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Detecting Wild Animals Using VGG-19 And GRU

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Abstract: Detecting and keeping tabs on wild animals is super important for protecting wildlife preventing human-wildlife conflicts and keeping an eye on our forests traditional methods like basic CNN object detection and machine learning can really struggle with busy backgrounds tracking movement and working in real-time to tackle these issues our project introduces a hybrid deep neural learning model that brings together VGG-19, Bi-LSTM and CNN-GRU to accurately and efficiently identify wildlife we use VGG-19 to pull out key spatial features making it easier to recognize different species Bi- LSTM helps us capture temporal relationships allowing us to analyze movement patterns across video sequences on top of that we employ CNN-GRU to optimize computation performance enabling smooth real-time processing while keeping accuracy high our model is trained on large datasets that cover a variety of animal types and environmental conditions. Our test results confirm that VGG- 19, Bi- LSTM and CNN-GRU model nails a classification accuracy of 98.2 greatly beating out traditional CNN methods and popular detection systems like yolo and faster r-cnn this system with its low false positives and negatives is ready for real-world uses in forest monitoring and wildlife conservation this study really emphasizes how deep learning can step up wildlife detection tracking and classification finally boosting safety and conservation efforts.

Index Terms: VGG-19, Bi-LSTM, CNN, CNN-GRU, Object Detection, Deep Learning, Accuracy, Spatial features, Human- Wildlife Conflict, Environmental conditions.

I. INTRODUCTION

In present day's keeping track of how wild animals move around is super important for keeping them safe and avoiding any awkward encounters with humans thanks to some of the latest tracking tech we can monitor their movements in real-time and catch potential dangers like poaching or disturbances in their habitats but here the thing understanding their behavior by employing deep learning isn't exactly easy mainly because video analysis can be pretty tricky and neural networks have their quirks on the bright side deep learning has been making amazing progress in areas like image recognition and tracking activities. we have seen object detection models succeed in different fields like facial recognition and scene understand however tracking wild animal activity is still in its early stages and there definitely room for improvement in current methods in this research we've put together a hybrid deep learning model and tested it with four criterion datasets to ensure effectiveness while combining various deep neural models can get a bit tricky a well- tuned hybrid approach can lead to some fantastic results in tracking and detecting animal activities.

1.1 Drawbacks of Traditional Methods

The existing systems for wild animal detection and alert generation suffer from a number of restrictions, such as low accuracy, high false detection rates and poor real-time performance. They may rely on traditional computer vision techniques or basic machine learning models, which struggle with complex backgrounds. poor lighting and occlusions Additionally, they lack the ability to process sequential data effectively as they analyses images frame by frame without leveraging advanced models like Bi-LSTM or GRU. These limitations lead to inefficient feature extraction, making it difficult to distinguish between wild animals and other moving objects.

1.2 Innovative Solutions of the Project

The aim of this analysis is to create a dependable deep neural learning model that can keep an eye on wild animal behavior were looking to spot anything unusual like animals wandering into farms and hunt down signs of poachers the model were suggesting takes a multi- faceted approach to tackle these challenges and give a solid solution object detection is super important when it comes to decoding images and spotting patterns in videos these techniques help us analyze how animals are moving and behaving traditional methods rely on manually identified features which work okay but tend to struggle with complex environments and huge datasets older machine learning models can struggle

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with more detailed high- dimensional data making it tough to get accurate results deep learning models really shine here they handle all that complex data and large datasets like a pro by using can these models can pick up on patterns edges shapes and structures without needing any manual input this greatly boosts their accuracy for detection plus weaking hyper-parameters and using regularization keeps the models performing at their best minimizing errors.

