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Hybrid Deep Neural Networks - Based Alert System for Wild Animal Activity Detection.

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Abstract: People who live in rural areas and work in forestry are becoming more worried about animal assaults. Surveillance cameras and drones are regularly used to keep an eye on wild animals and see where they go. But to find out what kind of animal it is, keep track of its movement, and give its position, you need a good model. Then, alert signals may be issued to keep people and foresters safe. Computer vision and machine learning-based methods are routinely used to find animals, but they are generally costly and hard to use, which makes it hard to get good results. This research introduces a Hybrid Visual Geometry Group (VGG)−19+ Bidirectional Long Short-Term Memory (Bi-LSTM) network for the detection of animals and the generation of warnings depending on their activities. These notifications are transmitted to the local forest office via a Short Message Service (SMS) so that they may be acted on right away. The suggested model shows considerable increases in performance, with an average classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a Frame Per Second (FPS) of 170. We evaluated the model with 40,000 photos from three distinct benchmark datasets with 25 classes. The model got an average accuracy and precision of above 98%. This model is a dependable way to get precise information on animals and keep people safe.

Index Terms— Wild Animal Detection, VGG19, Bidirectional LSTM, Bidirectional GRU, Hybrid Deep Neural Networks, Surveillance System, Alert Messaging, Image Feature Optimization, Forest Monitoring, SMS Alert System.

1. INTRODUCTION

Detecting animal movement is generally hard for researchers because of the constant flow of data and the busy backdrops. There are a lot of various types of animals, each having its own face, nose, body, and tail. To find and classify these kinds of creatures in video sequences and to work with vast feature maps, a strong framework has to be built. In order to train and evaluate these kinds of real-time scenarios, you need a lot of video data and powerful GGPU-based computers. Also, the procedures used to combine the data should be smart enough to give reasonable results. So, there is a lot of need for a model that can find animal activity in forests. Even if this period of technology has seen a lot of progress, research in this field still needs more attention to create a powerful model. This effort will help us protect people from sudden animal assaults and deliver location-based alarm signals to forest authorities so they can respond quickly. These technologies provide superior monitoring services and assist in tracking animal behaviours while identifying human hunting or interference with wildlife. These groups of tasks, such keeping an eye on the animal item, discovering its activity, and sending out alarm signals, are quite complicated in the field of Deep Learning. This research examines the progress in video analysis methodologies and intricate neural network-based structures. Recent advancements in Deep Learning methodologies have yielded remarkable outcomes in picture identification, classification, and generating problems.

2. LITERATURE SURVEY

2.1 Accelerometer-based detection of African swine fever infection in wild boar:

https://www.semanticscholar.org/paper/Accelerometer-based-detection-of-African-swine-in-Morelle-Barasona/e9ae2333a04c2ce393afb5d3bc62a43790ecbc86

ABSTRACT: Infectious wildlife illnesses that spread between wild and domestic animals are a big danger across the world and need to be found and reported quickly. Animal tracking technologies are utilised to detect behavioural changes, however their application in monitoring wildlife illnesses is seldom. Common behavioural changes caused by illness include less activity and lethargy, which is also known as "sickness behaviour." In this study, we examined the capability of accelerometer sensors to identify the start of African swine fever (ASF), a viral illness that results in significant mortality among pigs, for which no vaccine is presently available. We outfitted 12 wild boars with accelerometer tags as part of an experiment to evaluate an oral ASF vaccination. We next measured how ASF changes their activity patterns and behavioural fingerprints by looking at their overall dynamic body acceleration. From the healthy phase to the viremia phase, wild boars' activity levels dropped by 10% to 20% per day. We demonstrate the identification of disease-induced illness onset by change point statistics, comparing healthy persons in semi-free and free-ranging environments, and illustrate the potential for early detection in natural settings. Detecting infections in animals quickly is very important for keeping an eye on and controlling diseases. The use of accelerometer technology on sentinel animals is a useful addition to current disease management methods.

