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ARTIFICIAL INTELLIGENCE PERFORMANCE IDENTIFYING RODENTS IN IMAGES FROM CONNECTED CAMERAS

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Abstract Over the past several decades digital innovations have gradually been introduced into urban pest control. Nowadays pest control operators strongly rely on digital technology to fulfil their daily tasks. In 1992 Rentokil launched Mouse Alert, a trap with wireless communications. In 2004 remotely connected pest devices (radio communication and connected to Internet) were deployed for the first time, starting Rentokil's PestConnect system. In 2023, after several years of development, we incorporated connected cameras combined with Artificial Intelligence (AI). Using Machine Learning (ML), images taken by these cameras, specially designed for pest control, are analysed in order to autonomously identify pests. This process, with no direct human intervention, is not perfect. It is essential to find ways to improve the ML accuracy through direct training and pre- and post-processing of the results. Since AI does not result in 100% accuracy, a "human in the loop" is important to review output, measure the accuracy of the model and provide ongoing feedback and training. Around two million images have been taken by these cameras, with about 5% reviewed by a human. This is an ongoing and dynamic process, the latest evaluation results and interpretation for rodents will be presented. IoT, ML and AI are already improving urban pest management and have created huge expectations on how quickly they are becoming "game changers". But urban pest problems are complex, requiring multidisciplinary and evidence-based approaches. To keep improving, we must be critical with all our processes and tools, including our digital solutions.

Key Words Camera, Connected Pest Device, Artificial Intelligence, Machine Learning.

INTRODUCTION

Ever since humans established their first urban settlements, the unwanted presence of certain animals increased, and pest management became an important issue. Humanity has evolved and so have the techniques and knowledge to manage urban pests. But nowadays we face challenging times, United Nations expects world human population to reach 10 billion by 2050 and almost 70% will be living in urban areas. The rise of temperatures and the inexorable increase in the transport of goods and people, is causing pest to spread on a global scale.

The urban pest management industry plays a critical role in the preservation of public health and continues to innovate at a very rapid pace. Technological advances have been more and more present in its technician's daily routine for most of the last couple of centuries. But with the digital revolution, that started with the Information Age, in the mid-20th century, Urban Pest Management, as most of human activities, has undergone a huge transformation.

Communication and data mining are making pest control advance rapidly, the actions carried out by field experts are now based on, and supported by, documented information on pest activity

and the environmental factors that promote it. Data generated by recorded information is systematically stored and analysed, with continuous and immediate access to it by key stakeholders (technicians, researchers, clients, managers, governmental authority, etc.).

The latest milestone of technology is Artificial Intelligence (AI). The United States National Artificial Intelligence Act of 2020, determined the following definition:

> "The term 'artificial intelligence' means a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments."

The use of AI in the pest management industry can provide significant benefits, including more effective pest control, reduced chemical use, improved customer service, and cost savings (Dogget, S.L. 2023).

In 2025, the Rentokil Company will reach its 100th anniversary, showing a remarkable capacity to adapt and progress during these demanding years. Innovation has been, is and will be crucial to keep providing service to its clients all around the world. The Company has been researching for the best digital solutions in urban pest management for decades, having developed its first connected device, Mouse Alert, in 1992. This electric mouse trap was equipped with sensors to trigger a shutter to contain the mouse, and wireless communications to relay the capture to a technician. In 2014 the company launched the more advanced PestConnect system, including Radar, a trap that detects and captures mice and then releases CO2 to humanely dispatch them, sending data to a cloud-based system. This was one of the first pest control systems to use Internet of Things (IoT) technology and Big Data analytics, combined with an online pest management system.

Recently, in 2023, PestConnect Optix was included in the system, a novel smart device that was developed by its Israeli team. It incorporates a connected camera that can automatically detect movements, take a photograph, send the image to the AI cloud-based server, identify if there is a certain pest, for example rodents (*Rattus rattus*, *Rattus norvegicus* & *Mus musculus*), and trigger an alert. This process of electronic rodent monitoring is improved due to Machine Learning (ML), since the system acquires from the data (image) without being explicitly programmed.

