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Modernized Wildlife Surveillance and Behaviour Detection using a Novel Machine Learning Algorithm

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Abstract: In a natural ecosystem, understanding the difficulties of the wildlife surveillance is helpful to protect and manage animals also gain knowledge around animals count, behaviour and location. Moreover, camera trap images allow the picture of wildlife as unobtrusively, inexpensively and high volume it can identify animals, and behaviour but it has the issues of high expensive, time consuming, error, and low accuracy. So, in this research work, designed a novel wildlife surveillance framework using DCNN for accurate prediction of animals and enhance the performance of detection accuracy. The executed research work is implemented in the python tool and 2700 sample input frame datasets are tested and trained to the system. Furthermore, analyze whether animals are present or not using background subtraction and features extracted is performed to extract the significant features. Finally, classification is executed to predict the animal using the fitness of seagull. Additionally, attained results of the developed framework are compared with other state-of-the-art techniques in terms of detection accuracy, sensitivity, F-measure and error.

Keywords: Wildlife Surveillance, Identify animal, feature extraction, pixel variation, behaviour, frame retrieval.

I. INTRODUCTION

In the past decade, technologies in the digital epoch enable huge innovations and modernization of several computerized applications [1]. Among them, video surveillance is most crucial for security purposes [2]. It is significant not only for security but also for healthcare systems, defense, institutions, etc., for more than 70 years [3]. Thereby, a surveillance system becomes a necessary tool for day-to-day life activities for a better standard of living [4, 5].Moreover, the purpose of using video surveillance and remote still cameras detect and identify the pest species [6]. Nowadays, automatic recognition of animals is increased by using a monitoring detection system [7]. These techniques enhance the capability of capturing high resolution images [8]. Nevertheless, it is used for detecting animals in specific places to situations [9]. The wildlife management and conservation of humans require cost effective techniques for monitoring and identifying the animal behaviour or animal type [10]. As well, video camera and still can create large quantities of data that are expensive and laborious to screen the specific species [11].Additionally, Artificial Intelligence (AI) has been significantly growing from practical requirements [12]. The basic process of detection of animals is detailed in fig.1.

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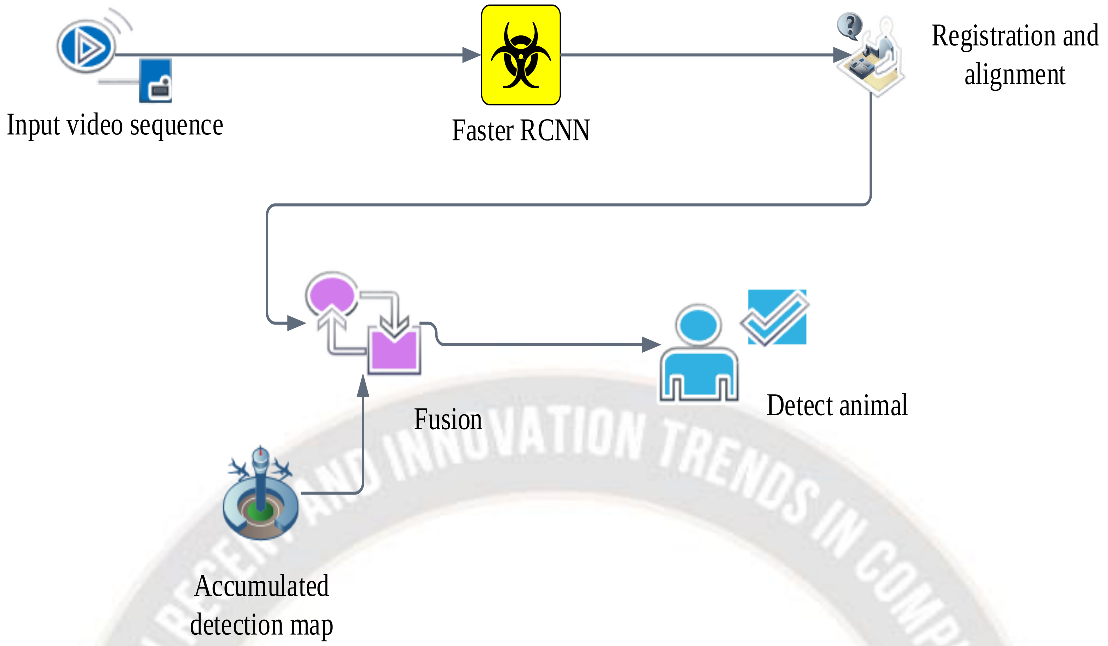

