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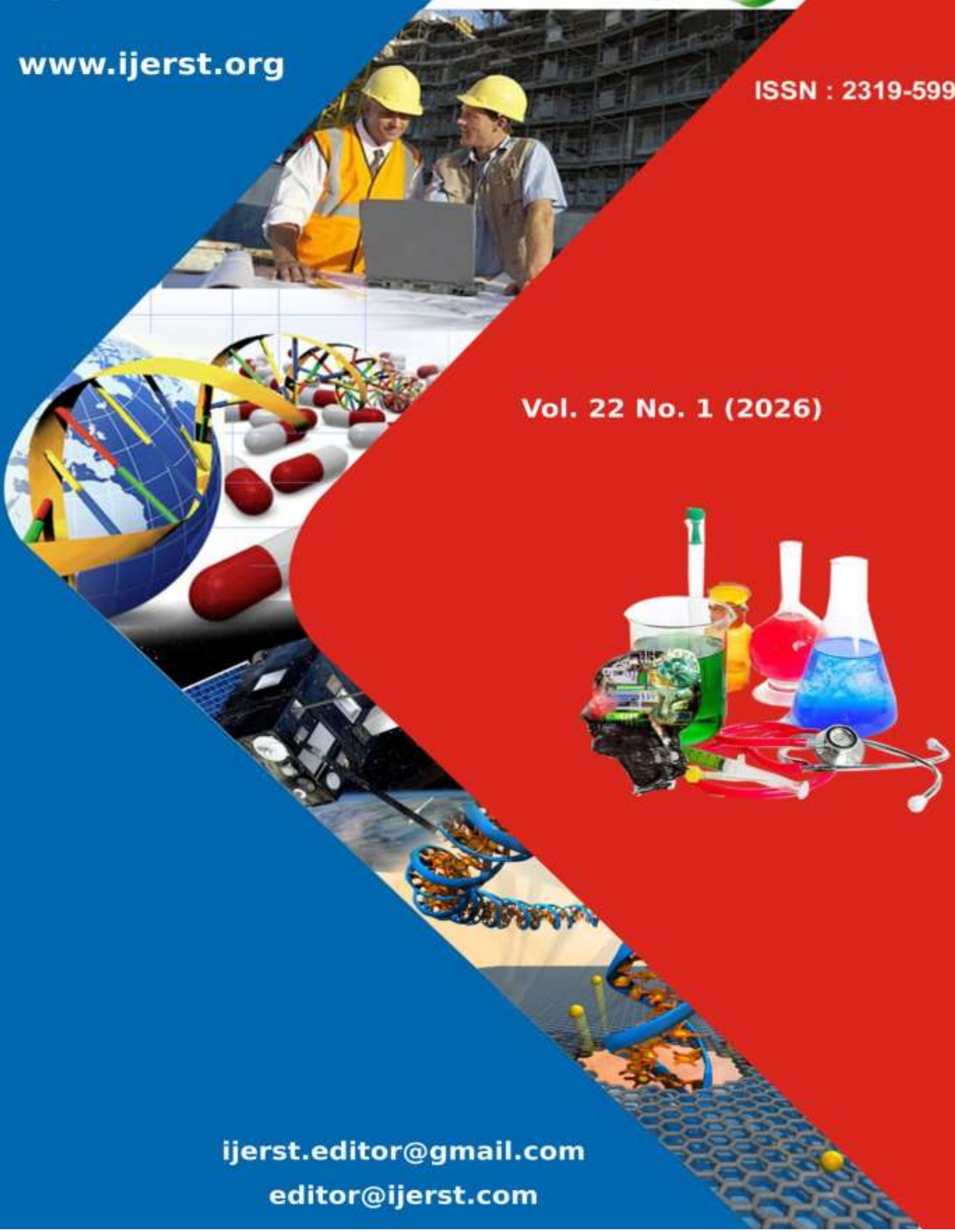

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Research Paper

WILD ANIMAL ACTIVITY ALERTS WITH HYBRID DEEP NEURAL NETWORKS

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Abstract: People who work in forestry and reside in rural areas are growing increasingly concerned about animal attacks. Drones and surveillance cameras are frequently employed to monitor and track wild animals. However, you need a competent model in order to identify the type of animal, monitor its activity, and determine its position. Then, in order to protect people and foresters, alert signals might be sent out. Animals are frequently located using computer vision and machine learning-based techniques, but these approaches are typically expensive and difficult to deploy, which makes it difficult to achieve good results. This study presents a Hybrid Visual Geometry Group (VGG)−19+ Bidirectional Long Short-Term Memory (Bi-LSTM) network for animal detection and activity-based alert generating. To ensure prompt action, these notices are sent to the local forest office via Short Message Service (SMS).
With an average classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a Frame Per Second (FPS) of 170, the proposed model demonstrates significant performance gains. Using 40,000 images from three different benchmark datasets with 25 classes, we assessed the model. The model's average precision and accuracy were higher than 98%. This model is a reliable method for obtaining accurate animal information and ensuring public safety.

