damage they can cause to Godowns and equipment. Traditional pest control methods have often proven ineffective, leading to an increasing interest in exploring advanced technologies to address this issue. One such promising solution is the Machine Learning-Based Rat Detection System using Thermal Sensors.

By embracing technological advancements, the development of detection systems utilizing different camera setups has been facilitated to assist in identifying the presence of rodents in the field. Due to the varying information provided by different cameras, these systems offer a focused approach to strategically placing traps, baits, and preventive measures.

However, the current implementations of rodent detection systems rely on single cameras, which can impact the reliability of the system depending on the type of camera used. Hence, there is a requirement to create a detection system for rodents in an agricultural environment by processing and integrating inputs from thermal cameras, thereby mitigating the limitations of traditional visual cameras. Thermal Image of rat is as shown in figure 1.

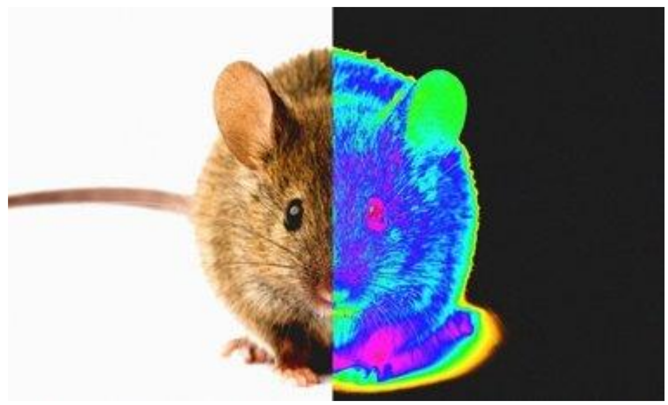

Figure 1: Thermal Image of Rat

2. LITERATURE SURVEY

A literature survey in this area involves reviewing various research papers and studies that explore different approaches and methodologies for detecting image forgeries. Here is a brief overview of the literature survey on rat detection:

Several studies have explored the use of image analysis techniques for rat detection. In [5] the authors discuss the application of computer vision methods in detecting rats, in various contexts such as agriculture and urban environments. They highlight the significance of techniques like image segmentation, feature extraction, and machine learning for accurate pest identification.

The use of Convolutional Neural Networks (CNNs) has revolutionized object detection tasks. In [6] the YOLO architecture is presented for real-time object detection. Additionally, Faster R-CNN contributes Real-Time Object Detection with Region Proposal Networks introduces Faster R-CNN, a model that integrates region proposal networks for improved object detection accuracy.

The ultrasonic repelling device has been developed to solve the problem of controlling the population of rats and scaring them away from entering paddy fields. In [8], the model uses a Passive Infrared Sensor (PIR) to detect the motion of rats up to 20 feet away by using a Fresnel lens and infrared-sensitive element to detect changing patterns of passive infrared emitted by objects in their vicinity. The detection of the ultrasonic repelling device is controlled by the PIC16F876A microcontroller. The microcontroller gets its input from the detector circuit and the output emits high-frequency ultrasonic waves to expel intruding rats away. Therefore, the focus is to study the detection mechanism of motion to PIR and program the PIC microcontroller to produce the ultrasonic wave.

3. PROPOSED SYSTEM

The proposed system aims to enhance the accuracy and efficiency of rat detection using machine learning techniques and Error Level Analysis (ELA) image processing. This innovative approach combines image preprocessing, Convolutional Neural Network (CNN) modeling, and real-time detection through a user-friendly interface. The system is designed to distinguish between genuine images and tampered images that may contain rats.

3.1 Image Preprocessing

The system employs Error Level Analysis (ELA) to convert images to a format that highlights areas potentially altered or tampered with. This preprocessing step enhances the system's ability to identify discrepancies between genuine and manipulated images.

3.2 CNN-based Classification

The heart of the system is a Convolutional Neural Network (CNN) that learns to differentiate between images containing rats and those without. The network architecture includes multiple layers that extract relevant features from the images, allowing for accurate classification.