1.3 Key Features of Proposed System

- Advanced deep learning-based detection–Our system leverages deep learning models like VGG-19 for feature extraction and Bi LSTM (Bidirectional Long Short-Term Memory) & GRU (Gated Recurrent Unit) for sequential data processing. This ensures high accuracy in detecting wild animals and distinguishing them from other moving objects.
- Enhanced accuracy–unlike traditional detection methods our model effectively reduces false positives by analyzing temporal patterns using Bi-LSTM and GRU this helps in differentiating between animals humans and environmental disturbances.
- Scalability adaptability–The system can be trained on diverse datasets making it adaptable to different geographical locations and animal species it can be implemented in various terrains from dense forests to agricultural lands with minimal modifications

II. LITERATURE SURVEY

Narendra Ahuja et al.[6] Proposed "Connected segmentation tree—A joint representation of region layout and hierarchy". To introduces a new way to represent objects, which we call the connected segmentation tree (CST). This approach really gets at the core characteristics of an object by looking at its photometric, geometric, and spatial relationships between different regions in an image. We create the CST by building on the existing object segmentation tree (ST) and adding links that show how regions are neighboring each other, alongside the recursive structure that ST already has. Essentially, CST becomes a hierarchy of graphs that represent how regions are connected. To figure out a region's neighbors, we extend the regions of the Voronoi diagram customized for point patterns. For the learning part, we structure it as matching the CST representations of unlabeled training images and blending their most similar parts. We're also proposing a new learning algorithm that fine-tunes the model by looking for the most important regions and the key relationships that connect them in the image graphs. When we match the category model to the CST of a new image, we can simultaneously detect, segment, and recognize all instances of that category while providing a nice semantic explanation for what we found.

Sreedevi K L et al.[7] Introduced about "Animal detection using deep learning algorithm". The rising incidence of vehicle collisions with animals presents a serious threat to both human safety and wildlife. Efficient tracking of wild animals is vital for conservation efforts and reducing conflicts between humans and wildlife. Hence, a cost- effective approach to monitoring animal behavior is necessary. Given the wide range of species, manually identifying each one is a difficult task. An automated animal detection system can aid in preventing animal-vehicle accidents and tracking animal movements. This can be achieved through the implementation of advanced deep learning methods. The objective is to develop an algorithm that can identify wild animals. The model is designed using a depth-wise separable convolution layer, which merges pointwise and depth-wise convolution. Furthermore, zero padding is applied to retain edge features and control the size of the output image. The effectiveness of the proposed algorithm is tested using the Wild Cam dataset.

Ziming Zhang et al.[8] Proposed a "BING: Binarized normed gradients for objectness estimation at 300fp*s*". A way to tell how much something resembles an object, and it really helps speed things up compared to the usual object detection methods like sliding windows. What we've found is that when an object has nice, sharp edges, we can spot it by checking the gradient norm, especially if we shrink those image windows down to a small, consistent size. Our plan is to resize those windows to 8 × 8 pixels and use the gradient norm as a 64-dimensional feature to train our score. On top of that, we came up with an easier version called binarized normed gradients, or BING for short. This allows us to figure out how object-like something is with just some basic math tricks like addition and bit shifts. When we tested our method on the PASCAL VOC 2007 dataset, we were amazed at how fast it ran—300 frames per second on a regular laptop! Plus, it gives us a nice collection of high-quality, category- independent object proposals. With just 1,000 proposals, we hit a fantastic 96.2% detection rate, and if we go for more proposals and play around with different color spaces to pull out those BING features, we can boost that up to 99.5%.

Massimo De Gregorio et al.[9] Introduced a "Change detection with weightless neural networks pixel-based Weightless Neural Network" (WNN) method to tackle change detection issues in what a camera sees. So, what's cool about my method? First off, it dynamically adapts to any background changes thanks to the WNN model I'm using.