Fig.1 Automated detection of animal using machine learning

In general, AI together with Machine Learning (ML) algorithms are combined with analytical applications which can be executed using networked devices like high-tech IP cameras integrated into embedded systems and cameras embedded in the computer as well as surveillance systems [13, 14]. These recent technologies provide several benefits such as helping to track dynamic objects, searching a particular object, helps to find the geographical location of an object, counting the number of instances in a specific location, and most importantly, it provides significant assistance in detecting anonymous or suspicious activities occurring in the field of the camera's view [15, 16]. For this reason, these technologies provide increased benefits in the field of surveillance systems [17]. An efficient surveillance system is possible only with the implementation of an appropriate algorithm that enhances the usability of the images captured by the camera [18]. For this digital image processing, several algorithms were implemented conventionally.

However, the efficiency of image analytics is limited due to complications in detecting moving objects, noises, and dynamic background issues [19]. There are many techniques are developed to overcome these issues such as automatically extracted deep neural technique [20], automated wildlife monitoring framework [21], Classify Me [22], and pre-trained deep learning framework [23] but still having the problem of more expensive, time consumption, noise, improper prediction, misclassification, and less detection accuracy. So this current research work enhances the performance of identifying wild animals using behaviour detection and optimized machine learning technique.

The arrangement of this article is structured as follows: The related work based on wildlife surveillance is detailed in section 2 and the system model and problem statement is elaborated in section 3. Also, the process of the proposed methodology is described in section 4. Finally, the achieved outcomes are mentioned in section 5 and the conclusion about the developed model is detained in section 6.

II. RELATED WORKS

A few recent literature surveys based on wildlife surveillance and animal detection are detailed below,

Mohammed Sadegh et al [20] have proposed an automatically extracted deep neural technique for identifying and detecting 48 species. Initially, the neural system automatically identifies the animals with the accuracy of 96.9% though performing a million image dataset. Thus the gained efficiency highlights the performance of detection rate using data extraction and deep neural technique but time consumption to identify the species is large.

Reliable and efficient monitoring of wild animals based on their natural habitat is more important for informing conservation and decision management. The automatic conversion of camera traps is the trending most popular tool to monitor wildlife because of reliability and effectiveness. Schindler et al [21] developed an automated wildlife monitoring framework for increasing the ability to filter animal images and automatically identify species. Thus the developed technique attains 88.4% accuracy to detect animal images but the noise rate is high when comparing other techniques.

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Greg Falzon et al [22] have developed a ClassifyMe software tool to identify animal species automatically. Moreover, developed techniques pre-trained the specific species by their location also upload an image from the camera trap. Initially, the developed technique allows the user access by camera trap images. Furthermore, the ClassifyMe technique gained better performance to detect the animal but it become more expensive while comparing other techniques.

Generally, the purpose of using camera traps is to obtain valuable information about behaviour and appearance of wild animals. Christin Carl et al [23] developed a pre-trained deep learning framework for detecting the rate of the correct region with 94%. The gained accuracy for classifying the correct species is 71%, which also increases the detection and classification results. It becomes more efficient and less expensive but improper classification because of data complexity.

Ruilong Chen et al [24] proposed two deep learning techniques for the purpose of detection process and identifying animals using video footage. The technique involves three processes such as automatic animal detection, filtering out non-animal images, and recognizing wild animals based on film footage. Thus the developed algorithm enhances the wildlife monitoring system using a large rate of data for certain species. However, it is more expensive.

The key steps of the designed paradigm are processed as follows,

- Initially, the input images from the dataset are collected and trained to the system using the python system.
- Hereafter, perform a background subtraction approach to detect whether any animal present in the camera's point of view.
- If any, then collect the images with animals and subject them to further feature extraction using Histogram of Oriented Gradients (HOG).
- Then, the extracted images are given to Deep Convolutional Neural Network (DCNN) for classification.
- Besides, the weights of the DCNN are optimized to enhance the accuracy performance.
- Consequently, the classified results are collected and send to a base station to report the animal intrusion.
- Finally, the performance of the proposed model is compared with other existing and the efficiency was verified in terms of, accuracy, sensitivity, specificity, F-measure, execution time, and precision.

