A Hybrid Approach for Understanding Animal Behavior Using Deep Learning Techniques

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***Abstract*—Animals need health and wellbeing monitoring. It requires constant care, and observation. Manual tracking involves humans visually observing and recording animal movements which makes data management difficult and time-consuming. This automated animal behavior tracking system uses machine learning to accurately observe and comprehend animal behavior. The suggested study uses VGG-16 and ResNet50 for animal identification and LRCN for behavior detection. ResNet50 and VGG-16 process camera tape data. ResNet50 outperforms VGG-16 in cat and dog identification. The LRCN model helps identify animal behavior accurately. The UCF-50 dataset was first created to predict general human behavior, but it did not specifically reflect the actions of cats and dogs, which limited its application to these animals. In order to close this gap and make sure the LRCN model could successfully adapt to cats and dogs, for this study, a customized dataset centered on their distinctive behavioral pattern was exclusively created. The problem of reducing false positives in behavior detection is also addressed by the hybrid strategy that combines LRCN with ResNet50, producing predictions that are more accurate and trustworthy. Proactive health and behavior monitoring is encouraged by this integration, which improves the system's capacity to recognize, detect, and forecast animal behaviors.**

Keywords—Deep Learning, ResNet50, VGG16, LRCN Algorithm, Computer Vision.

I. INTRODUCTION

Animal tracking and behavior prediction focuses on understanding the actions or activities of pets, such as cats and dogs, as well as monitoring forest animals. Anticipating animal behavior permits proactive approaches to pet care, enabling pet owners and caretakers to successfully anticipate and take care of the pets [1]. Additionally, the knowledge gathered from tracking animals helps build creative solutions that promote scientific studies as well as practical uses in fields such as autonomous robots and wildlife conservation. Traditional methods are manual, including direct observation, radio data collection, and GPS tracking [2]. They are used for tracking animals and observing their behavior. These conventional techniques have several drawbacks, such as the inability to record fine details of animal behavior, the possibility of bias among observers, and more expensive and complex tracking devices. Furthermore, the expansion capacity and real-time capabilities of old systems are inadequate for tracking and evaluating animal movement and interactions, which limits their efficacy in addressing current challenges in wildlife management and pet care. Therefore, the field of animal tracking needs innovation by leveraging emerging technologies in computer vision and deep learning. Developments in computer vision, Machine Learning (ML), and sensor interfaces make it possible to overcome the drawbacks of conventional approaches and open new avenues to comprehend and improve animal lives [3].

Data Collection Methods for tracking the animals is shown in Fig 1. In video tracking, high-definition video recordings of animals in their native environment are captured, and the video is analyzed using advanced computer vision algorithms. RFID tracking uses Radio-Frequency Identification (RFID) tags, which are that generate specific radio waves when triggered by an RFID reader. These tags relate to pets, such as collar or hearing tags, and allow researchers to monitor pet movements. Global Positioning System (GPS) devices are satellite-based navigation provide accurate location information in real time. GPS monitoring involves putting lightweight GPS trackers on animals, allowing specialists to monitor their movements and spatial ecology. Accelerometers are compact, lightweight sensors that detect acceleration changes across numerous axes. These sensors can be attached to animals as either standalone devices or as part of monitoring tags to track their movements and activity levels [4].

Behavior prediction is knowing what an animal is doing and why, as opposed to merely monitoring its whereabouts. Animal behavior prediction models can analyze data from a variety of sources. Advances in machine learning, to predict complex behaviors such as social interactions, stress levels, or feeding habits. Deep learning models, for instance, may be used to evaluate video data and identify actions, such as grooming, resting, or aggressive behaviors. While behavior prediction gives a lot more detailed knowledge, classic tracking methods still yield important information about the locations and movements of animals.

The transition from monitoring to behavior prediction reflects the increasing need for sophisticated technology that can do more than just track an animal's whereabouts and forecast its behavior in real time.