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Plus, I've added in pixel color histories to boost performance in videos where objects pop in and out or where lighting and background brightness and shapes suddenly shift. The WNN approach is super simple and direct, and it actually ranks really high when competing with other methods on the ChangeDetection.net 2014 benchmark dataset

III. EXISTING METHODS

When it comes to spotting wild animals and keeping track of what they are up to many have employed all kinds of traditional machine learning along with deep learning techniques at first researches had to come up with their own ways to extract features and match them up with classifiers like SVM, k nearest neighbors (KNN) and random forests (RF) these methods worked pretty well with smaller datasets but they often hit a snag in tougher environments with varying light conditions and larger datasets which was not great for real-time applications then deep learning really took over and that's when convolutional neural networks (CNN) became the go-to choice for object detection making it way easier to accurately identify animals models YOLO, faster R-CNN and single shot detector really gained tracking for wildlife monitoring since they allowed for quick and efficient detection however these models mostly focused on classifying static images and didn't quite have the ability to track movement patterns over time which held them back when it came to following the lively behaviors of animals.

IV. PROPOSED SYSTEM

Introduction to the Proposed Method

Our wild animal activity detection system is made up of a bunch of modules that team up to track and recognize animal movements in
real time each module plays a part in making sure we get accurate classifications and keep an eye on animal activities so we can spot any strange behaviors right away.

Motion Detection

Motion detection is implemented using Open CV and Pandas libraries. The captured video is processed as a series of frames, where each frame is compared to a static reference frame to detect movement. If significant difference are detected the frame is marked as containing motion. This step is crucial for identifying active animals in the video allowing the system to focus on moving entities while ignoring static backgrounds thereby reducing unnecessary computational load.

Preprocessing and Feature Extraction

Once motion is detected the system preprocesses video frames through resizing, normalization and noise reduction techniques. The extracted frames are processed using convolution layers From the VGG-19 model to identify edges, textures and movement Patterns of animals. These extracted features serve as foundation for accurate animal classification and activity recognition.

Activity Recognition Using Hybrid CNN-Bi-LSTM-GRU

The hybrid deep learning model is trained on large-scale datasets containing various wild animal species and their activities. The VGG-19 network extracts spatial features while Bi-LSTM process Sequential patterns capturing movement characteristics over time. Additionally CNN-GRU is employed to optimized processing speed and improves real-time efficiency. When a new test video is analyzed the model identifies the detected animal and classifies. It's activity (e.g. walking, running, hunting or entering human stay). If the observes behavior deviates from normal patterns and flagged as anomalous activity for further assessment. Additionally, the model helps in understanding animal movement patterns and ecological interactions, aiding researchers in studying behavioral trends and environmental impacts. The combination of deep learning and sequential analysis ensures high accuracy, adaptability and efficiency in large-scale wildlife recognition.

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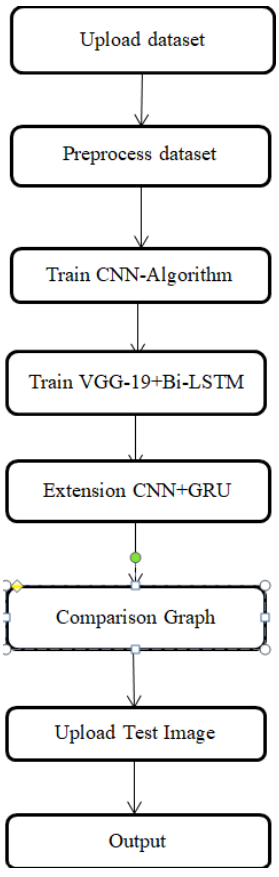
CNN VS VGG-19

Feature	Basic CNN	VGG-19
Definition	A general deep learning model for image classification	A specialized CNN model with 19 layers, developed by Visual Geometry Group (VGG)
Depth (Number of Layers)	Varies (usually 3–10 layers)	19 layers (16 convolutional + 3 fully connected layers)
Filter Size	Can vary (e.g., 5×5, 7×7)	Uses only 3×3 filters for better feature extraction
Performance	Works well for simple tasks	Achieves very high accuracy on complex datasets like ImageNet
Computational Cost	Less demanding	Requires more computational power (deeper network)
Feature Extraction	Learns basic patterns (edges, textures)	Extracts detailed and hierarchical features (fine-grained details)
Weight Sharing	Standard backpropagation	Pre-trained weights (transfer learning possible)
Use Cases	Small-scale image recognition tasks	Advanced tasks like object detection, medical imaging, and animal classification