In the aspect of pest detection and monitoring, ML offers powerful tools to analyse and interpret various types of data, like images, sensor readings, and environmental data, to identify and manage pest infestations effectively (L. Deng et al. 2018). This process, with no direct human intervention, is not perfect. It is essential to find ways to improve the ML accuracy through direct training and pre- and post-processing of the results. Since AI does not result in 100% accuracy, a "human in the loop" is important to review output, measure the accuracy of the model and provide ongoing feedback and training.

The device was initially trained with tens of thousands of images in laboratory conditions, photos were fed into the system and ML algorithms, developed and refined over time, would teach the AI server what was and wasn't true rodent activity. But now, for several years, the system has been trained based on real field events. By the end of 2024, the system is receiving more than 100000 images per month, from more than 2600 installed devices.

This paper presents the results obtained from the human feedback for the model training, based on the images (5750) obtained from April to June 2024. It is not a formal Study; the aim is to share part of the knowledge and experience gained during a real ongoing and dynamic

process. With standardized method of revision, rodent monitoring with AI will keep on improving, granting pest control operators an extremely valuable tool.

MATERIAL AND METHODS

PestConnect Optix device (Figure 1) includes motion-activated 2MP camera, that captures images within a 30-degree radius on each side, with both white and infrared LED, for day and night vision. The Passive Infrared Sensor (PIR) and the three infrared flashes work in tandem, to detect rodent activity in dark spaces.

The device can be installed in almost any place, but Rentokil technicians are trained to install them in cryptic spots, prone to rodent passage and avoiding activation by unwanted sources of movement. The battery life depends on the number of activations, but in normal conditions it will last for more than 3 months.

Once the PIR triggers the camera, the resulting image is sent from the device to a cloud computing platform, where ML based image classification models are run. Prior to the deployment of cameras, the algorithms of the model must be programmed to recognize and classify objects in the images, equivalent to the targeted pest. In this paper results are exclusive for rodents (*Rattus rattus*, *Rattus norvegicus* & *Mus* spp.). If pest activity is detected by the model, then the system will create an alert, and technicians will have access to the resulting image. This complete process, on most occasions, will take less than twenty seconds, but on average requires almost three minutes.

Figure 1. PestConnect Optix device.

Improving results, ML accuracy, is not a complex task. At the beginning, it will demand a human to review most of the images classified and confirm if the results are valid or not and feed the result back to the model. Gradually, as the number of objects identified grows, the model will improve, even without human intervention. But if a realistic level of accuracy must be measured, then a “human in the loop” is necessary. As a result of this effort, the model will improve at a

faster rate and an independent source will double check it, of course limited by the human capability to identify rodents in a photograph.

By the end of 2025 more than two million images have been classified by this system and roughly one hundred thousand have been reviewed by a human. As the model has improved and more devices are installed, the percentage of images reviewed is reduced. For the period studied, April to June 2024, 5750 images were selected randomly from a total of 117408 pictures processed for rodent presence (4,9%).

As a result of the careful review, by human eye, of each photo, we can confront predicted values with actual values and build a confusion matrix. A table that is used to define the performance of a classification algorithm (Singh K.K. et al.). Images are classified in: True Positive (actual rodent was detected by the model), False Positive (model detected an object as a rodent that was not a rodent), False Negative (model missed the rodent) and True Negative (model did not detect a rodent when there was no rodent).

The accuracy of the ML model is obtained with the percentage of images that predicted a true result ((TP+TN)/TOTAL). To complement the accuracy, and to take the two types of errors into consideration (FP and FN), the Precision (TP/(TP+FP)) and Recall (TP/(TP+FN)) have been calculated respectively and the F-measure by taking the harmonic mean of these two percentages (Kawatake, Y. et al.). Results of the period studied are compared with a small dataset from 2023, to point out the progress in the model training.

RESULTS AND DISCUSSION

For the period studied, the confusion matrix was built (Figure 2). The total accuracy was 0,923, whereas the precision was 0,877, recall was 0,943 and F-measure was 0,909. Most images had no rodents, almost 59,1%, PIR activates with minimum movements and even with optimal location of the devices, certain amount of no detections must be expected.