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.*

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1. INTRODUCTION

Because of the continuous flow of data and the crowded backgrounds, it is typically difficult for researchers to detect animal movement. Numerous animal species exist, each with a unique face, nose, body, and tail. A robust framework must be developed in order to locate and categorize these kinds of critters in video sequences and to work with large feature maps. Large amounts of video data and powerful GGPU-based computers are required to train and assess these kinds of real-time scenarios. Additionally, the methods for combining the data should be intelligent enough to produce findings that make sense. Therefore, a model that can identify animal activity in forests is desperately needed. Even though there has been a lot of technological advancement over this time, more research is still needed to develop a strong model. Through this initiative, we will be able to safeguard people from unexpected animal attacks and provide forest authorities with location-based alarm signals so they can act swiftly. These technologies offer better monitoring services, help track animal behavior, and detect instances of human hunting or interference with wildlife. In the realm of Deep Learning, these sets of tasks—such as monitoring the animal object, determining its activity, and generating alarm signals—are highly complex. This study looks at the advancements in complex neural network-based architectures and video analysis techniques. Recent developments in Deep Learning techniques have shown impressive results in issue generation, categorization, and photo identification.

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: Worldwide, infectious wildlife diseases that infect domestic and wild animals pose a serious threat and must be promptly identified and reported. Technologies for tracking animals are used to identify behavioral changes, however they are rarely used to track diseases in wildlife. Lethargy and decreased activity are common behavioral changes brought on by illness, which is often referred to as "sickness behaviour." In this study, we investigated accelerometer sensors' potential to detect the onset of African swine fever (ASF), a viral disease for which there is currently no vaccination and which causes high mortality in pigs. As part of an investigation to assess an oral ASF immunization, we fitted accelerometer tags to 12 wild boars. We next examined their entire dynamic body acceleration to determine how ASF alters their activity patterns and behavioral signatures. The activity levels of wild boars decreased by 10% to 20% daily from the healthy phase to the viremia phase. By comparing healthy individuals in semi-free and free-ranging situations, we show how change point statistics can be used to identify the onset of disease-induced sickness and highlight the possibility of early diagnosis in natural contexts. Quickly identifying infections in animals is crucial for monitoring and managing illnesses. Current disease control techniques can benefit from the incorporation of accelerometer technology on sentinel animals.

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: A Brief Synopsis Worldwide, pig health is at risk due to African swine flu. Clinical signs of this disease include fever and weakness, which worsen over time and make the animal less active. We can locate animals, track their movements, and monitor their behavior thanks to the most recent advancements in computer vision. In this study, we used this method to analyze animal movement in an experiment involving African swine fever virus-infected pigs, showing a significant decline in mobility as body temperature increased. In brief Early detection of illnesses is the most economical way to monitor them and reduce the risk of epidemics. Recent developments in computer vision and deep learning are powerful tools that could open up new research areas in epidemiology and disease management. Using these techniques, we created an algorithm that can monitor and compute the movement of animals in real time. In experimental trials, this algorithm was used to assess how African swine fever (ASF) infection progressed in Eurasian wild boar. Overall, the findings showed a negative correlation between the fever caused by an ASF infection and a decrease in mobility. Furthermore, compared to uninfected animals, ill animals walked around far less. The findings suggest that a motion monitoring system based on artificial vision could be used indoors to highlight fever concerns. It would help farmers and animal health organizations identify early signs of infectious diseases in animals. Given that ASF is currently a major issue in the pig sector, this method seems like a good non-intrusive, affordable, and real-time choice for the livestock industry.