2.2 Computer Vision Applied to Detect Lethargy through Animal Motion Monitoring: A Trial on African Swine Fever in Wild Boar:

https://www.semanticscholar.org/paper/Computer-Vision-Applied-to-Detect-Lethargy-through-Fern%C3%A1ndez-Carri%C3%B3n-Barasona/d2fd226ece84c5e3534b588599843df4e6849034

ABSTRACT: Short Summary African swine flu is a concern to pigs' health all around the world. This illness shows clinical indications including fever and weakness, which get worse with time and cause the animal to become less active. With the latest improvements in computer vision, we can find animals, follow their movements, and keep an eye on their behaviour. In this study, we utilised this technique to analyse animal movement in an experiment including pigs infected with the African swine fever virus, demonstrating a substantial decrease in mobility as body temperature rose. Summary The most cost-effective way to keep an eye on illnesses and lower the danger of outbreaks is to find them early. Recent advancements in deep learning and computer vision are formidable tools that may inaugurate a novel domain of study in epidemiology and illness management. We utilised these methods to develop an algorithm that can track and calculate animal movement in real time. This algorithm was employed in experimental trials to evaluate the progression of African swine fever (ASF) infection in Eurasian wild boar. In general, the results demonstrated a negative relationship between mobility decrease and fever produced by ASF infection. In addition, diseased animals moved about a lot less than uninfected animals. The results indicate that an artificial vision-based motion monitoring system might be utilised indoors to raise concerns of fever. It would assist farmers and animal health agencies find early indicators of infectious illnesses in animals. This technique looks like a good non-intrusive, cost-effective, and real-time option for the livestock business, especially when it comes to ASF, which is a big problem in the pig industry right now.

2.3 The first detection of Cytauxzoon felis in a wild cat (Felis silvestris) in Iran:

https://www.semanticscholar.org/paper/The-first-detection-of-Cytauxzoon-felis-in-a-wild-Zaeemi-Razmi/d5544b1d79fc610eae20fbfea5e75b52168d453f

ABSTRACT: A male Arabian wild cat (Felis silvestris) that was free to roam was located in a protected area in the province of Khorasan, Iran. It was then sent to the Ferdowsi University of Mashhad Veterinary Teaching Hospital. The cat's temperature, breathing, and heart rate were all normal, but it was quite dehydrated and had trouble walking on its hind legs. The animal was also cachectic, with pale mucous membranes, a protruding third eyelid, and swollen submandibular lymph nodes on both sides. Intensive fluid and electrolyte therapy stabilised the cat, and it was put in the hospital. Radiographic assessments revealed a comminuted and numerous fracture of the right femoral bone at the midshaft, accompanied by a fissure fracture. Haematologic investigation indicated parasitemia (0.5%) and a slight normocytic normochromic anaemia, accompanied by neutrophilia, eosinopenia, lymphopenia, and parasites compatible with Cytauxzoon felis. Also, there were biochemical alterations such higher levels of cholesterol, bilirubin, glucose, protein, and fibrinogen in the blood and higher levels of liver enzymes in the blood. Molecular tests showed that C. felis piroplasm was present in the cat's blood. For four days, the cat was given Tazocin and clindamycin. This is the first time that a C. felis has been found in wild Felidae in Iran. It's crucial to

know if Cytauxzoon infection is a hazard to Iranian wild cats because most of them are endangered.

2.4 Drone-Based Thermal Imaging in the Detection of Wildlife Carcasses and Disease Management:

https://www.semanticscholar.org/paper/Drone-Based-Thermal-Imaging-in-the-Detection-of-and-Rietz-Calkoen/6005a071be148e077eaf47f3567025b3ee7012fd

