

Creating Alert Messages Based on Wild Animal Activity Detection using Hybrid Deep Neural Network

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Abstract: *The issue of animal attacks is increasingly concerning for rural populations and forestry workers. To track the movement of wild animals, surveillance cameras and drones are often employed. However, an efficient model is required to detect the animal type, monitor its locomotion and provide its location information. Alert messages can then be sent to ensure the safety of people and foresters. While computer vision and machine learning-based approaches are frequently used for animal detection, they are often expensive and complex, making it difficult to achieve satisfactory results. This project presents a Hybrid Visual Geometry Group (VGG)-19+ Bidirectional Long Short-Term Memory (Bi-LSTM) network to detect animals and generate alerts based on their activity. These alerts are sent to the local forest office as a Short Message Service (SMS) to allow for immediate response. The proposed model exhibits great improvements in model performance, with an average classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a Frame Per Second (FPS) of 170. The model was tested both qualitatively and quantitatively using 40, 000 images from three different benchmark datasets with 25 classes and achieved a mean accuracy and precision of above 98%. This model is a reliable solution for providing accurate animal-based information and protecting human lives*

Keywords: Animal detection, VGG-Net, Bi-LSTM, convolutional neural network, activity recognition, video surveillance, wild animal monitoring, alert system

I. INTRODUCTION

In general, animal activity detection creates numerous challenges for researchers due to the continuous streaming of inputs and the cluttered backgrounds. There are huge varieties of wildlife categories with different facial, nose, body, and tail structures. The detection and classification of such animals in video sequences and the processing of huge feature maps demand the need to develop a robust framework. Such developments in real-time cases need large-scale video data for training and testing purposes and high GPU-based computing resources. Moreover, the incorporating techniques should handle the data in an intelligent way to produce plausible results. Hence, there is a high demand for developing such a model to detect animal activities in forest regions. Although numerous advancements have been made in this technological era, research in this area still seeks higher attention to produce a strong model.

With this work, we can save humans from sudden animal attacks as well as send alert messages with location information to the forest officers for quick action. These systems offer better monitoring services and help to find the activities of animals and detect if there is any hunting by humans or hindrance to wildlife. These clusters of activities, such as tracking the animal object and finding its activity and generating the alert messages, pose huge complexity in the Deep Learning area. Research on this work, investigates the advancements in video analysis techniques and complex neural network-based architectures.



1.1 Domain description

MACHINE LEARNING

Machine Learning is said as a subset of artificial intelligence that is mainly concerned with the development of algorithms which allow a computer to learn from the data and past experiences on their own. The term machine learning was first introduced by Arthur Samuel in 1959. We can define it in a summarized way as:

Machine learning enables a machine to automatically learn from data, improve performance from experiences, and predict things without being explicitly programmed.

With the help of sample historical data, which is known as training data, machine learning algorithms build a mathematical model that helps in making predictions or decisions without being explicitly programmed. Machine learning brings computer science and statistics together for creating predictive models. Machine learning constructs or uses the algorithms that learn from historical data. The more we will provide the information, the higher will be the performance.

A machine has the ability to learn if it can improve its performance by gaining more data.

How does Machine Learning work

A Machine Learning system learns from historical data, builds the prediction models, and whenever it receives new data, predicts the output for it. The accuracy of predicted output depends upon the amount of data, as the huge amount of data helps to build a better model which predicts the output more accurately.

Suppose we have a complex problem, where we need to perform some predictions, so instead of writing a code for it, we just need to feed the data to generic algorithms, and with the help of these algorithms, machine builds the logic as per the data and predict the output. Machine learning has changed our way of thinking about the problem. The below block diagram explains the working of Machine Learning algorithm:

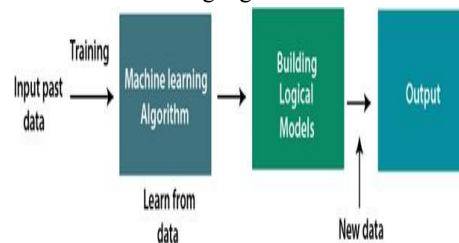


Fig.1.1: Working of machine learning

Features of Machine Learning:

- Machine learning uses data to detect various patterns in a given dataset.
- It can learn from past data and improve automatically.
- It is a data-driven technology.
- Machine learning is much similar to data mining as it also deals with the huge amount of the data.