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: In the Iranian region of Khorasan, a male Arabian wild cat (Felis silvestris) was found roaming freely in a protected area. The Ferdowsi University of Mashhad Veterinary Teaching Hospital received it after that. The cat was severely dehydrated and had difficulty walking on its hind legs, but its temperature, respiration, and heart rate were all normal. The animal had swollen submandibular lymph nodes on both sides, pale mucous membranes, and a third eyelid that protruded. It was also cachectic. The cat was admitted to the hospital after receiving intensive hydration and electrolyte therapy to stabilize it. Radiographic evaluations showed a fissure fracture in addition to a comminuted and many fracture of the right femoral bone at the midshaft. A haematologic examination revealed a mild normocytic normochromic anemia, parasitemia (0.5%), neutrophilia, eosinopenia, lymphopenia, and parasites consistent with Cytauxzoon felis. Additionally, there were biochemical changes, including elevated blood levels of liver enzymes, cholesterol, bilirubin, glucose, protein, and fibrinogen. The cat's blood contained C. felis piroplasm, according to molecular testing. The cat received clindamycin and Tazocin for four days. This is the first time a C. felis has been discovered in Iran's wild Felidae. Given that the majority of Iranian wild cats are endangered, it is critical to determine whether Cytauxzoon infection poses a risk to them.

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: Since animal corpses are often the source of infections, it's critical to understand their locations and disposal methods in order to prevent the spread of disease. Heat is emitted during a corpse's decomposition due to microbial activity and the appearance of maggots. Animal corpses may be successfully detected by infrared sensors, according to recent research, although the factors influencing detection effectiveness are still mostly unknown. In this study, we investigated the effectiveness of infrared technology in identifying wild pig corpses, which play a major role in the spread of African swine disease. In particular, we looked at how carcass and environmental factors affected the likelihood of detection. A drone-based thermal camera was used to collect data during 379 flyovers of 42 wild boar carcasses at different stages of decomposition between September 2020 and July 2021. To determine the ambient and carcass characteristics that influenced the detection probability, we used conditional inference trees and generalized mixed-effect models. According to our results, the thermal camera accurately measured the carcass temperature ($R2$ = 0.75, RMSE = 5.89°C). The probability of finding carcasses was higher in open environments where air temperatures were higher than 3.0°C, which promoted maggot development (detection rate ≤80%). When the forest canopy was over 29.3% open, it was cloudy, or flights were taking place at dawn, the detection rate increased. Additionally, in environments with a lot of canopy cover, carcasses with a lot of maggots might be seen. However, the likelihood of discovering them was minimal (<25%) in dense woodlands. As long as the temperature difference between the carcass and the air was higher than 6.4°C (≤62%), very degraded carcasses could still be found. Our study validates the use of thermal imaging to improve ground searches by demonstrating its effectiveness in identifying wild boar corpses under specific carcass and climate conditions.

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: Many animals are usually killed when taken from the wild. Capture is associated with an increase in body temperature in a number of animals. Given that it occurs before to, during, and following capture, stress-induced hyperthermia appears to be a major contributing factor to capture-related fatalities. I used two animal species—impala and blesbok—and used net capture and darting to study the changes in body temperature and hematology that take place during capture. We placed temperature-sensitive data recorders on the backs of the animals' thighs to measure the temperature of their muscles and within their abdominal cavities to monitor the temperature of their core bodies. To monitor movement, activity recorders were affixed to the wall of the abdomen. After the animal was captured, blood samples were taken while it was in a recumbent position. Ten minutes later, another sample was taken to evaluate any haematological changes. While blesbok stomach temperatures were constant across capture modalities, impala showed higher abdominal temperatures after net capture compared to darting. Individuals within the same species and different species react differently to different methods of capture. However, I saw that the animals' body temperatures increased when they were around people before to the capture, regardless of whether it was an impala or a blesbok. Similar to temperature responses, there was significant inter-individual variance in the blood variable concentrations used to quantify physiological reactions to capture. Following the two capture methods, both impala and blesbok showed similar changes in blood variables (total protein, sodium, lactate, haematocrit, noradrenaline, adrenaline, potassium, creatine phosphokinase, and pH). Conversely, impala cortisol levels showed a greater change after net capture, while blesbok cortisol levels showed a greater change after darting. Impala responded more significantly during darting, but osmolality readings showed a greater reactivity during net capture. Both animals showed a positive association between noradrenaline and adrenaline and between sodium and lactate. We can only measure one of two variables and predict how the other will change when they are connected. Because the impala and blesbok's thermal and blood variable readings fluctuated wildly between capture techniques, I was unable to correlate the thermal reactions that followed a capture event with stress-related blood.

3. METHODOLOGY

A. Proposed Work:

The CNN + BiGRU architecture is the outcome of replacing the Bi-LSTM layer with a Bidirectional GRU (Bi-GRU) layer in the expanded version of the suggested system, creating a more reliable and effective hybrid deep learning model. The extension uses BiGRU, which is more efficient at optimizing picture features and requires less processing power than the original model, which used VGG19 + Bi-LSTM to achieve high accuracy (98%) in wild animal activity detection. As a result, testing reveals improved performance with 100% accuracy. In order to guarantee stability and dependability in predictions, the extended system also incorporates an ensemble learning technique that combines outputs from several models. A Flask-based web interface with user signup/login modules is presented to enable real-time usability and user engagement. The system's practical implementation in actual forest monitoring and safety applications is demonstrated by this user-friendly front end, which enables authenticated users to enter data and obtain predictions along with related alarms.