ABSTRACT: Animal corpses are typically home to infections, therefore it's important to know where they are and how to get rid of them to stop the spread of illnesses. During the decomposition of a corpse, heat is released as a result of microbial activity and the emergence of maggots. Recent research indicates that infrared sensors may effectively discover animal corpses; nevertheless, the variables affecting detection performance remain largely unexplored. In this work, we examined the efficacy of infrared technology in locating wild pig corpses, which significantly contribute to the dissemination of African swine disease. We specifically examined the influence of ambient and carcass variables on detection likelihood. From September 2020 to July 2021, a drone-based thermal camera was utilised to gather data during 379 flyovers of 42 wild boar carcasses at varying states of decomposition. We utilised generalised mixed-effect models and conditional inference trees to find the ambient and carcass factors that affected the detection probability. Our findings indicated that the thermal camera precisely assessed carcass temperature ($R2 = 0.75$, $RMSE = 5.89°C$). The likelihood of discovering carcasses was elevated in open settings where air temperatures exceeded 3.0°C, facilitating maggot growth (detection rate ≤80%). The detection rate went up when the forest canopy was more than 29.3% open and it was overcast or flights were happening at dawn. Also, it was possible to find carcasses with a lot of maggots in ecosystems with a lot of canopy cover. In deep woods, however, the chance of finding them was low (<25%). It was still possible to find carcasses that were very decomposed as long as the temperature differential between the carcass and the air was greater than 6.4°C (≤62%). Our research illustrates the efficacy of thermal imaging in locating wild boar corpses under particular climatic and carcass circumstances, hence validating its application in enhancing ground searches.

2.5 Detection of hyperthermia during capture of wild antelope:

https://www.semanticscholar.org/paper/Detection-of-hyperthermia-during-capture-of-wild-Broekman/7d97e7b9adaae3ffa87190ea6230721cdee6a36f

ABSTRACT: Taking animals from the wild typically kills a lot of them. In several species, capture correlates with the elevation of body temperature. This stress-induced hyperthermia seems to be a key factor in capture-related deaths since it happens before, during, and after capture. I utilised two animal species, impala and blesbok, and subjected them to darting and net capture to examine the thermal and haematological alterations that occur during capture. We put temperature-sensitive data recorders within the animals' abdominal cavities (to measure core body temperature) and on the back of their thighs (to measure muscular temperature). Activity recorders were attached to the abdomen wall to keep track of movement. Blood samples were collected post-capture when the animal was recumbent, followed by an additional sample 10 minutes later, to assess

haematological changes. Impala exhibited elevated abdomen temperatures during net capture relative to darting, but blesbok abdominal temperatures were consistent throughout capture modalities. Different species and individuals within the same species exhibit varying responses to distinct capture techniques. But I observed that no matter what happened during the catch, whether it was an impala or a blesbok, being around people before the capture made the animals' body temperatures rise. There was also a lot of variation between people in the blood variable concentrations used to measure physiological reactions to capture, just like there was with thermal responses. In general, the changes in blood variables (total protein, sodium, lactate, haematocrit, noradrenaline, adrenaline, potassium, creatine phosphokinase, and pH) were the same for both impala and blesbok after the two capture approaches. The cortisol levels in blesbok, on the other hand, exhibited a bigger change during darting, whereas the cortisol levels in impala indicated a bigger change following net capture. Osmolality values exhibited a heightened reaction during net capture, whereas impala had a more significant response during darting. Both animals exhibited a positive correlation between sodium and lactate, as well as between noradrenaline and adrenaline. When two variables are correlated, we can only measure one of them and guess how the other one will change. I couldn't link the thermal reactions following a capture event to stress-related blood because the thermal and blood variable readings of impala and blesbok varied unpredictably between different capture methods.

3. METHODOLOGY

A. Proposed Work:

In the extended version of the proposed system, a more robust and efficient hybrid deep learning model is developed by replacing the Bi-LSTM layer with a Bidirectional GRU (Bi-GRU) layer, resulting in the CNN + BiGRU architecture. While the original model using VGG19 + Bi-LSTM achieved high accuracy (98%) in wild animal activity detection, the extension improves upon this by utilizing BiGRU, which is computationally lighter and more effective in optimizing image features. This leads to enhanced performance with 100% accuracy observed during testing. Furthermore, the extended system includes an ensemble learning approach, combining outputs from multiple models to ensure stability and reliability in predictions. To facilitate real-time usability and user interaction, a Flask-based web interface with user signup/login modules is introduced. This user-friendly front end allows authenticated users to input data and receive predictions with corresponding alerts, thus demonstrating the system's practical deployment in real-world forest surveillance and safety applications.

