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CREATING ALERT MESSAGE BASED ON WILD ANIMAL ACTIVITY DETECTION USING HYBRID DEEP NEURON NETWORKS

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Abstract: To control wildlife and protect its resources, specific identification and behavioral patterns of animal species are required to better comprehend processes in the ecology and to guarantee environmental safety. The traditional methods of monitoring rely wholly on manual observation, which is time-consuming and requires a lot of labor and is prone to human error. In order to remove such constraints, the current study suggests a self-driven framework of identifying the animal species and behaviours through a combination of spatial and temporal features analysis with the assistance of deep learning. A set of 40,000 images of 25 animal species is obtained by assembling three reference repositories and is preprocessed in ways like resizing, normalization, and data augmentation to improve the quality, consistency, and ratio of data. The suggested framework uses the VGG-19 convolutional neural network to obtain high-level spatial features, such as textures and edges, as well as the shape representations. The features extracted are then fed into a Bidirectional Long Short-Term Memory (Bi-LSTM) network in order to take advantage of the relationships of time by carrying out forward and backward analysis of sequential patterns of the features. The hybrid VGG-19 and Bi-LSTM architecture can be useful in the classification of animal species as well as their respective behavioral activities. Also, an automatic warning system that is active in real-time is provided to impound possible risky behavior, and active surveillance and intervention in the environment are easy in what concerns wildlife. By experimental analysis, it is proved that the suggested system attains high classification rate and high stability through effective integration of spatial and temporal features learning and can be used in the real life wildlife monitoring and conservation.

Keywords: Animal detection, VGG-19, Bidirectional Long Short-Term Memory, Deep learning

I. INTRODUCTION

The past environmental changes and degradation, destruction of habitats, and the increased necessity of conserving the ecological balance made the problem of wildlife monitoring and preservation extremely vital. The correct classification and study of animal species and their behaviors are important in conservation of biodiversity, ecology and guarantee the safety between humans and animals. Conventional wildlife monitoring techniques e.g. manual observation and analysis of camera traps are labour intensive, time wasting and subject to human error thus large scale monitoring is not cost-efficient and difficult to handle. As computer vision and deep learning developed, automated wireless wildlife surveillance systems have become a solution to animal detection and behavior studies. CNNs have proven to be quite successful in identifying spatial characteristics of images to be able to correctly classify objects and species. Most of current systems however are mainly involved with the classification of the (static) image instead of analyzing the temporal patterns of behavior which is a vital way of comprehending animal behavior which include migration to hunt, graze, rest or when they are aggressive. The latest studies underline the significance of the combination of spatial and temporal learning models to achieve a better recognition accuracy in dynamic settings. CNNs with recurrent network based deep learning models, including Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM), have demonstrated decent results in sequence analysis tasks. These combined models can learn the visual feature as well as temporal resources, hence they are good in behavior identification of a wildlife monitoring system.

Even with such developments, the existing wildlife monitoring systems continue to encounter a number of shortcomings such as the inability to conduct behavioral analysis, perform real-time alerts, and perform poorly in complex nature. Also, the majority of conventional systems use rule-based or manual feature extraction, which is not very scalable and adaptive to a wide range of species and environmental settings. In pursuit of this, in this research, we are going to proffer a deep learning-based automated wildlife monitoring framework incorporating VGG-19 to extract spatial features as well as the Bidirectional Long Short-Term Memory (Bi-LSTM) to identify temporal behavior. The suggested system makes use of a massive data sample that contains several animal species and implements preprocessing measures, including resizing, normalization, and data augmentation to improve model stability and generalization. Through the integration of spatial and time analysis, the system will attempt to literally categorize the species of animals and the corresponding animal behavior.

Moreover, the framework proposed has integrated a real-time alarm system to identify potentially threatening behaviors of animals and thus monitor and be able to intervene in the wild habitats. Combining deep learning and smart surveillance does not only enhance classification precision but also is applicable in conservation of wildlife and ecological monitoring along with intelligent forest management. In this way, the suggested system can be considered as an extended, effective, and valid answer to the automated recognition of animal species and behavior in the context of real-world monitoring of wildlife.