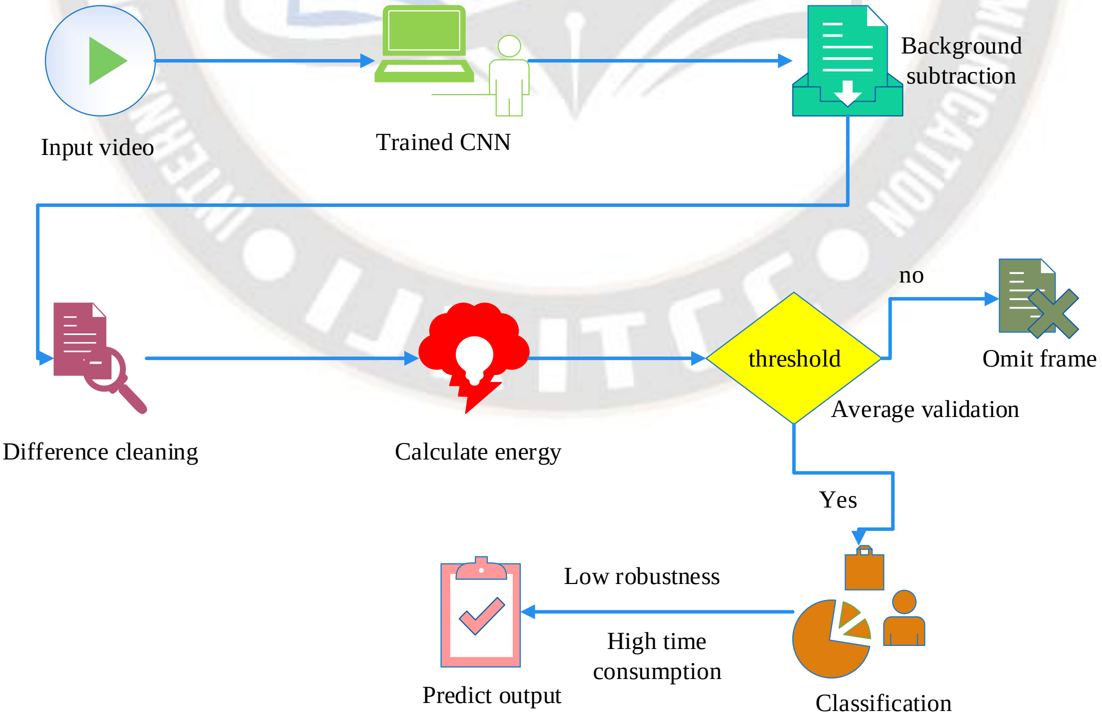

Fig.2 System model and problem definition

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III. SYSTEM MODEL AND PROBLEM DEFINITION

The video footage of the wild animal dataset is tested and trained to the system. Moreover, trained CNN is directly imported to the video footage subsequently films are denoted as a sequence of image frames. All the images are converted into grey scale for increasing the detection process. While the images are detected via potential frame, colour images are used for recognition. Moreover, the movement of the animals is identified based on the various pixels of adjacent frames. Furthermore, background subtraction extracts the features from the footage and different cleaning removes irrelevant information from the film. As well, classification is performed based on the threshold value of each footage; while the threshold level is large means neglect the frame. Finally, predict the animal present in the video footage using a threshold value. But it has consumed more time for classification and prediction also low robustness. Thus the system model and problem definition have illustrated in fig.2.