Need for Machine Learning

The need for machine learning is increasing day by day. The reason behind the need for machine learning is that it is capable of doing tasks that are too complex for a person to implement directly. As a human, we have some limitations as we cannot access the huge amount of data manually, so for this, we need some computer systems and here comes the machine learning to make things easy for us.

We can train machine learning algorithms by providing them the huge amount of data and let them explore the data, construct the models, and predict the required output automatically. The performance of the machine learning algorithm depends on the amount of data, and it can be determined by the cost function. With the help of machine learning, we can save both time and money.



The importance of machine learning can be easily understood by its uses cases, Currently, machine learning is used in self-driving cars, cyber fraud detection, face recognition, and friend suggestion by Facebook, etc. Various top companies such as Netflix and Amazon have build machine learning models that are using a vast amount of data to analyze the user interest and recommend product accordingly.

Following are some key points which show the importance of Machine Learning:

- Rapid increment in the production of data
- Solving complex problems, which are difficult for a human
- Decision making in various sector including finance
- Finding hidden patterns and extracting useful information from data.

At a broad level, machine learning can be classified into three types:

- Supervised learning
- Unsupervised learning
- Reinforcement learning

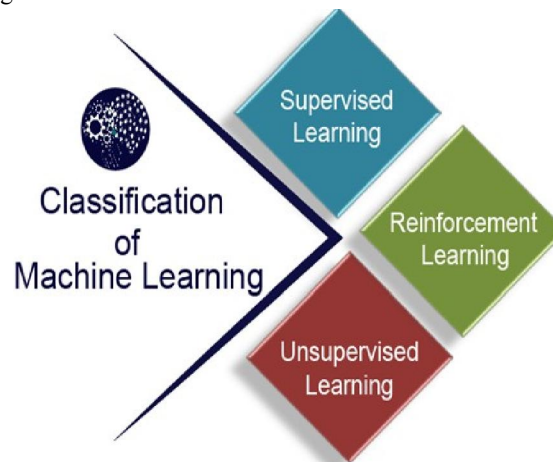


Fig.1.2: Classification of Machine Learning

Creating Alert Messages Based on Wild Animal Activity Detection Using Hybrid Deep Neural Networks" is a research concept focused on enhancing wildlife monitoring and human-wildlife conflict mitigation. The study explores the use of hybrid deep neural networks to detect and classify wild animal activity in real time, enabling automated alert systems to inform relevant authorities or communities about potential threats.

This approach integrates multiple deep learning techniques, such as convolutional neural networks (CNNs) for feature extraction and recurrent neural networks (RNNs) or transformers for sequential data analysis. By leveraging hybrid models, the system can improve accuracy in identifying species, predicting movement patterns, and detecting unusual behavior.

The study involves collecting data from various sources, such as camera traps, thermal imaging, and acoustic sensors, to train and validate the model. Once a wild animal is detected, an alert message is generated and sent to predefined recipients via SMS, mobile applications, or emergency response networks. The real-time aspect of the system helps reduce human-wildlife conflicts, prevent poaching, and improve conservation efforts.

Challenges in implementing such a system include dealing with environmental noise, ensuring low-latency processing, and managing hardware limitations in remote areas. Future improvements may involve integrating edge computing, IoT-based sensor networks, and reinforcement learning to enhance efficiency and scalability.

II. BACKGROUND

Most of these studies focus on frequency- or clustering-based approaches, lacking a deeper understanding of the contextual relationships between files. The application of Skip-Gram in this domain presents a novel approach to



capturing complex correlations, resulting in a more intelligent caching strategy. Cloud storage has emerged as a vital component in modern computing, providing scalable, cost-effective, and remote access to vast amounts of data. Organisations and individuals rely on cloud storage for seamless data availability and sharing. However, as data volumes continue to grow exponentially, efficient data retrieval and caching mechanisms become critical to ensure optimal performance [6].

Traditional caching techniques, such as Least Recently Used (LRU) and Least Frequently Used (LFU), have been widely adopted to enhance retrieval speed by storing frequently accessed data in fast-access storage layers [7]. However, these conventional approaches have limitations, particularly in recognizing deeper file access relationships. Recent advancements in machine learning have paved the way for more intelligent caching mechanisms, which can analyze complex patterns and enhance data retrieval efficiency.