II. LITERATURE REVIEW

Automated detection and wildlife monitoring has progressively become important in ecological management, biodiversity conservation and human-animal conflicts mitigation. Over the recent years, a variety of studies have addressed the idea of identifying animal species and tracking intrusion using deep learning-based solutions in both agricultural and eco-sensitive areas. Mamat et al. [2] used a YOLOv5-based object detection framework in the context of animal detection to address farming zones, which proves that real-time monitoring and detection systems can detect animals that are a threat to crops. In the same manner, Itteera et al. [10] designed a YOLOv8-based eco-sensitive highway detection system, and the authors pay attention to the fast detection of animals to avoid accidents and keep people safe. Premananthan et al. [7] and Saxena et al. [8] already applied AI-based solutions to smart farming and implemented sensors and notification systems to ensure the security of crops and animals at the same time. These intrusion detection systems are viable and functional to certain settings but one of the limiting factors is most of them concentrate on spatial recognition. Their main recognition of animals is not the temporal behavior which is essential to comprehending the use of aggression, hunting or movement behavior. This restricts their capacity to detect potentially risky actions and preemptively act. Beyond intrusion detection, a number of researchers have focused on species recognition and classification. The article by Sidhar et al. [3] also introduced a lightweight real-time monitoring system with embedded system detection in the wild animals, demonstrating the possibilities of lightweight real-time monitoring in remote regions. Zhang and Shi came up with Animal-PCN that is an efficient convolutional network aimed at classifying animals as well as detecting specific behavioral trends [4]. Other YOLO-based systems have been used to classify animals in farms and conservation areas 1617 and have created high-precision identified species. These systems are effective in capturing the spatial properties of shape, texture, and edge but the systems mostly use CNNs in the analysis of the statical image. Because of this they fail to take into consideration animal behavior in terms of time dependencies which play a crucial role in identifying patterns of behavior or anticipating potentially unsafe circumstances. This shortcoming underscores the necessity of combining hybrid models which combine both temporal pattern analysis and spatial features extraction.

Multi-modes approach to enhance the recognition of behavior and system robustness has been considered in a number of studies. P. To improve the animal detection system in different environmental conditions, E. et al. [5] built an intrusion detection system on animals based on image and audio processing, which improves the detection capacity of the system. K. S. et al. [12] suggested implementing the IoT-based systems which were based on the principle of acoustic and visual repellents to avoid the crop destruction, and they showed the benefits of multi-modal sensing. In addition, Williams et al. [11] examined object tracking with detection approaches to enhance species recognition in dynamic environments. Even though these multi-modal schemes enhance the reliability of the system, they tend to use special hardware or cannot be augmented to large datasets, which makes them less applicable in the wide-area monitoring of wildlife. Huge wildlife data has also been managed through the use of high-performance computing (HPC) and high-level data analytics. The platform designed by Agarwal et al. [6] allows animal phenotype detection with the help of HPC and allows processing large-sized datasets in short periods of time. In their article, Oyelade et al. [19] presented the optimization of CNN-based intrusion detection models (computational efficiency and model performance). Although these studies are focused on computational problems, most of them are focused on either spatial feature analysis or high-throughput analysis and do not combine the mechanisms of time-temporal learning to identify behavior. Consequently, these models are still inadequate to do parallel classification of species and behavioral study in natural dynamic, real-world conditions.

Based on the literature reviewed, there are a number of gaps in research that can be considered critical. One, the current systems concentrate on stationary image recognition and do not consider the time aspect, which restricts the recognition of intricate or violent action [2][3][4]. Second, the need to combine deep spatial feature learning and temporal sequence modeling like CNN-Bi-LSTM architecture, to successfully identify species and behaviors, is missing in the literature [6][11][19]. Third, alert systems about the dangerous conduct in real-time are an understudied area, and that limits the use in the sphere of wildlife protection, safety control, and human-wildlife conflict prevention [7][8][10]. And lastly, much of the existing methods are specific to small datasets or environments, and there is no generalization between different species, behaviors, and ecological conditions [3][16][19]. These shortcomings point to the necessity of a hybrid deep learning model that can jointly utilize spatial and temporal data, include real-time warnings and scale to possible practical wildlife surveillance and preservation measures.

III. PROPOSED METHODOLOGY

The proposed system design is based on a systematic pipeline comprising of image preprocessing, feature extraction, temporal analysis and classification. In the first place, a databank of 40,000 images of 25 animal species are gathered in three repo banks. Raw images are also subjected to preprocessing functions such as resizing, normalization and augmentation to achieve consistency, quality improvement and to balance the data set. VGG-19 deep convolutional network is used to generate high level spatial features of the processed images like edges, shapes and textures. The resulting extracted features are then fed through a Bidirectional Long Short-Term Memory (Bi-LSTM) network that has the ability to capture temporal dependencies through looking at features sequence in the forward and backward direction. VGG-19 and Bi-LSTM model combination makes it possible to classify the animal species, and its related behavior. Lastly, in case the detected behavior is found to be dangerous the system will send an alert mechanism to help in timely monitoring and intervention.