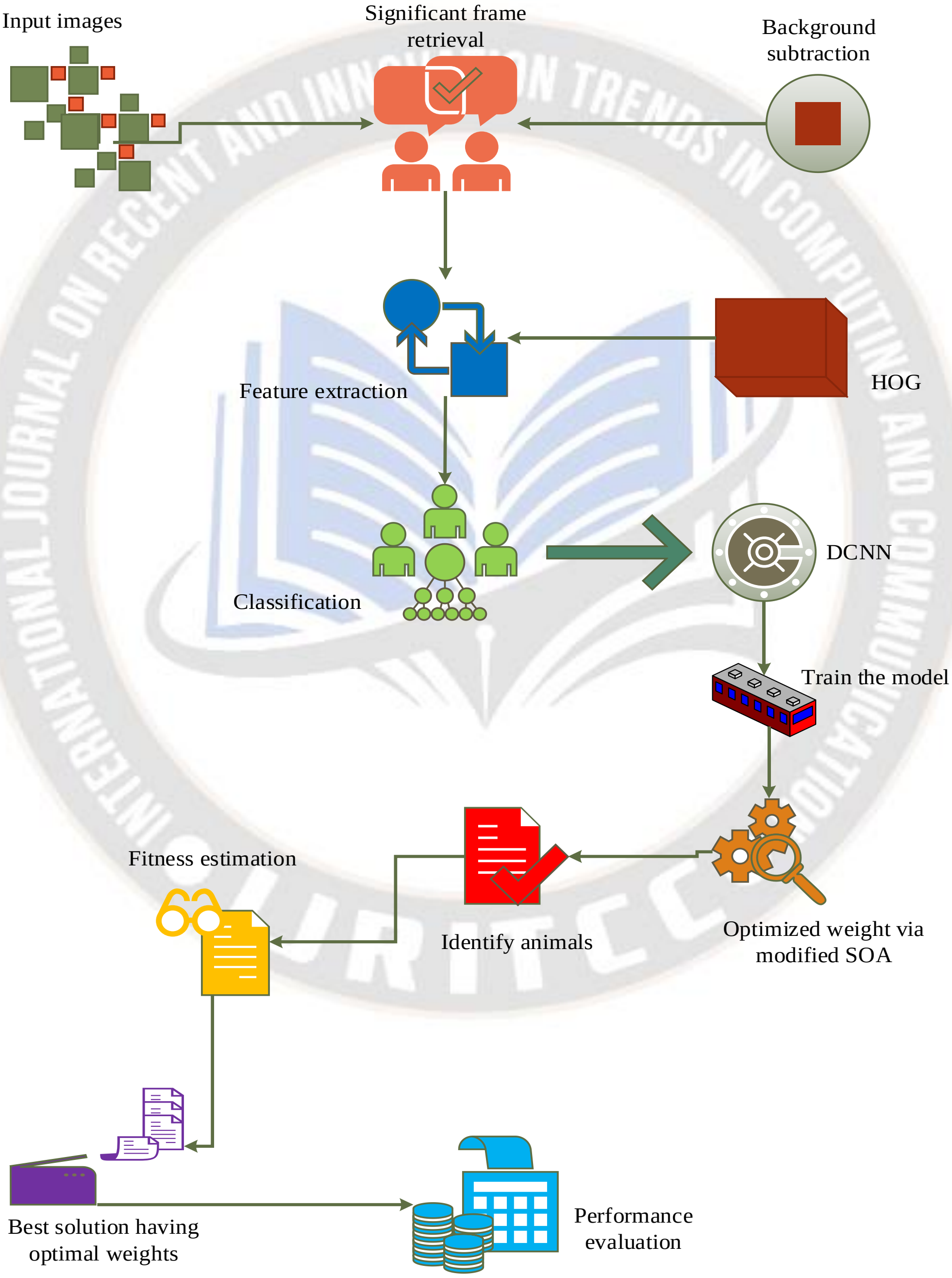

Fig.3 Proposed Framework

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Generally, video cameras and still surveillance produce a massive quantity of data that is expensive and laborious for screening the species. Moreover, camera trap allows wildlife pictures to be calm unobtrusively, inexpensively and high volume but identification and detection of wild animals, manual tasks, and time-consuming are riskier. To overcome these problems designed a novel optimized machine learning framework and the developed framework attain better results for detection accuracy and time consumption.

IV. PROPOSED METHODOLOGY

Intending to improve the performance, this proposal presents a proficient optimization model which enhances the performance as well as accomplishes better accuracy than traditional models. The architecture of the proposed framework is shown in fig.3.

This proposal presents a wildlife surveillance model, in which the input images are initially subjected to an image detection process to find whether the image has any animals or not through performing a background subtraction approach. Secondly, HOG feature extraction is applied to extract the significant features. Finally, the extracted features are given to classification using the DCNN model. Here, the performance of DCNN is improved by using the efficiency of the Seagull Optimization Algorithm (SOA) through optimizing the weights of CNN. Moreover, the developed technique is implemented in the python tool and attains better detection accuracy while comparing other state-of-the-art techniques.

4.1 Significant frame retrieval

Initially, find out whether any animals are present in the camera frame or not using background subtraction.If any, then collect the images with animals and subject them to further feature extraction. Moreover, background or foreground subtraction is extreme sensitivity used for detecting dynamic changes of scenes in the image sequences that may allow the foreground of the images for extracting further processing. Furthermore, identify animals present in the camera trap images based on the binary classification of each pixel in an image. The variation of pixel rate identifies whether any animals are present or not. Thus the identification of animals using background subtraction is obtained using eqn. (1).

$$\frac{\eta(BG/p(t))}{\eta(FG/p(t))}=\frac{\eta(p(t)/BG)\eta(BG)}{\eta(p(t)/FG)\eta(FG)}$$
(1)

Where, $p(t)$ is denoted as input frame, $\eta(BG/p(t))$ and $\eta(FG/p(t))$ are denoted as horizontal and vertical pixel location. Moreover, $\eta(p(t)/BG)$ is considered as the current pixel value in the location of t and $\eta(BG)$, $\eta(FG)$ are denoted as colour distribution of pixel variation.