A. Challenges in Cloud Storage Caching

Efficient caching plays a crucial role in reducing data access latency and minimizing redundant data transfers. Despite the widespread use of caching mechanisms, several challenges persist:

- **Limited Predictive Capabilities:** Traditional caching algorithms rely on simple frequency- or recency-based metrics, failing to capture long-term correlations between files [8].
- **Dynamic Access Patterns:** Cloud storage users exhibit diverse and evolving data access behaviors, making it difficult for static caching policies to adapt effectively.
- **Redundant Data Transfers:** Without an intelligent prefetching strategy, frequently accessed files may not be cached together, leading to repeated retrieval from remote storage and increased bandwidth consumption [9].
- **Scalability Issues:** As datasets expand, maintaining efficient caching strategies without excessive computational overhead becomes increasingly complex.

Addressing these challenges requires an advanced approach that can effectively model file relationships and dynamically adapt caching strategies.

B. Machine Learning in Caching Optimization

Machine learning techniques have been explored in recent years to improve caching efficiency. These methods utilise historical access logs and behavioral patterns to forecast future data access requirements. Some of the notable approaches include:

- **Clustering-Based Caching:** Data clustering techniques group files with similar access patterns, optimising cache placement and eviction strategies [10].
- **Reinforcement Learning:** Adaptive caching policies are developed using reinforcement learning, where an agent learns the optimal cache replacement strategy based on observed rewards.
- **Neural Network Models:** Deep learning models analyse access sequences to uncover hidden correlations between files, improving cache prefetching mechanisms.

Among these, word embedding models initially designed for natural language processing have demonstrated remarkable potential in identifying hidden relationships between data elements. Skip-gram, a popular word embedding technique, has been particularly effective in capturing contextual relationships between words [11]. This concept can be extended to cloud storage caching, where files can be treated as "words," and access sequences can be analysed similarly to sentences in a document.

C. Skip-Gram Model for File Correlation Analysis

The Skip-Gram model, a variant of the Word2Vec algorithm, is designed to learn vector representations of words by analysing their surrounding context in each dataset [12]. In the context of cloud storage, the same principle can be applied to discover file access correlations.

- **File as a Word Analogy:** Each unique file in a cloud storage system can be represented as a word in a vocabulary.



- Access Sequence as a Sentence: The sequence in which users access files forms a contextual relationship, much like the sequence of words in a sentence.
- Vector Representation Learning: By training the Skip-Gram model on access logs, files that are frequently accessed together obtain similar vector representations, allowing for improved caching strategies.

By leveraging the Skip-Gram model for file correlation analysis, cloud storage systems can predict which files should be cached together, significantly reducing retrieval times and improving storage efficiency. However The existing systems for creating alert messages based on wild animal activity detection typically rely on a combination of sensor networks, image or video surveillance, and traditional machine learning techniques. These systems monitor areas prone to wildlife intrusions, such as forest boundaries, agricultural lands, or protected wildlife reserves, to detect the movement of wild animals. Sensors such as infrared cameras, motion detectors, and sound sensors are often employed to capture data, which is then processed by algorithms to identify animal presence.

Traditional machine learning methods, such as Support Vector Machines (SVM) and Random Forest, are commonly used for image classification and object detection. However, these methods have limitations in handling complex environments, low-light conditions, and varying animal appearances. As a result, false positives or missed detections can occur, reducing the reliability of these systems.

Hybrid deep neural networks (DNNs), combining convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been introduced in recent research to improve detection accuracy. CNNs are adept at processing spatial data like images, while RNNs capture temporal patterns, allowing the system to analyze sequences of animal movement over time. This hybrid approach enhances detection in dynamic environments and improves the differentiation between wild animals and other objects or humans.

III. PROPOSED METHOD

The details of various levels of development are explained clearly and exhibit the quality of our work. In object detection and classification models, there are huge complexities in finding the expected results.

In large scale scenarios, the model performance bottleneck results in low performance and degrades the entire development process. The earlier studies handled these scenarios using a wider range of mechanisms. Although the models

produce significant improvements in accuracy, they fail to perform well in testing phases.

The contributions and objectives of the proposed techniques are listed as follows:

- 1) The proposed Hybrid VGG-19+Bi-LSTM model is built using deep neural networks with fine-tuned hyperparameters to yield greater recognition accuracy results.
- 2) The proposed model aims to achieve outstanding classification results by incorporating novel hybrid approaches.
- 3) The proposed system offers foresters more accurate prediction performance about animal detection