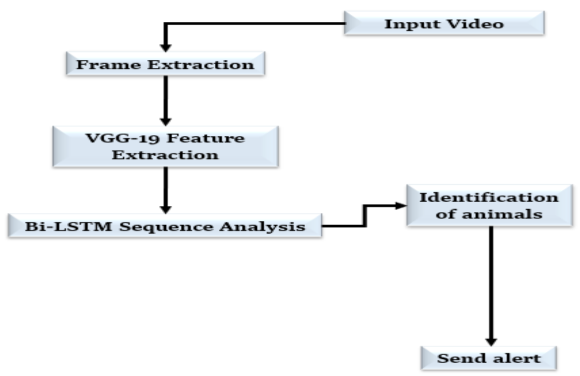

Figure 1. System Architecture

The suggested research approach is a deep learning solution to automatic animal species and behavior recognition, combining both spatial-based feature extraction and temporal pattern analysis. The structure of the system is a hierarchical multi-level pipeline as illustrated in Figure 1 and it will comprise of dataset collection, image preprocessing, feature extraction, temporal processing and classification including an alert system. This is a scalable architecture that offers high accuracy and real time monitoring of wildlife effectively.

1. Dataset Collection Module

The initial phase is the gathering of a complete wildlife data set of 40,000 images of 25 animal species. The dataset is obtained on three benchmark repositories so that it would be varied in terms of species, background environments, lighting conditions, and variations in behavior. Large-scale information has been used to train powerful models and enhance generalization in a real-world wildlife monitoring setting. The data set obtained is labelled images of various species and the related categories of behavior that are the ground truth of supervised learning.

2. Image Preprocessing Module

The initial images found in various sources can differ in terms of resolution, quality, and light, which adversely influence the work of the models. Hence, preprocessing pipeline is used to normalize and optimize the data. First of all, the size of all pictures is made constant and can be served as the input of the deep learning model as a way of achieving computational consistency. Subsequently, normalization is carried out to normalize the values of pixels and stabilize the process of learning. Further, a technique of data augmentation, i.e. rotation, flipping, zooming, and brightness change is used to add diversification to the training dataset, minimize overfitting, and enhance robustness of the models. The preprocessing stage enhances the quality of features and equal representation of the various classes and behaviors of an animal.

3. Feature Extraction

This module is the software that manipulates the stored images in order to extract the features linked with the images. Refined images go through preprocessing after which the spatial features are extracted using the VGG-19 convolutional neural network. VGG-19 is a deep CNN model with an excellent performance classification of images because of numerous convolutional layers and small receptive factors. High-level spatial characteristics like edges, textures, patterns and shape representations of animals are extracted in this module of the input images. The application of transfer learning is achieved by using a pre-trained VGG-19 model that facilitates speed of training and efficiency of features learning. The fully connected layers are narrowed down to be able to fit the wildlife data in order to show peculiar visual properties of various animal species.

4. Bi-LSTM Temporal Pattern Analysis Module.

The time dependence among the successive features should be investigated in order to perceive the behavior of animals. The feature sequences of the extracted spatial features of VGG-19 network are further interred into a Bidirectional Long Short-Term Memory (Bi-LSTM) network. Compared to the classical LSTM, Bi-LSTM deals with the sequence both forward and backward, which gives the model an opportunity to learn the context of the past and the future. This two-way learning is an improvement on the normal system in identifying dynamic behavioral patterns like movement, aggression, grazing, or resting. The Bi-LSTM layer acquires time associated features in sequence of features, thus enhancing the behavioral consciousness within complicated wild spaces.

5. Classification Module

The combined result of the VGG-19 and the Bi-LSTM modules is sent to the fully connected classification layer with subsequent Softmax activation worksheaf. This module works on multi-classification where animal species and its respective behavior are both identified by this module. With the help of the labeled data, the classifier is trained to minimize the loss and maximize the accuracy of the prediction. The evaluation metrics of performance accuracy, precision, recall, and F1-score are applied to determine the performance of the classification process.