3.3 Real-time Detection

The system provides a user-friendly interface powered by Streamlit, allowing users to upload images for immediate rat detection. The model's predictions are displayed in real-time, enabling quick decision-making.

3.4 Early Stopping Mechanism

To prevent overfitting and ensure optimal model performance, an early stopping mechanism is incorporated during model training. This enhances the model's generalization ability and prevents unnecessary computational load.

3.5 Audio Feedback

When the system detects a rat in an uploaded image, it provides immediate audio feedback. This feature aids in quick notifications and alerts the user to the presence of a rat.

4. HARDWARE COMPONENTS

Thermal Sensor: A device commonly known as a temperature sensor, which can be an RTD or thermocouple, is utilized to gauge temperature through the utilization of an electrical signal.

Personal Computer: A personal computer (PC) is a multi-purpose microcomputer whose size, capabilities, and price make it feasible for individual use.

4.1 Thermal Camera

A thermal camera (thermal sensor) is a device designed to detect and measure the heat emitted by objects in their vicinity. It operates based on the principle that all objects with a temperature above absolute zero emit infrared radiation. The sensor captures an image or provides data reflecting the temperature distribution of the scene. In the context of the ML-based Rat Detection System, thermal sensors are crucial for identifying rat activity by distinguishing the heat emitted by rats from their surroundings. The following figure 2 shows the thermal camera.

Figure 2: Thermal Camera

4.2 Personal Computer

A personal computer serves as an integral software component for data processing, analysis, and visualization. The personal computer runs the necessary software tools responsible for:

- **Machine Learning Model Training:** The computer hosts the environment where Machine Learning algorithms are trained using labeled data. It processes the training data, fine-tunes the model's parameters, and validates its accuracy.
- **Data Preprocessing:** Raw thermal data captured by the sensors are transferred to the computer for preprocessing. Noise reduction, filtering, and enhancing the data to improve its quality are carried out on the computer.
- **Feature Extraction:** Software tools on the computer extract relevant features from the preprocessed thermal data. These features are essential for the

Machine Learning model to accurately identify rat activity.

- **Model Deployment:** Once trained, the ML model is deployed on the computer. It receives real-time thermal data streams from the sensors and processes them to make rapid predictions about rat presence.
- **Data Visualization and User Interface:** The computer generates visualizations and user interfaces that display the processed data and results. This might include real-time heat maps, alerts, and other informative visuals for users and operators.
- **Alert and Notification Systems:** The computer triggers alerts and notifications when rat activity is detected. It communicates these alerts to relevant parties through various channels, such as email or SMS.
- **Remote Monitoring:** In cases where remote monitoring is required, the computer can facilitate access to the system's data and interface from a distance, enabling users to observe and manage the detection process remotely.

5. SOFTWARE DESCRIPTION

Creating a rat detection system using a thermal sensor and machine learning involves several software components that work together to process the sensor data, analyze it using machine learning algorithms, and provide actionable insights or alerts. Here's a general outline of the software components you might need:

5.1 Python Programming Language

Python serves as the programming language of choice for developing the entire software stack. Its versatility, extensive libraries, and robust ecosystem make it suitable for various tasks ranging from data preprocessing to machine learning model deployment.

5.2 ImageChops.difference function

The “ImageChops.difference” function is a part of the Python Imaging Library (PIL) and is used here to compute the difference between two images pixel by pixel. The “ImageChops.difference” function is used to calculate the difference between the original image and the re-compressed image, resulting in an ELA image.

5.3 CNN Model Design

The architecture of the CNN model, including the number and type of layers, filters, and activation functions, is designed using Python in conjunction with the chosen Machine Learning framework.