4.2 Feature extraction

After the identification of animals present in the input images, extract the significant features using HOG. Furthermore, HOG is commonly used for computer vision applications to detect image or videos by feature extraction. It includes five blocks such as colour normalization, gradient computation, cell histogram, block distribution, and blocks normalization.

- **Colour Normalization**

Initially, input images are sending to the colour normalization blocks to execute object recognition from the coloured images. This block removes the intensity values present in the images while stabilizing colour values.

- **Gradient Computation**

Subsequently, the colour normalization, measure the computation of gradient values and the gradient values are calculated by vertical and horizontal directions. Moreover, filtering the grey scale images is more essential and the image filtration is obtained by eqn. (2).

$$GS_X=\begin{bmatrix}-1 & 0 & 1\end{bmatrix} \text{ And } GS_Y=\begin{bmatrix}1\\0\\-1\end{bmatrix} \tag{2}$$

Where, GS_X and GS_Y are denoted as filtering gradient images. Also, S is represented as images. Moreover, calculate the magnitude and orientation of gradient values by eqn. (3) and (4).

$$|M_G|=\sqrt{S_X^2+S_Y^2} \tag{3}$$

$$\theta_o=\arctan\left(\frac{S_Y}{S_X}\right) \tag{4}$$

Where, M_G is called as the magnitude of gradient value and θ_o is considered as the orientation of gradient values, S_X^2 and S_Y^2 are denoted as convolution operation of x and y derivation of images, $S_X^2=1*GS_X$, and $S_Y^2=1*GS_Y$.

- **Cell Histogram**

At next, create the cell histogram, based on the obtained values of gradient computation, and the cell histogram creation executed using each pixel present in rectangular cell. The histogram channels are equally spread over $0-180°$ or $0-360°$ based on the signed or unsigned gradient. Additionally, pixel contribution is the square of gradient magnitude. Thus the gradient strength is normalized by the essential of grouping cells.

- **Block Distribution**

The normalized grouping cells are connected into the blocks and the blocks are naturally overlapped and each cell contributes more than one meaning. It contains two blocks as Rectangular HOG (R-HOG) and Circular HOG (C-HOG). Thus the R-HOG block is a square grid structure using three parameters and it is obtained by eqn. (5).

$$R-HOG = n(c/b), n(p/c), n(ch/c) \tag{5}$$

Let, $n(c/b)$ is called as a number of cells per block, $n(p/c)$ is represented as a number of pixels per cell, and $n(ch/c)$ is denoted as a number of channels per cell.

- **Blocks Normalization**

Generally, groped cells present in the block are normalized based on the all histogram in the block which is represented as $|B_n|$. It can reduce the overlap of some elements and the blocks are normalized with the help of eqn. (6), (7), and (8).

$$L1(N_f) = \frac{B}{\sqrt{|B|_1 + e}} \tag{6}$$

$$L2(N_f) = \frac{B}{\sqrt{|B|_2^2 + e^2}} \tag{7}$$

$$L1(S_f) = \sqrt{\frac{B}{\sqrt{|B|_1 + e}}} \tag{8}$$

Where, $L1(N_f)$ is denoted as the normalized frequency of L1, $L2(N_f)$ is denoted as the normalized frequency of L2 and $L1(S_f)$ is denoted as the square frequency of L1. Moreover, e is constant.

4.3 Classification

Then the extracted features are imported to the DCNN in a dense layer. The main purpose of using DCNN is to predict the animals present in the image. Furthermore, the classification of animals is essential because the images contain the possibility of more than one animal. Consequently, Seagull fitness is updated to the CNN for optimized the weight of CNN which enhances the performance of accuracy. Then the extracted features are trained to the DCNN through convolutional and Maxpooling layer and the input image contain 192×192 pixel that is reduced $5 \times 5 \times 128$ using the feature vector of HOG. As well, update the fitness of seagull in dense layer for optimizes the weight. Moreover optimized weight of DCNN using eqn. (9)

$$O(w_c)^n = (1-\eta) \times L(N_f) + \eta \times j_s \left(O(w_c)^{n-1}\right) \tag{9}$$

Where, $L(N_f)$ is denoted as current pixel value of extracted features from the dataset, j_s is considered as the fitness of seagull and n is denoted as the vertical and horizontal location of the pixel.