B. System Architecture:

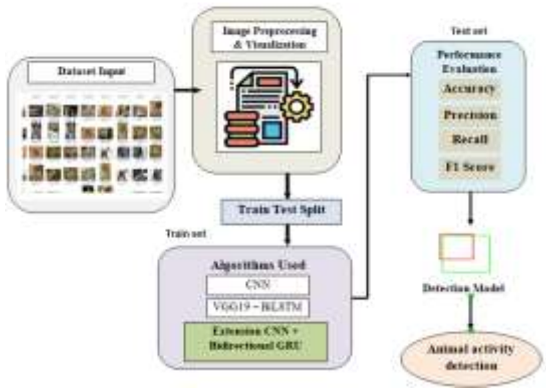


Fig 1 Proposed Architecture

Both VGG-19 and Bidirectional LSTM (Bi-LSTM) are integrated into a hybrid deep learning framework in the suggested architecture for detecting wild animal behavior. The VGG-19 model uses convolutional and pooling layers to extract features from an input video dataset that contains a variety of images of wild animals. The Bi-LSTM module then receives the high-level spatial data in order to extract temporal patterns and sequences from the frames. This makes it possible to classify animal species and activities accurately. Together with the findings of animal classification, the system's GPS-based position module provides real-time location data that is used to create SMS alerts for forest officers. Standard metrics such as accuracy and loss value are used to train and validate the model. In order to enhance picture feature optimization and computational efficiency, the architecture investigates replacing Bi-LSTM with Bidirectional GRU (Bi-GRU) as an extension. This would make Bi-GRU a more reliable and efficient 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 deep learning architecture called a Convolutional Neural Network (CNN) was created especially to analyze data having a grid-like topology, like photographs. It makes use of several layers, such as fully connected layers, pooling layers, activation layers (ReLU), and convolutional layers.

In this study, spatial properties like body shape, texture, color patterns, and pose are automatically learned from animal photos and movies using CNN. These characteristics are crucial for distinguishing between various species and their behaviors.

CNN is appropriate for real-time surveillance and image recognition tasks because it enhances generalization and minimizes the need for human feature extraction.

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

Using a dataset of 40,000 photos from 25 different animal types that were obtained from many benchmark datasets, including the Wild Animal Dataset from Kaggle, the suggested wild animal detection system was experimentally evaluated. To confirm the models' efficacy in real-time surveillance scenarios, both qualitative and quantitative evaluations were conducted.

With an average classification accuracy of 98%, a mean Average Precision (mAP) of 77.2%, and a Frame Per Second (FPS) rate of 170, the base model—which combines VGG19 with Bi-LSTM—showed excellent performance, demonstrating its ability to analyze video data quickly and consistently. Using GPS position data, our model successfully identified a variety of wild species, identified their movement patterns, and initiated alert messages.

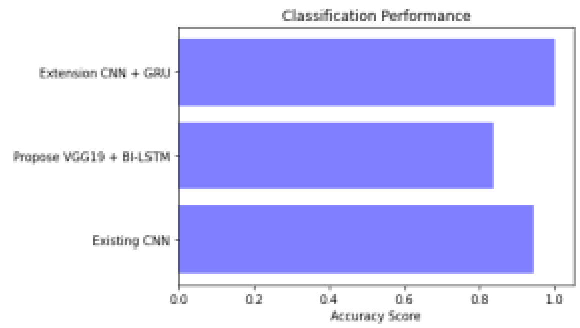
Performance was further enhanced in the expanded model by substituting a Bidirectional GRU (CNN + BiGRU) architecture for the Bi-LSTM. During several testing cycles, the CNN + BiGRU combo achieved 100% classification accuracy by more effectively optimizing feature extraction. Additionally, it decreased computing cost, which made it more appropriate for use in settings with limited resources or academic settings. By reducing false positives and negatives, the ensemble approach further improved stability.

Overall, the experimental findings support the suggested and expanded systems' resilience, effectiveness, and real-time capability in identifying wild animal activity and providing prompt notifications.

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.