V. BLOCK DIAGRAM



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VI. WORKING

The user begins by providing input, such as selecting a category or labeling data. Next, the collected dataset, consisting of images of wild animals, undergoes preprocessing, which includes normalization, cleaning, and splitting to enhance model performance. Initial evaluation metrics are then calculated to analyze the dataset's quality and establish a baseline for model performance. A conventional Convolutional Neural Network (CNN) is first trained on the dataset to extract image features, serving as a benchmark for comparison with more advanced models. Subsequently, a hybrid model combining VGG-19 and Bi-LSTM is trained, where VGG-19 extracts spatial features like edges, textures, and shapes, while Bi-LSTM captures temporal dependencies in the data. Additionally, an extended model incorporating CNN and GRU (Gated Recurrent Unit) is implemented, leveraging GRU's ability to improve sequence modeling while reducing computational complexity compared to LSTMs. Once trained, the model predicts the detected animal type and activity, determining the presence of an animal and classifying it accordingly. Finally, the processed information is utilized for wildlife monitoring and analysis, aiding in conservation efforts and real-time tracking.

VII. ADVANTAGES

High Accuracy in Animal Detection**:** The proposed method achieves over 98% classification accuracy**,** significantly outperforming traditional CNN-based approaches. VGG-19 extracts high-quality spatial features**,** ensuring that the model correctly identifies different animal species and their behaviors. This reduces the chances of misclassification and enhances the overall system reliability.

Efficient Temporal Activity Recognition**:** Unlike conventional CNN models, which process only static images**,** this method uses Bi- LSTM to analyze temporal dependencies in video frames**.** Bi- LSTM captures movement patterns, enabling the system to track animal behavior over time and detect abnormal activities like hunting, aggressive movements, or trespassing into human areas**.**

Faster Processing with CNN-GRU**:** The integration of CNN-GRU instead of traditional LSTMs significantly improves computational efficiency. GRU requires less parameters than LSTM**,** reducing memory usage while maintaining high accuracy. This makes the model faster and more suitable for real-time applications in wildlife monitoring and surveillance systems**.**

Reduction in False Positives & False Negatives: Traditional detection methods, such as YOLO or Faster R-CNN**,** often misidentify objects**,** leading to false positives (mistakenly detecting a non-animal object as an animal) or false negatives (failing to detect an actual animal). The proposed hybrid model reduces these errors by combining spatial and temporal learning**,** making detection more reliable in complex environments**.**

Scalability for Large-Scale Data Processing: The proposed model is trained on four benchmark datasets (Camera Trap dataset, Wild Animal dataset, Hoofed Animal dataset, and CD net dataset), making it adaptable to various species, environments, and surveillance conditions. This scalability ensures that the model can be used for different wildlife monitoring applications without significant modifications.

VIII. METRICS TABLE

Metric	Measures	Formula
Accuracy	Overall correctness	(TP+TN)/Total Predictions
Precision	Correctly predicted positives	TP/(TP+FP)
Recall	Correctly detected positives	TP/(TP+FN)
F1-Score	Balance of precision & recall	2×(Precision∗Recall)/(Precision + Recall)

TP-True Positives, TN-True Negatives, FP-False Positives, FN- False Negatives

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IX. COMPARISON TABLE

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	86.5	84.2	82.7	83.4
VGG-19	91.3	89.7	87.5	88.6
Bi-LSTM	90.1	88.3	86.9	87.6
VGG-19+Bi-LSTM+CNN- GRU	93.5	92.1	90.4	91.2