Algorithm:1 Develop wildlife surveillance framework for identifyinganimals

Start
{
Initialize dataset, $p(t)$
// $p(t)$ -input frame
//total-2700, tiger-300, cheetah-300 and elephant-300
Significant frame retrieval //convolutional layer
For all t=1,2.3,….n
{
Analyze animal
// pixel variation based background subtraction
}
End for

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Feature extraction``` // Maxpooling layer
{
- **Colour Normalization**

$p(t) \rightarrow object\_recognition$
// remove intensity value
- **Gradient Computation**

Filter grey scale image x and y
For θ **=1 to x**
{
$S_X^2 = 1 * GS_X$
}
// GS_X and GS_Y - filtering gradient images
// S_X^2 and S_Y^2 - Convolution operation
For θ **=1 to y**
{
$S_Y^2 = 1 * GS_Y$
}
End for
- **Cell Histogram**

Create cell histogram
// every pixels generate group cells
- **Block Distribution**

Grouping cells $\rightarrow Blocks$
- **Blocks Normalization**

Normalize $|B_n|$
// reduce overlap of element
}
Classification // dense layer
{
Update seagull
// optimized weight of DCNN
$\boldsymbol{if}\ \max(L(N_f)) \leq \theta$
{
Identify animal
}
End if
// $L(N_f)$ - current pixel value of extracted features
Classified animal //Output layer
}
Output
Fitness estimation
}
End

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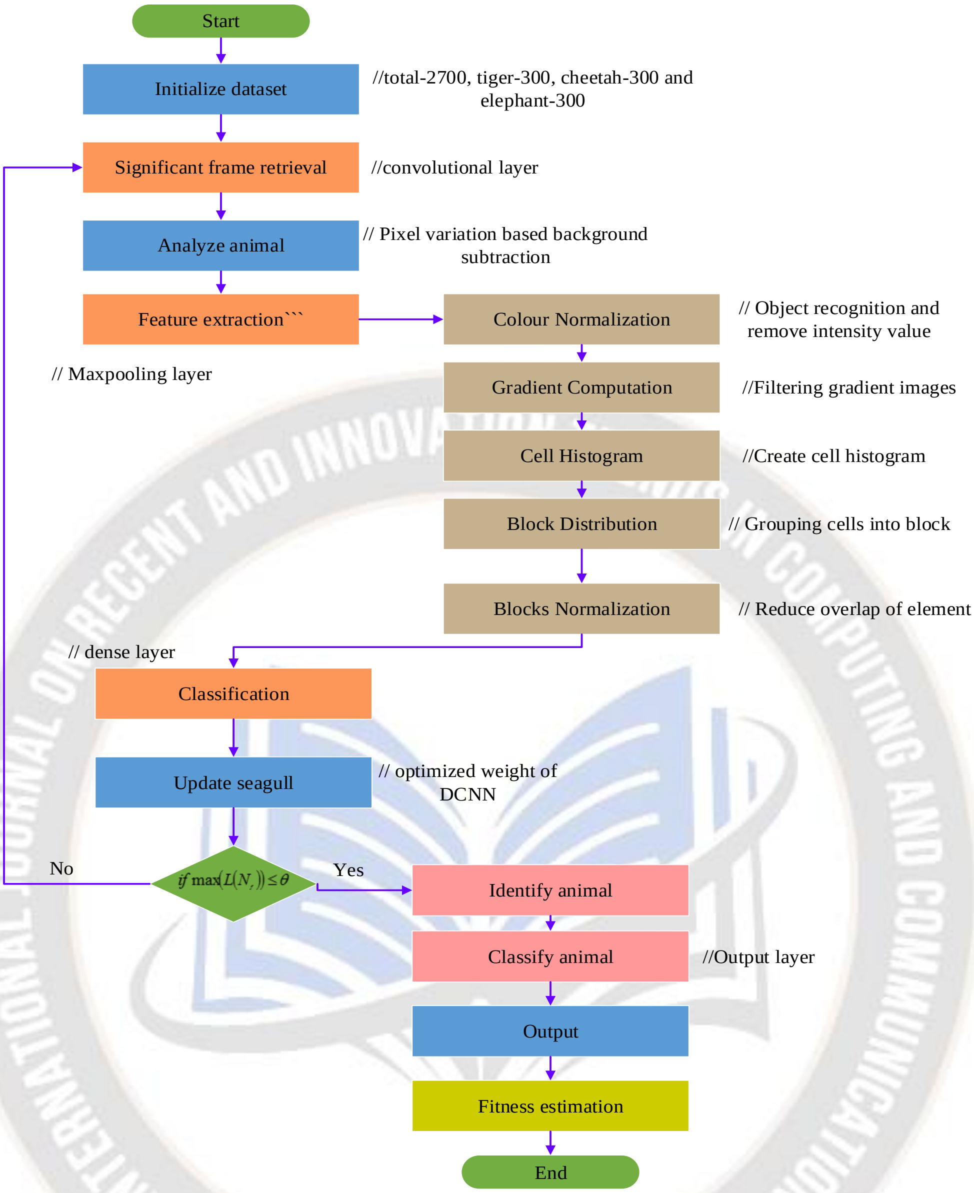