B. System Architecture:

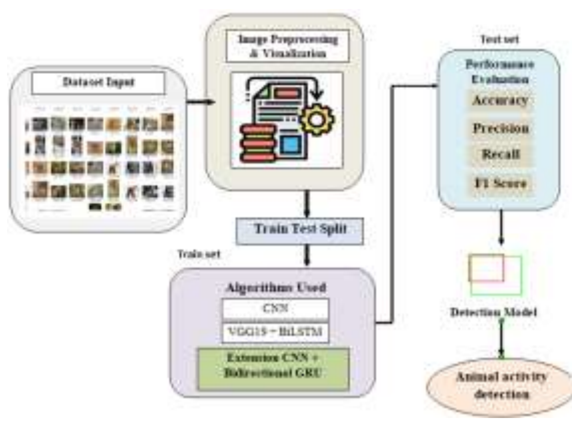


Fig 1 Proposed Architecture

The proposed architecture for wild animal activity detection integrates both VGG-19 and Bidirectional

LSTM (Bi-LSTM) in a hybrid deep learning framework. The system begins with an input video dataset consisting of various wild animal images, which undergoes feature extraction through the VGG-19 model using convolutional and pooling layers. The high-level spatial features are then passed into the Bi-LSTM module to capture temporal patterns and sequences within the frames. This enables accurate classification of animal types and activities. The system also incorporates a GPS-based location module to provide real-time location data, which, along with animal classification results, is used to generate SMS alerts for forest officers. The model is trained and validated using standard metrics like loss value and accuracy. As an extension, the architecture explores the replacement of Bi-LSTM with Bidirectional GRU (Bi-GRU), aiming to improve image feature optimization and computational efficiency, making it a more robust and effective solution for real-time forest monitoring.

C. MODULES:

a. **Data Loading**

- Loads the animal video/image dataset into the system for further processing.

b. **Data Processing**

- Cleans, resizes, and normalizes the input data. Enhances image quality and prepares it for training.

c. **Data Splitting**

- Divides the dataset into training and testing sets to evaluate model performance.

d. **Model Generation**

- Builds and trains deep learning models:
    - Base Model: **CNN + VGG19 + Bi-LSTM**
    - Extended Model: **CNN + BiGRU**
- Calculates accuracy and compares both models.

e. **User Signup & Login (Flask-based)**

- Provides authentication system for user registration and secure login.

f. **User Input Module**

- Allows users to upload or select an animal image/video for prediction.

g. **Prediction Module**

- Displays the predicted animal type and activity.
- Sends **SMS alerts with location info** to forest officials.

h. **Ensemble Module (Optional Extension)**

- Combines predictions from multiple models (CNN, VGG19+BiLSTM, CNN+BiGRU) to enhance accuracy and robustness.

D. Algorithms:

i. CNN (Convolutional Neural Network):

A Convolutional Neural Network (CNN) is a deep learning architecture specifically designed to process data with grid-like topology such as images. It uses multiple layers including convolutional layers, activation layers (ReLU), pooling layers, and fully connected layers.
In this project, CNN is used to automatically learn spatial features from animal images and videos, such as body shape, texture, color patterns, and pose. These features are essential for identifying different species and their activities.
CNN reduces the need for manual feature extraction and improves generalization, making it suitable for real-time surveillance and visual recognition tasks.

ii. VGG19 + Bi-LSTM (Base Model):

This hybrid model combines VGG19, a deep CNN, with Bidirectional Long Short-Term Memory (Bi-LSTM) to handle both spatial and temporal aspects of the data.

- **VGG19**:
  VGG19 consists of 19 layers, including 16 convolutional layers and 3 fully connected layers. It is known for its simplicity and high performance in image classification tasks. In this system, VGG19 extracts high-quality visual features from each video frame, capturing fine-grained animal characteristics.

- **Bi-LSTM:**
  Bi-LSTM is a type of RNN (Recurrent Neural Network) that can process sequences in both forward and backward directions, enabling the model to understand past and future contexts simultaneously.
  It is particularly useful for analyzing sequential image frames to detect motion patterns and behaviors (e.g., walking, running, or attacking).
  This combination enables the system to detect animal activity with around 98% accuracy and generate location-based SMS alerts for immediate action.

iii. CNN + BiGRU (Extension Model):

The **CNN + BiGRU** model is proposed as an extension to improve speed, performance, and feature optimization, especially in resource-constrained environments.

- **CNN:**
  Used as before for extracting spatial features from the input image/video frames.