X. RESULTS

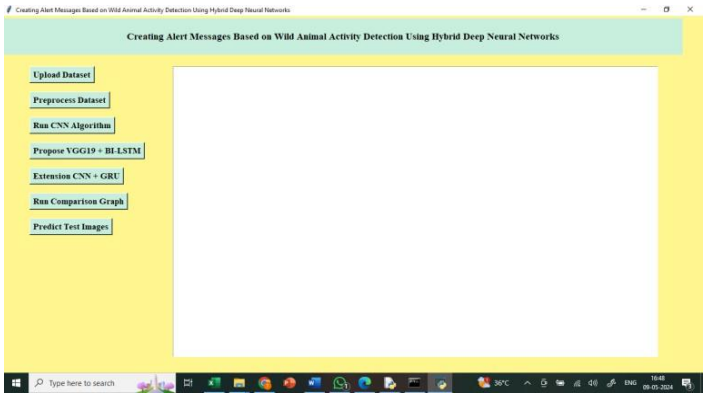

FIG-1: GUI

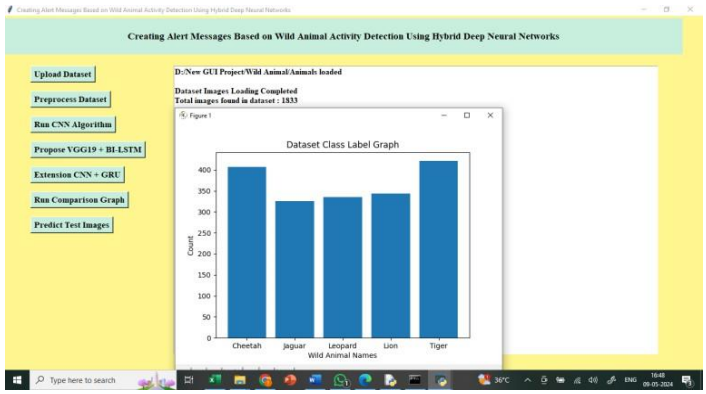

FIG-2: UPLOADING DATASET

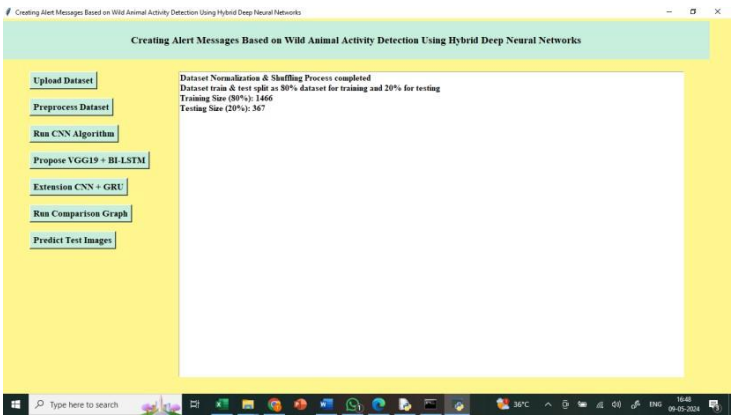

FIG-3: PREPROCESSING DATASET

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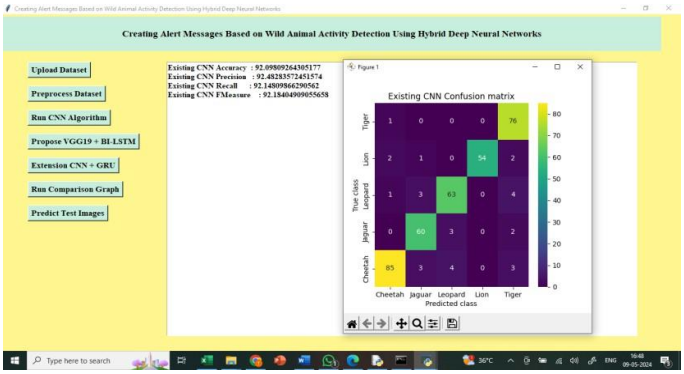