Fig.4 Workflow of developed framework

Then developed framework identifies the animals present in the dataset from the trained model of DCNN using eqn. (10).

$$k_z^t = \begin{cases} if \max(L(N_f)), & k_z < \theta \\ otherwise, & k_z \end{cases}$$
(10)

Let, k_z^t is considered as classified results of animals and k_z is represented as pixel variation of extracted features. Thus the developed framework identifies the animal using the optimized weight of DCNN through seagull fitness. As well, a workflow of the proposed framework is detailed in fig.4.

V. RESULTS AND DISCUSSION

The developed wildlife surveillance technique for detecting animals is processed using a python tool; the success rate of the projected model is assessed by current existing mechanisms in the terms of detection accuracy, sensitivity, error rate, and F-measure. In this approach, 2700 datasets are tested and trained for the system. Here, the proposed wildlife surveillance framework analyze whether any animals are present in the input image at the initial stage and identify the animal using the fitness function of a seagull and optimized weight of DCNN. As well, gained results of detection accuracy with the number of epochs are shown in fig.5.

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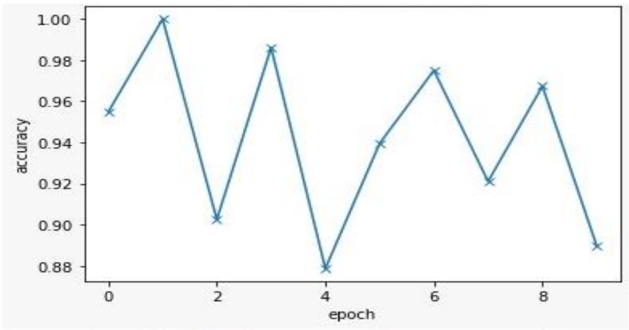

Fig.5 Accuracy Vs.No.of. Epochs

Thus the developed framework attains better results in detection accuracy. Moreover, the testing and validation loss rate of the developed technique has illustrated in fig.6.

Hence, the developed model attained better performance in prediction accuracy, sensitivity, and F-measure also low rate in error can prove the reliability of the developed framework.

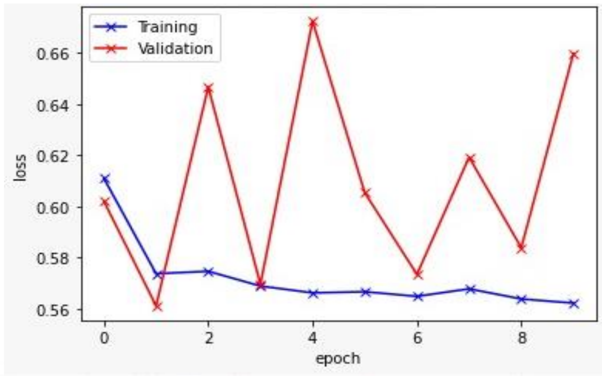

Fig.6 Loss Vs. No.of. Epochs

5.1 Case study

In recent years, wildlife research and management are rapidly grown through the use of video surveillance and remote still cameras. The main purpose of surveillance is to identify the species and behaviour. Thus the developed framework is executed in a wildlife surveillance system and the basic process is elaborated in fig.7.