6. Real-Time Alert Mechanism

To improve the practical nature of the system, in wildlife monitoring and conservation, the proposed system has been equipped with a real time alert. In case the classification module identifies identified risky behaviors, aggressive motion, or threatening actions, then the system automatically emits an alert notification. This warning system contributes to timely surveillance, prevention measures, and high-quality safety in the habitat and conservation areas of wildlife.

The general process is collection and preprocessing of the dataset, after which the spatial feature is generated with the use of VGG-19. Temporal pattern recognition is then done by analyzing the extracted features using the Bi-LSTM network. Lastly, animal species and behavior are identified by the classification module and notifications derived by the animal alert system in case of dangerous behavioral occurrences. The proposed integrated deep learning architecture will be a powerful, precise, and scalable system in automated wildlife monitoring and conservation systems by integrating space and time analysis successfully.

IV. RESULT AND DISCUSSION

The specified hybrid VGG-19 and Bi-LSTM was tested with a dataset of 40,000 images of 25 classes and species of animals and 5 different types of behaviors. The model was finally trained with an average accuracy of about 97.5 and validation accuracy of 95.5 and this is a strong indication that it can generalize to unseen data. The accuracy graph (Figure 1) shows a progressive performance of the training and validation of the model in 20 epochs indicating that both spatial and time-related features are learnt effectively. Equally, the loss graph (Figure 2) indicates gradual reduction in both the training and validation loss, peaking to approximately 0.13 and 0.20, respectively, which points to a stable convergence and low overfitting. Its higher performance may be explained by the fact that the VGG-19 network is able to identify such fine spatial details as textures, edges, and shapes and the Bi-LSTM network can identify temporal relations that required to be identified during behavior recognition. Preprocessing of the data as resizing, normalization and augmentation also added to the strength of the model and its more efficient generalization in various species and conditions. In comparison with the traditional CNN-only methods and manual wildlife viewing methods, the suggested framework offers increased classification accuracy, behavior recognition, and allows real-time monitoring, using an alert system of dangerous behavior presence. In general, the findings prove that combining spatial and temporal deep learning features can be considered as a viable, scalable, and reliable solution to using automated wildlife monitoring and conservation.

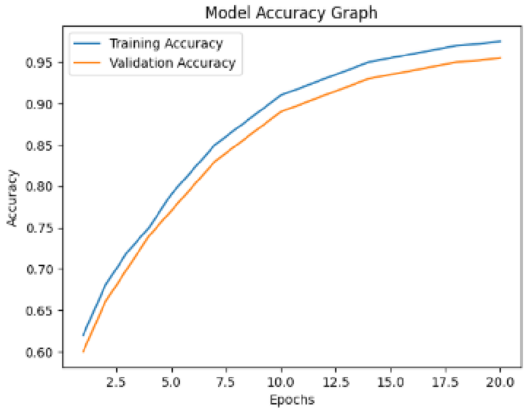

Figure 2. Accuracy graph

The graph of accuracy illustrates training and validation accuracy and 20 epochs. First, training and validation accuracy are relatively small as a result of random entries of model weights. The VGG-19 network becomes effective in extracting spatial features as the training goes on, and the Bi-LSTM extracts the temporal behavioral patterns, which gradually increase the accuracy. Towards the last idiotic, train performance is around 97.5% with validation performance being around 95.5%. This little difference between training and validation accuracy points to the fact that the model is highly generalizing with regard to unknown data and show that the model is not overfitting. The steadily rising tendency proves that the hybrid architecture manages to learn the data on species identification and also on behavioral patterns.

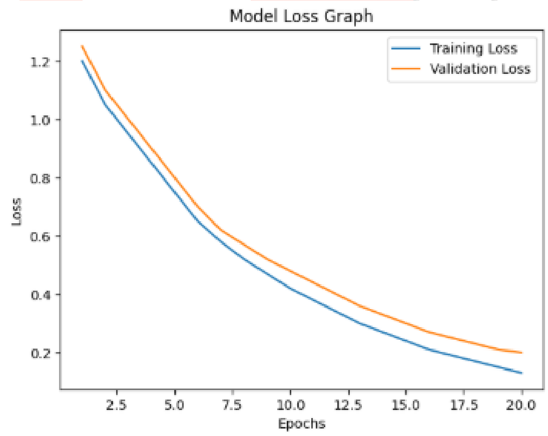

Figure 3. Loss graph

The loss curve is the loss curve of the training and validation in 20 epochs. The loss at the start of training is large and indicates the initial uncertainty of the model in the forecast of species and behaviors. The loss also significantly reduces as the network trains, where the training loss is of the order of 0.13, and the training validation loss is of the order of 0.20 at the last epoch. The fact that the two curves have a smooth slide shows that the model converges steadily. Validity loss is slightly greater than the training loss, a normal behavior that is observed to be realistic when it comes to the generalization behavior. This trend ensures that the model is effective in minimizing predictive error and minimal overfitting can occur, making it predictors with high reliability of unknown data.