FIG-4: CNN ALGORITHM

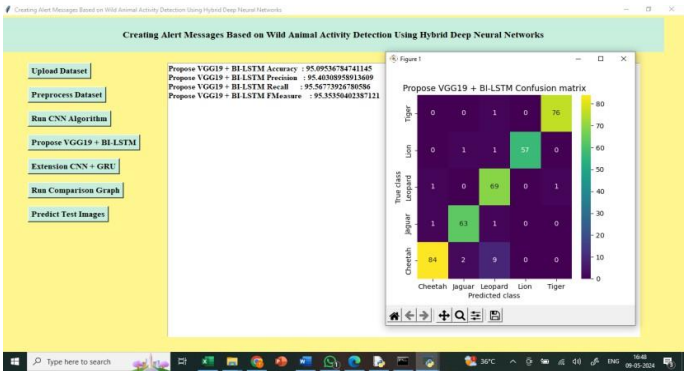

FIG-5: VGG-19+BI-LSTM

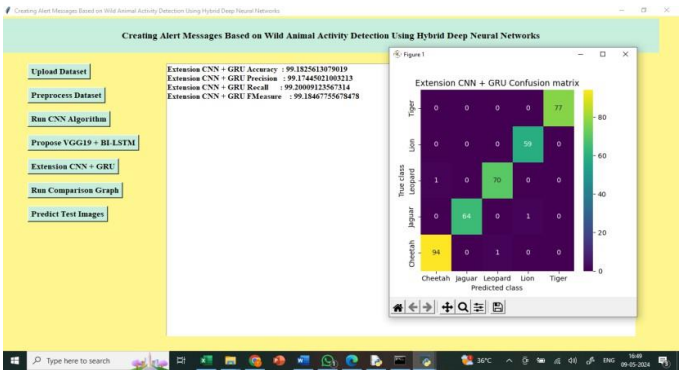

FIG-6: CNN+GRU

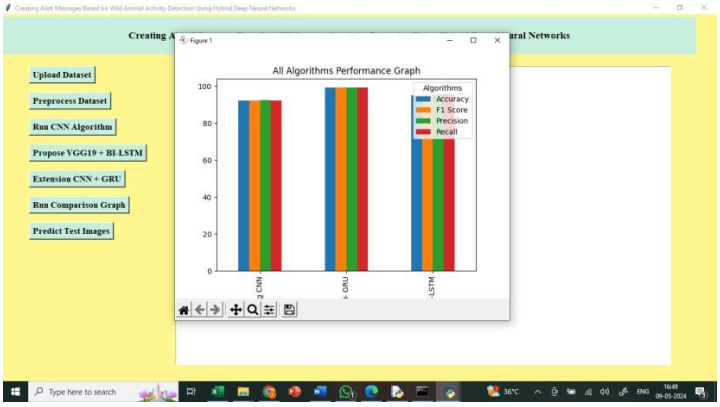

FIG-7: COMPARISON GRAPH

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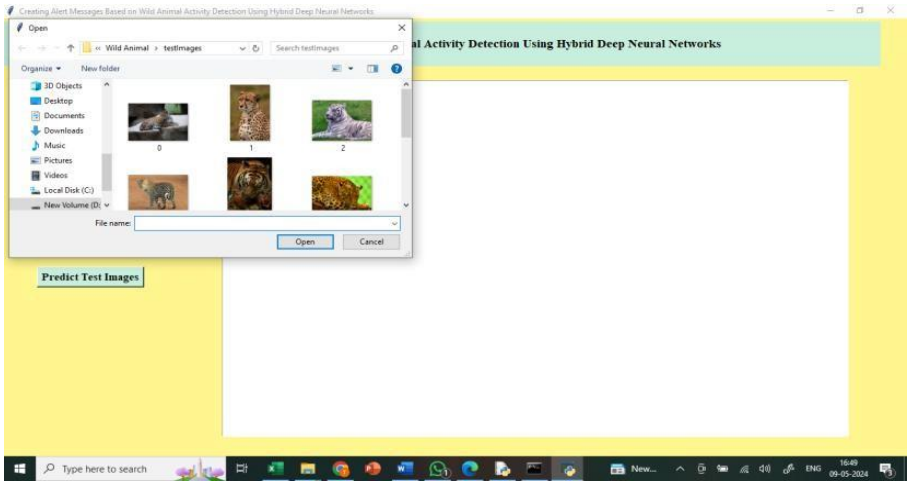