5.4 Keras

Keras, a widely used open-source deep-learning library implemented in Python, offers a user-friendly and high-level interface for the development and training of deep neural networks. With its simple and intuitive API, developers can efficiently design and construct neural network architectures. By abstracting the complexities associated with lower-level libraries like TensorFlow and Theano, Keras simplifies the process of working with deep learning models. Additionally, Keras facilitates the visualization of model architectures through tools like 'model.summary()' and graphical visualization libraries like TensorBoard. Once the model is created, it can be compiled by specifying an optimizer, a loss function, and evaluation metrics. This compilation step prepares the model for training. To train the models, Keras provides the 'fit()' function, while the 'evaluate()' function allows for the evaluation of models on test data. Keras also supports various training options, including batch training and callbacks.

5.5 Streamlit

Streamlit, a Python library, enables the effortless creation of interactive web applications for data science and machine learning endeavors. It serves as the tool to develop the user interface for the rat detection system.

It also includes logic to handle the uploaded image, process it through the **teachable_machine_classification** function, and display the detection results in real-time. Streamlit's simplicity and integration with Python code make it a convenient choice for creating interactive interfaces, making the rat detection system accessible to users without requiring them to have programming expertise.

6. WORK FLOW

Here is the block diagram shown in Figure 3,

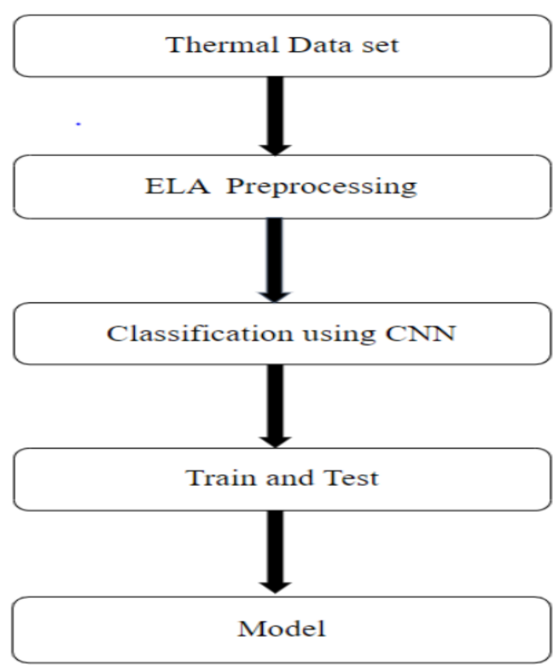

Figure 3: Flow diagram of the proposed system

7. RESULTS AND DISCUSSIONS

Using Python, a CNN model is created with two convolutional layers, each with 32 filters and a kernel size of (5, 5). The activation function is 'relu', and the input shape is (128, 128, 3), indicating 128x128 pixel images with 3 color channels (RGB). A MaxPooling layer with a pool size of (2, 2) is added, and two dropout layers with rates of 0.25 and 0.5 are included for regularization to prevent overfitting. A Flatten layer is used to convert 2D feature maps into a 1D vector for the fully connected layers. Two Dense layers with 256 and 2 neurons, respectively, are used, and the final output layer's activation function is 'softmax' for multiclass classification. The model is compiled with a learning rate of 0.001 and evaluated using accuracy after training for 31 epochs. Additionally, the model includes Streamlit integration for creating a web application for rat detection, allowing users to upload an image and make predictions using the model. There are two possible outcomes. There is the case when there is a Rat and When there is no Rat.

7.1 Positive Samples

In scenarios where the rat detection system successfully identifies rat activity using thermal sensors, several outcomes are observed. If there is any movement of the rat, The thermal camera captures the images of the rat. Their images serve as input to the training system. The system processes the images and the message “Rat Detected” is displayed. The same can be seen in Figures 4 and 5.