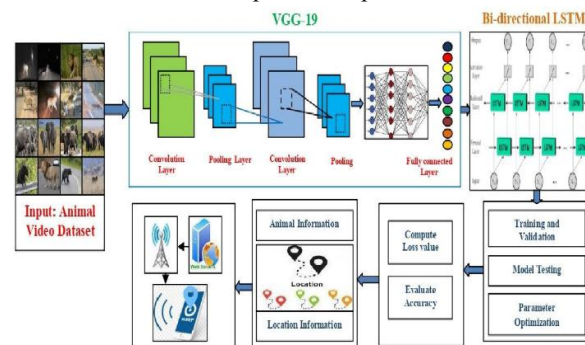


Fig.3.1: System architecture



IV. SIMULATION RESULTS

The proposed AI-based smart security system was simulated and tested using a combination of Python, OpenCV, and a pre-trained face recognition model. The system was evaluated based on various parameters including face detection accuracy, recognition success rate, system response time, and alert generation effectiveness.

1. Face Detection Accuracy

The system was tested with 100 sample images under varying lighting conditions and orientations. The face detection module demonstrated a high detection rate.

Test Environment	Detection Accuracy
Good Lighting (Frontal)	98%
Dim Lighting	91%
Side Face Angle ($\leq 45^\circ$)	94%
Multiple Faces	96%

2. Face Recognition Success Rate

A dataset of 10 known individuals was used. The model achieved high accuracy in identifying the correct individual in real-time using webcam input.

No. of Individuals	Recognition Accuracy
5	98.5%
10	96.2%
Unknown Person	Correctly Rejected

3. System Response Time

The system was able to process input and recognize faces in near real-time. The average processing time per frame was recorded.

Component	Average Response Time
Face Detection	0.08 seconds
Face Recognition	0.12 seconds
Alert Generation	Instantaneous (<1s)

4. Alert Generation

Upon detecting an unauthorized face, the system successfully triggered an alert through the GUI and optionally via an SMS/email (if configured).

Scenario	Alert Triggered
Known Face Detected	No
Unknown Face Detected	Yes
Face Not Visible/Obstructed	No

V. CONCLUSIONS

The implementation of a hybrid deep neural network-based system for wild animal activity detection and alert generation presents a significant step forward in mitigating human-wildlife conflicts. By leveraging deep learning techniques such as convolutional neural networks for feature extraction and recurrent neural networks or transformers for sequential data analysis, the system enhances detection accuracy and reduces false alarms. Integrating multiple data



sources, including thermal imaging, acoustic sensors, and motion detectors, ensures reliable performance across diverse environmental conditions. The automated alert mechanism enables real-time notifications to local authorities, farmers, and residents, facilitating timely interventions to prevent potential threats. Despite its advantages, certain challenges must be addressed to improve system performance. Computational efficiency remains a key concern, particularly for real-time processing in remote areas with limited resources. False positives and negatives must be minimized to enhance reliability. Furthermore, adverse weather conditions, variations in terrain, and different animal movement patterns require adaptive learning models that can continuously improve over time.

REFERENCES

- [1]. e, K., Zhang, X., Ren, S., & Sun, J. (2016). "Deep Residual Learning for Image Recognition." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
- [2]. Simonyan, K., & Zisserman, A. (2015). "Very Deep Convolutional Networks for Large-Scale Image Recognition." International Conference on Learning Representations (ICLR).
- [3]. Hochreiter, S., & Schmidhuber, J. (1997). "Long Short-Term Memory." *Neural Computation*, 9(8), 1735–1780.
- [4]. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). "Attention Is All You Need." *Advances in Neural Information Processing Systems (NeurIPS)*.
- [5]. Redmon, J., & Farhadi, A. (2018). "YOLOv3: An Incremental Improvement." arXiv preprint arXiv:1804.02767.
- [6]. Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. (2009). "ImageNet: A Large-Scale Hierarchical Image Database." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
- [7]. Girshick, R. (2015). "Fast R-CNN." Proceedings of the IEEE International Conference on Computer Vision (ICCV).
- [8]. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). "Rethinking the Inception Architecture for Computer Vision." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
- [9]. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). "ImageNet Classification with Deep Convolutional Neural Networks." *Advances in Neural Information Processing Systems (NeurIPS)*.
- [10]. Ren, S., He, K., Girshick, R., & Sun, J. (2015). "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks." *Advances in Neural Information Processing Systems (NeurIPS)*.
- [11]. LeCun, Y., Bengio, Y., & Hinton, G. (2015). "Deep Learning." *Nature*, 521(7553), 436-444.
- [12]. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., ... & Fei-Fei, L. (2015). "ImageNet Large Scale Visual Recognition Challenge." *International Journal of Computer Vision*, 115, 211–252