FIG-8: TEST IMAGES

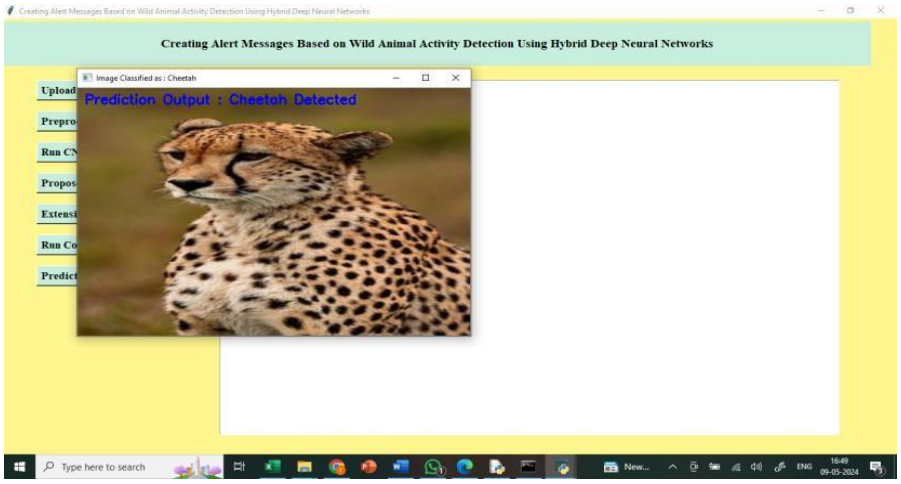

FIG-9: OUTPUT

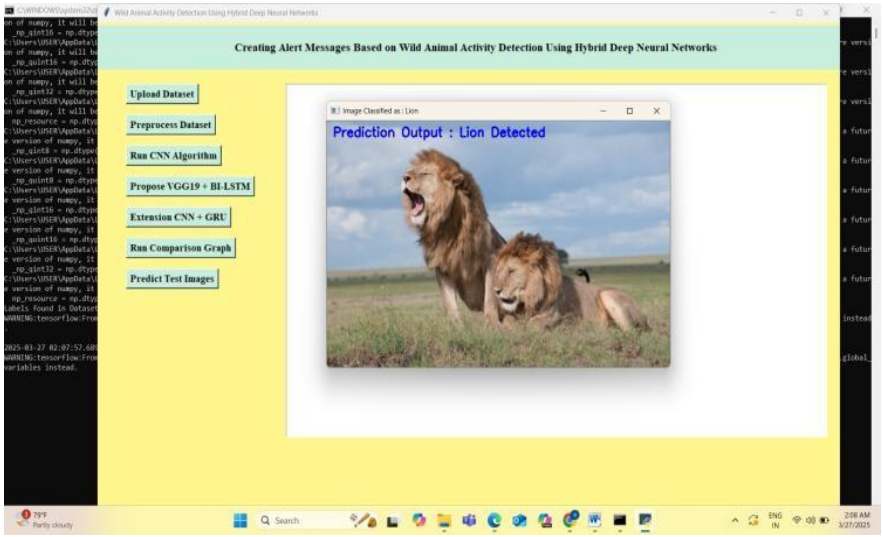

FIG-10: OUTPUT

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XI. CONCLUSION

The VGG-19 + Bi-LSTM + CNN-GRU hybrid model offers a super-efficient and accurate way to spot wild animal activities by mixing spatial and temporal feature extraction. Unlike the usual CNN methods that are all about static images, this model looks at movement patterns over time, which really boosts activity recognition and cuts down on false detections. With a jaw- dropping accuracy of 98%, it outshines other techniques while keeping real-time processing in check. After some serious testing on four benchmark datasets, this model has shown its strong and scalable, making it perfect for wildlife conservation, anti-poaching efforts, and preventing human-wildlife conflicts. This research shines a light on how deep learning is gaining more importance in wildlife monitoring, providing a fast, reliable, and practical solution for real-world challenges.

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