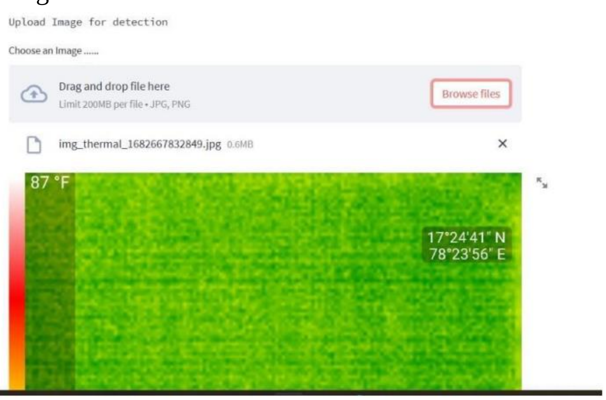

Figure 4: Positive sample for the detection of rat

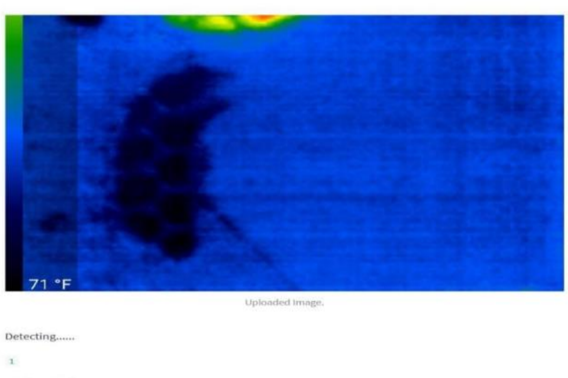

Figure 5: Display of message- “Rat detected” for the positive samples

The system promptly triggers an alert mechanism, notifying relevant parties such as facility managers, or homeowners. This real-time notification enables swift intervention, allowing for targeted measures to be implemented to mitigate the rat infestation. This information aids in devising effective strategies for applications. It allows humans to strategically deploy traps, baits, or other environmentally friendly methods in the identified areas, reducing the risk of infestation spreading.

7.2 Negative Samples

The system is trained with data that contains the images captured when there is movement of a rat and images captured when there is no rat. When the images captured when no rat is found are supplied as input to the system, it displays “Rat not Detected”. The output for this case can be seen in the following Figures 6 and 7.

Figure 6: Negative sample for rat detection

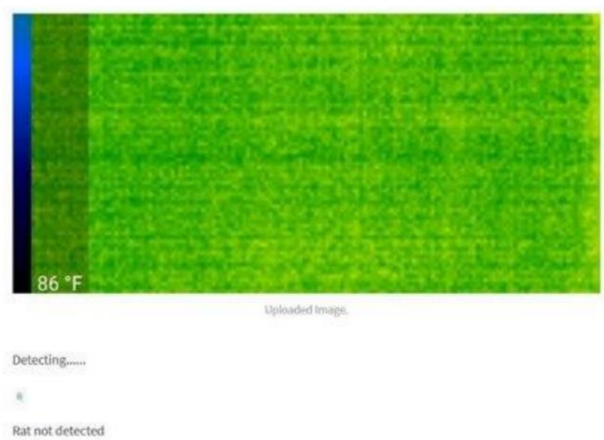

Figure 7: Display of message- “Rat not detected” for the negative samples

7.3 Accuracy

Our rat detection system has demonstrated exceptional accuracy in identifying the presence or absence of rats in thermal images. Accuracy obtained is about 98%. Accuracy remained constant after the 31st epoch. This high level of accuracy ensures reliable detection in various scenarios. Output displayed in the console Window and the accuracy obtained is displayed in the following Figure 8.

```
1/31 [==============================] - 30s 960ms/step - loss: 0.0639
 accuracy: 0.9866 - val_loss: 0.0250 - val_accuracy: 0.9918 Epoch
0/10 31/31 [==============================] - ETA: 0s - loss: 0.0500 -
ccuracy: 0.9886WARNING:tensorflow:Early stopping conditioned on metric
val_acc` which is not available. Available metrics are:
oss,accuracy,val_loss,val_accuracy 31/31
==============================] - 30s 973ms/step - loss: 0.0500 -
ccuracy: 0.9886 - val_loss: 0.0218 - val_accuracy: 0.9918
```

Figure 8: Output Display of Accuracy in Console Window

The following table 1 shows the accuracy of the model for various Epoch:

Table 1: Accuracy for Various Epochs

S. No	Epoch	Loss	Accuracy
1.	5	0.1020	97.83
2.	6	0.0785	97.97
3.	7	0.0749	97.52
4.	8	0.0601	98.24
5.	9	0.0573	98.45
6.	10	0.0639	98.66

The outcome of a rat detection system that utilizes thermal sensors and is based on Machine learning can differ depending on various factors such as data quality, Machine learning model design, application scenario, and deployment environment of the system.