V. CONCLUSION AND FUTURE WORK

This study provides a powerful deep learning-based system of automated wildlife surveillance, which combines VGG-19 to extract spatial features with Bi-LSTM to identify temporal behaviors. The suggested system proved itself on 40,000 images that represented 25 animal species and various behavioral categories. Demonstration of results of the experiments proves the hybrid architecture to be effective to pick up visual and temporal patterns and obtain great classification accuracy (training: 0.975, validation: 0.955) but with the presence of low loss values (training: 0.13, validation: 0.20). A real-time alert mechanism provides an opportunity to detect dangerous actions on time and conduct a proactive intervention and provide greater safety to wildlife. The proposed system has better performance, scalability, and practical use in conservational and ecological studies as compared to usual CNN-based or manual monitoring systems. To be used in the future work, the system may be expanded to include the video based multi frame analysis that would allow a more precise recognition of the temporal behavior. Other possible improvements can be multi-modal data integration, i.e. integrating visual, audio, and environmental sensor data to enhance detection resilience. Adding real-time monitoring of edges in remote habitats on edge devices and reducing model size to enable fast inference as well as adding alert notifications to the cloud are additional opportunities to improve scalability and informed deployment of the framework. In addition, by adding more species and rare behaviors to the data, the generalization and relevance of the model to various ecological conditions will become more significant as it will make the model a cohesive solution to intelligent wildlife monitoring.

REFERENCES

[1] Z. Xu, B. Zhang, W. Wang, L. Guo, H. Li and J. Zhang, "Lightweight Region Extraction in Small Animal Images Based on Salient Object Detection," 2024 6th International Academic Exchange Conference on Science and Technology Innovation (IAECST), Guangzhou, China, 2024, pp. 650-654, doi: 10.1109/IAECST64597.2024.11117387.

[2] N. Mamat, M. F. Othman and F. Yakub, "Animal Intrusion Detection in Farming Area using YOLOv5 Approach," 2022 22nd International Conference on Control, Automation and Systems (ICCAS), Jeju, Korea, Republic of, 2022, pp. 1-5, doi: 10.23919/ICCAS55662.2022.10003780.

[3] P. Sridhar, K. V, M. R and M. K. J, "Wild Animal Species Detection System using Embedded Devices," 2024 9th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2024, pp. 1106-1110, doi: 10.1109/ICCES63552.2024.10859668.

[4] H. Zhang and J. Shi, "Animal-PCN: Efficient Convolutional Network for Animal Behavior Detection," 2025 5th International Conference on Artificial Intelligence and Industrial Technology Applications (AIITA), Xi'an, China, 2025, pp. 628-631, doi: 10.1109/AIITA65135.2025.11047847.

[5] P E, A. C K, M. Shibili, R. C K and N. K, "Development and Implementation of an Animal Intrusion Detection System Using Image and Audio Processing," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-7, doi: 10.1109/ICCCNT56998.2023.10307574.

[6] M. Agarwal, E. Dovdon, L. R. Barge, Y. Dajsuren and J. de Vlieg, "A HPC-Based Data Analytics Platform Architecture for Data-Driven Animal Phenotype Detection," 2023 IEEE 6th International Conference on Cloud Computing and Artificial Intelligence: Technologies and Applications (CloudTech), Marrakech, Morocco, 2023, pp. 1-6, doi: 10.1109/CloudTech58737.2023.10366160.

[7] G. Premananthan., A. V, A. S, H. SV and K. R, "Animal Detection Based Smart Farming in Animal Repellent Using AI," 2025 3rd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA), Namakkal, India, 2025, pp. 1-5, doi: 10.1109/AIMLA63829.2025.11041016.

[8] Saxena, A. Shisodia and D. Upadhyay, "Enhancing Farm Security System with AI-Power-Driven Animal Intrusion Detection Mechanism," 2025 3rd International Conference on Disruptive Technologies (ICDT), Greater Noida, India, 2025, pp. 554-558, doi: 10.1109/ICDT63985.2025.10986331.