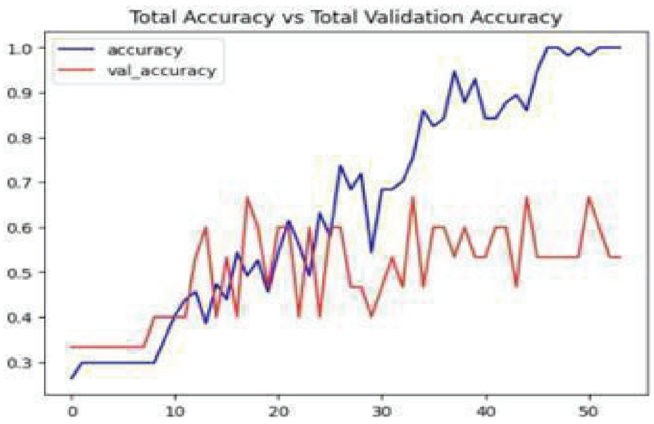

Fig. 10. Accuracy obtained using LRCN

VII. CONCLUSION AND FUTURE WORK

In order to improve knowledge of pet behavior, this work combines deep learning models (LRCN, VGG-16, and ResNet-50) to categorize behaviors in cats and dogs, including eating, sleeping, biting, and aggressiveness. Under the 80-20 data split, ResNet-50 fared better than VGG-16, with 88% accuracy as opposed to 66% for VGG-16. The LRCN model performed exceptionally well in real-time behavior analysis, attaining 91% accuracy for tasks like DogAggressive and CatEating, while ResNet-50 showed exceptional precision and F1 scores, capturing intricate behavior patterns. This demonstrates how LRCN may be used for dynamic applications that go beyond static picture categorization, improving behavior monitoring and advancing pet care.

Future improvements may involve adding more species and behaviors to the dataset, which would improve generalization and maintain the models' efficacy. Smart sensors and Internet of Things devices might enable real-time pet monitoring, giving veterinarians and pet owners insightful information. By working with specialists in animal behavior, the system might be brought into line with international welfare programs, promoting better care and enhanced animal welfare via automated behavior prediction and monitoring.

REFERENCES

[1] A. K. Schütz, "Computer vision for detection of body posture and behavior of red foxes," *Animals*, vol. 12, no. 3, art. no. 233, 2022.

[2] G. Del Serrone, G. Cantisani, and P. Peluso, "Speed data collection methods: a review," *Transportation Research Procedia*, vol. 69, pp. 512–519, 2023.

[3] A. Hlimi, S. El Otmani, F. Elame, M. Chentouf, R. El Halimi, and Y. Chebli, "Application of precision technologies to characterize animal behavior: a review," *Animals*, vol. 14, no. 3, art. no. 416, 2024.

[4] N. Sundaram and S. D. Meena, "Integrated animal monitoring system with animal detection and classification capabilities: a review on image modality, techniques, applications, and challenges," *Artificial Intelligence Review*, vol. 56, pp. 1–51, 2023.

[5] E. Bocaj, D. Uzunidis, P. Kasnesis, and C. Z. Patrikakis, "On the benefits of deep convolutional neural networks on animal activity recognition," in *Proceedings of the International Conference on Smart Systems and Technologies*, pp. 83–88, 2020.

[6] S. Suryawanshi, V. Jogdande, and A. Mane, "Animal classification using deep learning," *International Journal of Engineering Applied Sciences and Technology*, vol. 4, no. 11, pp. 305–307, 2020.

[7] A. Saxena, D. K. Gupta, and S. Singh, "An animal detection and collision avoidance system using deep learning," *Lecture Notes in Electrical Engineering*, vol. 668, pp. 1069–1084, 2020.

[8] M. S. Norouzzadeh, D. Morris, S. Beery, N. Joshi, N. Jojic, and J. Clune, "A deep active learning system for species identification and counting in camera trap images," *Methods in Ecology and Evolution*, vol. 12, no. 1, pp. 150–161, 2020.

[9] L. Lin, "Household animals classification using deep learning," *CS229: Machine Learning*, Stanford University, 2020.

[10] W. Li, S. Swetha, and M. Shah, "Wildlife action recognition using deep learning," *Environmental Science, Computer Science*, University of Central Florida, 2020.

[11] M. Ganesh, T. Radhesh, V. Kalyan, and L. Suneel, "Monitoring the movements of wild animals and alert system using deep learning algorithm," *International Journal of Food and Nutritional Sciences*, vol. 12, no. 4, 2023.

[12] F. Schindler and V. Steinhage, "Identification of animals and recognition of their actions in wildlife videos using deep learning techniques," *Ecological Informatics*, vol. 61, 2021.

[13] R.-C. Chen, V. Suthamathi Saravanarajan, and H.-T. Hung, "Monitoring the behaviors of pet cats based on YOLO model and Raspberry Pi," *International Journal of Applied Science and Engineering*, vol. 18, no. 5, 2021.

[14] D. A. Borges Oliveira, "A review of deep learning algorithms for computer vision systems in livestock," *Livestock Science*, vol. 253, 2021.

[15] G. Li, Y. Huang, Z. Chen, G. D. Chesser, J. L. Purswell, J. Linhoss, and Y. Zhao, "Practices and applications of convolutional neural network-based computer vision systems in animal farming: a review," *Sensors*, vol. 21, no. 4, art. no. 1492, 2021.

[16] K. Manjari, K. Singhal, M. Verma, and G. Singal, "AnimNet: an animal classification network using deep learning," in *Machine Learning Algorithms and Applications*, pp. 247–265, 2021.

[17] P. C. Sen, M. Hajra, and M. Ghosh, "Supervised classification algorithms in machine learning: a survey and review," *Advances in Intelligent Systems and Computing*, pp. 99–111, 2019..