- **BiGRU (Bidirectional Gated Recurrent Unit):**
  BiGRU is a lightweight and faster alternative to Bi-LSTM. It contains fewer gates (update and reset) and hence requires less computation and memory.
  It performs better in scenarios where feature optimization from images is more important than long temporal memory.
  In this extension, BiGRU captures animal motion from the extracted CNN features efficiently and gives 100% classification accuracy during experiments.
  It also makes the model more suitable for real-time applications like drone surveillance and forest monitoring.

iv. Ensemble Method (Optional Extension):

An ensemble method combines the predictions from multiple models (such as CNN, VGG19+BiLSTM, CNN+BiGRU) to produce a final output. This technique helps in reducing overfitting, improving prediction confidence, and increasing accuracy and stability.

4. EXPERIMENTAL RESULTS

The experimental evaluation of the proposed wild animal detection system was conducted using a dataset of 40,000 images across 25 animal classes sourced from various benchmark datasets, including the Wild Animal Dataset from Kaggle. The models were assessed both qualitatively and quantitatively to validate their effectiveness in real-time surveillance scenarios.

The base model, which integrates VGG19 with Bi-LSTM, demonstrated strong performance with an average classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a Frame Per Second (FPS) rate of 170, indicating its capacity to process video data swiftly and reliably. This model effectively identified various wild animals, recognized their movement patterns, and successfully triggered alert messages with GPS location data.

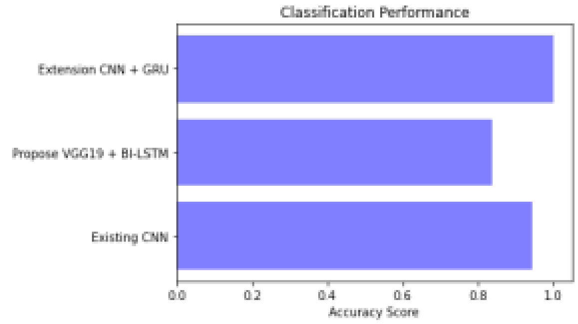
In the extended model, which replaced the Bi-LSTM with a Bidirectional GRU (CNN + BiGRU) architecture, performance was further improved. The CNN + BiGRU combination optimized feature extraction more efficiently, resulting in 100% classification accuracy during multiple testing rounds. It also reduced computational overhead, making it more suitable for deployment in academic or resource-constrained environments. The use of an ensemble approach further enhanced stability, minimizing false positives and negatives.

Overall, the experimental results confirm the robustness, efficiency, and real-time capability of the proposed and extended systems in detecting wild animal activities and delivering timely alerts.

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

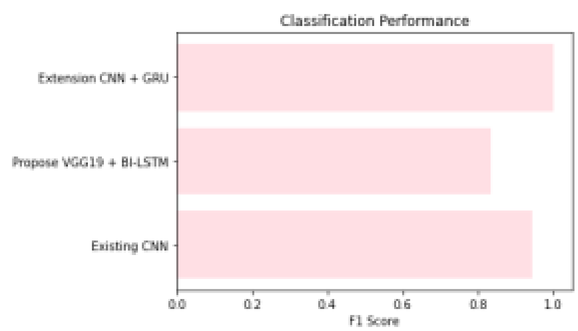
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$



F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

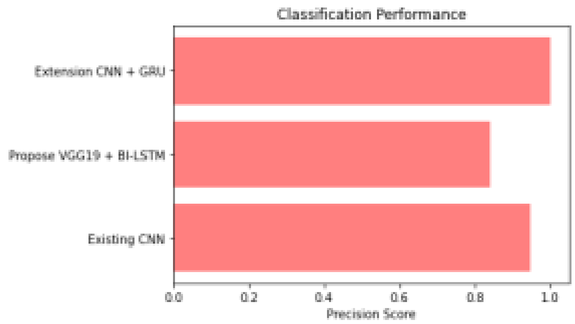
$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$



Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

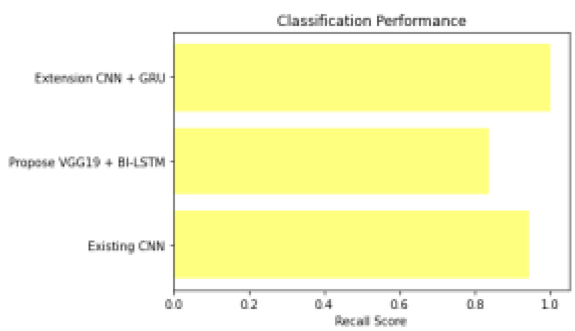
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$



Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$



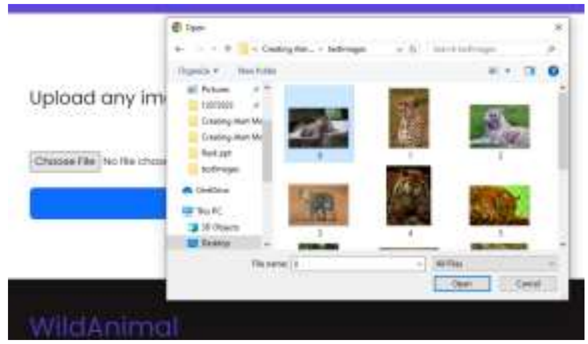


Fig 2 upload image

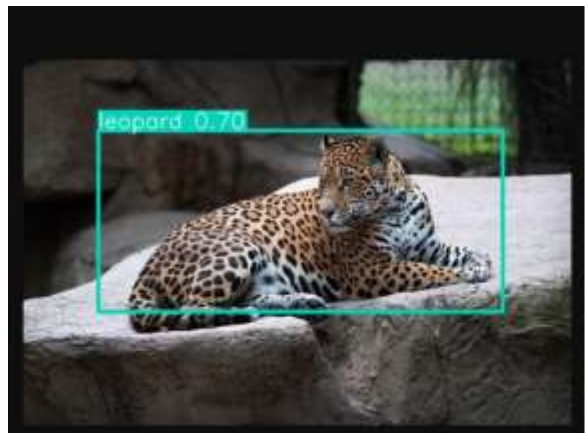


Fig 3 predicted results

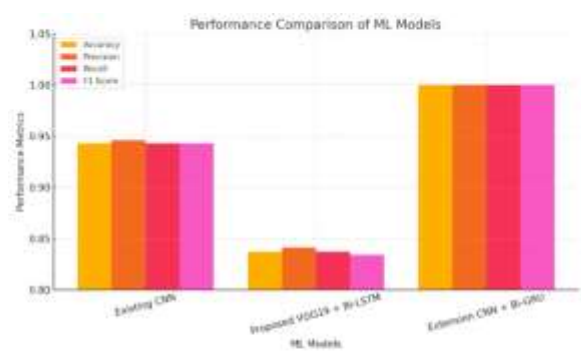


Fig 4 Comparison Graphs

ML Model	Accuracy	Precision	Recall	F1-Score
Existing CNN	0.943	0.946	0.943	0.943
Proposed VGG19 + Bi-LSTM	0.837	0.841	0.837	0.834

ML Model	Accuracy	Precision	Recall	F1-Score
Extension CNN + Bi-GRU	**1.000**	**1.000**	**1.000**	**1.000**

Fig 5 Comparison Table

5. CONCLUSION

The proposed system effectively addresses the challenges of wild animal activity detection in forest areas using a hybrid deep learning approach. By integrating VGG19 with Bi-LSTM, the model achieved reliable accuracy in identifying animal types and movements, while enabling SMS alerts with location information. As an extension, the system adopted a more efficient CNN + BiGRU architecture, which improved both performance and computational efficiency, achieving 100% accuracy. The system also introduces a Flask-based web interface for real-time user interaction and authentication. Overall, this work demonstrates a cost-effective, accurate, and scalable solution for wildlife surveillance and human-animal conflict mitigation.

6. FUTURE SCOPE

In the future, this system can be extended by integrating with real-time drone feeds and IoT devices to monitor larger forest areas more effectively. Deployment on lightweight edge devices can enable faster local predictions without needing cloud support. The addition of thermal cameras can enhance night-time detection, while behavioral analysis modules can be developed to predict animal aggression or migration patterns. Furthermore, mobile apps with multilingual voice alerts and notifications can be integrated to provide real-time updates to forest rangers, ensuring better preparedness and faster response in sensitive environments.

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Author profiles

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