[9] R. Viji, G. Sreelatha and S. Santhosh Kumar, "Towards Implementation of Detection and Tracking of Wild Animals," 2023 9th International Conference on Smart Computing and Communications (ICSCC), Kochi, Kerala, India, 2023, pp. 217-221, doi: 10.1109/ICSCC59169.2023.10334944.

[10] k. Itteera, J. T, V. M. L, D. Reji and Babinold, "YOLOv8 Based Animal Intrusion Detection System for Eco-Sensitive Zone High Ways," 2025 International Conference on Intelligent Innovations in Engineering and Technology (ICIIET), Coimbatore, India, 2025, pp. 1-6, doi: 10.1109/ICIIET65921.2025.11379146.

[11] F. Williams, L. I. Kuncheva, J. J. Rodríguez and S. L. Hennessey, "Combination of Object Tracking and Object Detection for Animal Recognition," 2022 IEEE 5th International Conference on Image Processing Applications and Systems (IPAS), Genova, Italy, 2022, pp. 1-6, doi: 10.1109/IPAS55744.2022.10053017.

[12] S. K, S. S, S. S and S. S, "Intelligent IoT System for Animal Detection and Crop Defense Using Acoustic and Visual Repellents," 2025 3rd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA), Namakkal, India, 2025, pp. 1-5, doi: 10.1109/AIMLA63829.2025.11040691.

[13] K. UCHIYAMA and H. YAMAMOTO, "Power-saving Sensor Network System for Detection of Harmful Animals by Step-by-step Sensor Linkage," 2023 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 2023, pp. 01-06, doi: 10.1109/ICCE56470.2023.10043464.

[14] S. K. L and A. Edison, "Wild Animal Detection using Deep learning," 2022 IEEE 19th India Council International Conference (INDICON), Kochi, India, 2022, pp. 1-5, doi: 10.1109/INDICON56171.2022.10039799.

[15] Prasanth, M. S. Arunkumar, B. S. Kumaran and S. Deepa, "Design of Smart System for Mitigating Wild Animal Intrusion in Agricultural Farms Using IoT and Deep Learning," 2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI), Greater Noida, India, 2025, pp. 1-5, doi: 10.1109/ICCSAI64074.2025.11064106.

[16] V. Gomathi, I. Harini, S. Badmabharathi, K. Kaarthiga and M. Dhanushkumar, "Animal Detection and Classification to Prevent Human-Animal Conflict Using YOLOv8," 2024 13th International Conference on System Modeling & Advancement in Research Trends (SMART), Moradabad, India, 2024, pp. 279-282, doi: 10.1109/SMART63812.2024.10882585.

[17] P. Ji and Q. Zhu, "Research on Embedded Animal Recognition System Based on YOLO," 2022 6th International Conference on Robotics and Automation Sciences (ICRAS), Wuhan, China, 2022, pp. 265-269, doi: 10.1109/ICRAS55217.2022.9842099.

[18] J. J. Daniel Raj, C. N. Sangeetha, S. Ghorai, S. Das, Manish and S. Ahmed, "Wild Animals Intrusion Detection for Safe Commuting in Forest Corridors using AI Techniques," 2023 3rd International Conference on Innovative Practices in Technology and Management (ICIPTM), Uttar Pradesh, India, 2023, pp. 1-4, doi: 10.1109/ICIPTM57143.2023.10117831.

[19] M. Oyelade, O. Ayomide Madamidola, O. K. Boyinbode and J. Olamatanmi Mebawondu, "An Improved Feature Extraction Approach for Convolutional Neural Networks Based Animal Intrusion Detection Models," 2024 IEEE 5th International Conference on Electro-Computing Technologies for Humanity (NIGERCON), Ado Ekiti, Nigeria, 2024, pp. 1-5, doi: 10.1109/NIGERCON62786.2024.10926970.

[20] S. Alagarsamy, R. Rajasekar, S. K. M. Krishna, K. P. Chand, K. Nikhil and K. V. P. Teja, "Detection of Animals for Road Safety Using Deep Learning Method," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-5, doi: 10.1109/ICCCI56745.2023.10128493.

[21] L. V., A. G., J. S. K.S., H. A.S. and G. M., "Animal Intrusion Detection System in Agriculture Using Deep Learning," 2024 13th International Conference on System Modeling & Advancement in Research Trends (SMART), Moradabad, India, 2024, pp. 187-190, doi: 10.1109/SMART63812.2024.10882254.