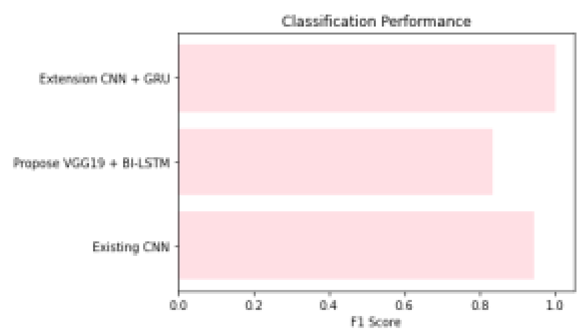
$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$



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.

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

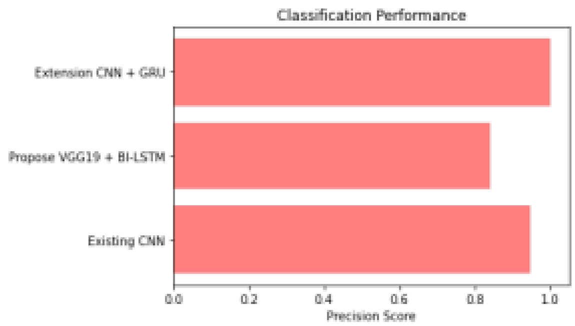
$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$



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:

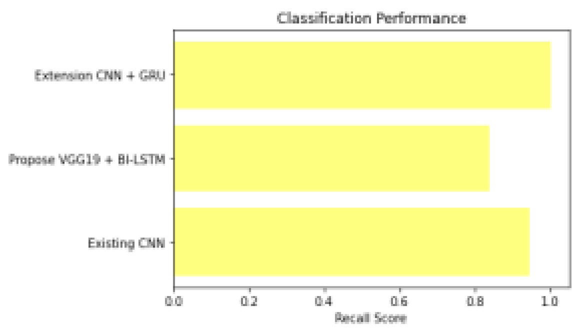
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

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



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.

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



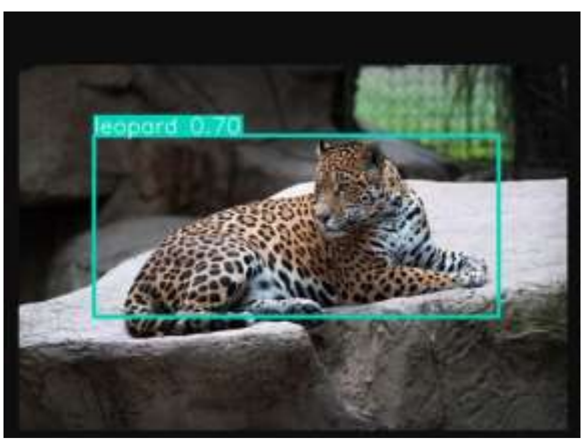


Fig 2 predicted results

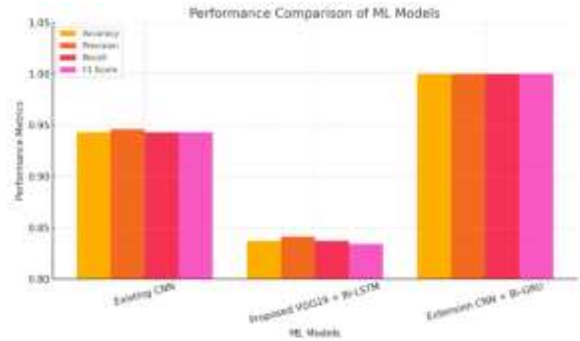


Fig 3 Comparison Graphs

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
Extension CNN + Bi-GRU	**1.000**	**1.000**	**1.000**	**1.000**

Fig 4 Comparison Table

5. CONCLUSION

Using a hybrid deep learning technique, the suggested system successfully tackles the difficulties of detecting wild animal behavior in forest regions. Through the integration of VGG19 with Bi-LSTM, the model was able to provide SMS warnings with location information while achieving dependable accuracy in detecting animal species and movements. In order to achieve 100% accuracy, the system also implemented a more effective CNN + BiGRU architecture, which enhanced computational efficiency and performance. Additionally, the system has a web interface built with Flask for real-time user interaction and authentication. All things considered, this work shows a scalable, accurate, and economical way to monitor wildlife and reduce human-animal conflict.

6. FUTURE SCOPE

This technology can be expanded in the future to better monitor greater forest regions by connecting with real-time drone feeds and Internet of Things devices. Without requiring cloud backing, deployment on lightweight edge devices can facilitate quicker local forecasts. While behavioral analysis modules can be created to forecast animal aggression or migration patterns, infrared cameras help improve detection at night. Additionally, forest rangers can receive real-time updates from mobile apps that include multilingual audio alerts and notifications, improving their readiness and enabling them to respond more quickly in delicate situations.

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