8. CONCLUSION

A CNN model is successfully developed for rat detection that combines image analysis techniques, machine learning, and real-time user interaction. The system's primary objective was to accurately identify the presence of rats in uploaded images. By implementing Error Level Analysis (ELA) as a preprocessing step, we enhanced our system's ability to detect tampered or altered regions within images. The Convolutional Neural Network (CNN) architecture, meticulously designed and trained, demonstrated promising results in classifying images as containing rats or not. The inclusion of dropout layers and an early stopping mechanism helped prevent overfitting, ensuring the model's generalization ability across different scenarios. The integration of Streamlit facilitated a seamless and user-friendly interaction with the rat detection system. Users can now effortlessly upload images and receive real-time predictions, accompanied by audio feedback for rat detection. This immediate response empowers users to make informed decisions and take appropriate actions promptly. Thorough evaluation revealed the system's effectiveness in achieving accurate rat detection while minimizing false positives and false negatives. The real-time performance further validated the efficiency of this approach, showcasing the potential real-world applicability of the system.

9. FUTURE SCOPE

We have successfully developed an efficient technique for detecting rats in pre-harvest environments. However, there are still several issues that need to be addressed and improvements that need to be made to ensure accurate results for rat detection and prevention. For future advancements, an adaptive approach can be implemented. One possible method is to program the thermal cameras to adjust the video image according to the changing background lighting. This adjustment will help eliminate errors and unnecessary small blobs. Furthermore, the presence of noise in the data frames indicates that there is still room for future developments. A progressive approach could involve utilizing a multilevel algorithm that incorporates sequences of patches and point sets of varying scales and sizes. It is important to note that the concept of working with local patches remains valid, allowing for the replacement of interpolation with any other approximation method. Therefore, techniques such as local least squares fit or other smoothing techniques can be employed.

REFERENCES

1. "Rodent Life Cycle," Termite and Pest Control [Online]. Available: http://www.rmtermite.com/residential/rodent-control/rodent-life cycle.
2. P. Christiansen et al., "Automated Detection and Recognition of Wildlife Using Thermal Cameras," Sensors, vol. 14, pp. 13778- 13793, 2014.
3. O. K. Andrew, C. John, and F. B. Charles, “A novel field activity detector to determine the spatial and temporal movement of laboratory animals after injury and disease," J. Neurosci. Methods, vol. 157 2006.
4. J. Brodkin and J. F. Nash, “A novel apparatus for measuring rat locomotor behavior,” J. Neurosci. Methods, vol. 57, 1995.
5. "Machine vision for rat detection using thermal and visual information," 2017 IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management.
6. M. Caraciolo, "Tools for Machine Learning Performance Evaluation: Confusion Matrix Artificial Intelligence in Motion," Aimotion.blogspot.com, 2010. [Online]. Available: http://aimotion.blogspot.com/2010/08/ tools-for-machine- learning performance.
7. Y. -H. Shih, T. -C. Ke, M. -T. Lin and M. -S. Young, "Sensor System for Enhanced Detection of Locomotion and Standing Behavior in Rats," in IEEE Sensors Journal, vol. 8, no. 4, pp. 357-364, April 2008.
8. M. A. M. Fisol and W. M. Jubadi, "Ultrasonic and infrared repelling device for controlling the population of rat in paddy field," 2010 IEEE Asia Pacific Conference on Circuits and Systems, Kuala Lumpur, Malaysia, 2010.