TOTAL **5750** IMAGES	**DETECTED RODENT**	**DETECTED NO RODENT**
ACTUAL RODENT	**2220** IMAGES *38,6%* **TRUE POSITIVE**	135 IMAGES *2,3%* **FALSE NEGATIVE**
NO ACTUAL RODENT	**310** IMAGES *5,4%* **FALSE POSITIVE**	**3085** IMAGES *53,7%* **TRUE NEGATIVE**

Figure 2. Confusion matrix.

Accuracy is generally used as an indicator of success of any prediction, this model manages to get 92% of the detections right and we can consider that a good result. Recall or sensitivity, that considers the errors made detecting actual rodents, reveals that 94% of the photos

that have actual rodents are detected by the model, which is the most important indicator for a model predicting pest activity. A false positive can be reported by operators, that will receive the alert and review the photo, but false negatives will not generate a report and will underestimate pest activity. That is why a lower precision, 88% of images with detected activity have actual presence of rodents, is not so relevant. Another value that can be observed, is the Specificity, that counts for the percentage of occasions the model is accurate detecting no actual rodent, 91% for this model. Almost the same value as the F-measure, that for our model can be taken as a general result.

Although PestConnect Optix is not a perfect solution for monitoring rodents, almost one out of ten classifications are not precise, it represents a major advance versus previous monitoring options and is already achieving good results in real field scenarios. Baits in stations require rodents to enter and gnawn the attractant, traps need to be efficient, thorough inspections require a lot of dedication and expertise by technicians, reviewing images with human eyes is tedious and is also time consuming. Most importantly, human eye site is not perfect, and AI means the model will improve, as it already has done.

In Figure 3 results from the present study are compared to those of a smaller dataset from 2023, with almost one thousand images reviewed by humans. Since the difference in the number of images is relevant, individual results will not be included in this paper, but the chart clearly shows an improvement in results and supports the improvement of the ML model.

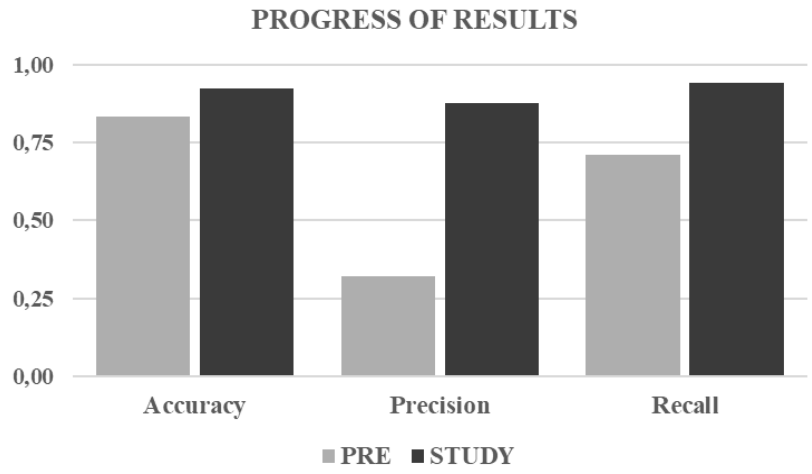

Figure 3. Result comparison chart (2023 light grey & Apr-Jun24 dark grey).

CONCLUSIONS

Pest detection and identification are essential duties of any pest control operator. Monitoring pests can be troublesome and reducing the time gap between the start of the infestation and control measures is crucial. Evaluating and reporting the results of recommendations, indirect actions, or control measures, direct actions, is also fundamental. All these critical phases of Integrated Urban Pest Management are improving with PestConnect Optix. Almost no proof is as convincing as a real picture of a rodent, at the site and received a few seconds after the photo was taken.

IoT, ML and AI are already improving urban pest management and have created huge expectations on how quickly they are becoming "game changers". But we should not forget that urban pest problems are complex, requiring multidisciplinary and evidence-based approaches. Without proper human intervention, these are futile tools, we must keep seeking for greater knowledge. Precisely with these devices, the relevant effort made by technicians to monitor areas with no activity can be reduced and that valuable time can increase effectiveness, as we record new valuable data on pest activity.

To keep improving, we must be critical with all our processes and tools, including our digital solutions. Rentokil will always keep a "human in the loop" and expects to continue improving the accuracy of digital devices.

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