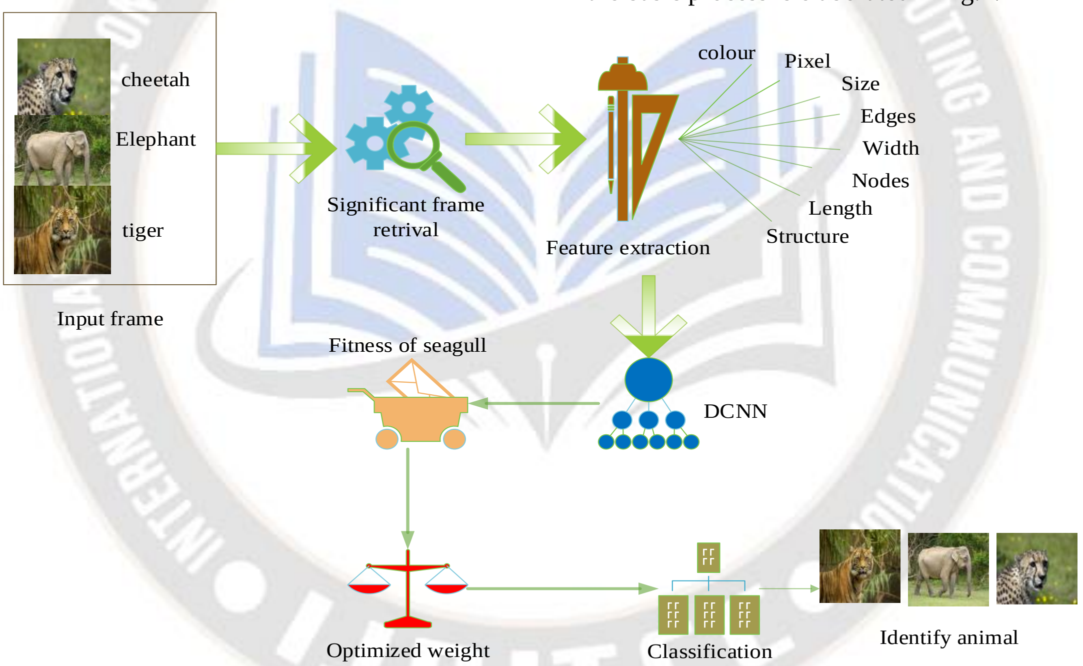

Fig.7 Basic process of the developed framework

Initially, 2700 input frames are collected from the net source and trained to the system and the input frame contains tiger, cheetah, and elephant images, and the description of the dataset is detailed in table.1.

Table.1 Dataset description

Class	Training	Testing
Tiger	900	100
Elephant	900	100
Cheetah	900	100

At next, retrieve the significant frames present in the input frame using background subtraction. It analyze whether any animal present in the input frame or not. After that, feature extraction is performed for extracting the significant features such as size, width, length, structure, colour, pixel rate, and edges, etc. Then the extracted features are sending to the DCNN for classifying the animals from the trained model. In this phase, update the fitness function of the seagull in dense layer it has the ability to identify the correct location for avoiding collision [26]. Thus the bird identifies the new location of the search agent based on the frequency of other birds. The purpose of using seagull fitness is it optimized the weights of DCNN and provides an

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accurate prediction of an animal. Finally, the classification layer predicts the animal present in the input frame.

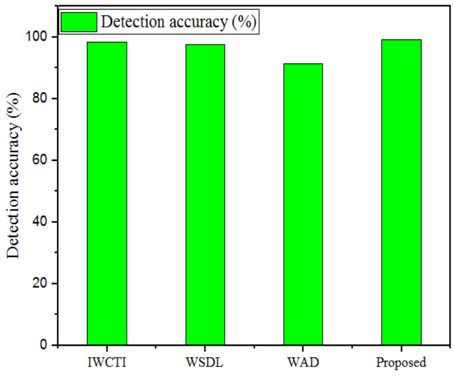

Fig. 8 Accuracy comparison

5.2 Performance metrics

The implementation work of the developed wildlife surveillance technique is done by the python tool and the parameters like detection accuracy, sensitivity, error rate, and F-measure are calculated. Moreover, the developed approach is validated using existing methods like Identification of Wildlife using Camera Trap Images (IWCTI) [22], Wildlife Surveillance using Deep Learning (WSDL) [24], and Wild Animal Detection Using DCNN (WAD) [25].

5.2.1 Prediction accuracy

The term prediction accuracy is defined as the closed measurement of accepted or true value which is possible for varying precise nonetheless not absolutely accurate. Moreover, the degree of gained measurement of correct prediction of animal or standard prediction of animal is measured using eqn. (11).

$$A = \frac{C_p + C_n}{C_p + C_n + W_p + W_n} \tag{11}$$

Where, C_p is denoted as the correct prediction of animal, C_n is denotes as the correct negative prediction of animal, W_p is considered as the wrong prediction of animal and W_n is denotes as the wrong negative prediction of an animal. Moreover, accuracy comparison with existing technique is detailed in fig.8.

The achieved detection accuracy rate of developed technique is compared with other existing techniques such as IWCTI, WSDL, and WAD. Moreover, the IWCTI replica attained 98.5% and WSDL technique gained 97.58%. Also, WAD techniques gained a detection accuracy rate are 91.4%. The developed framework attained high accuracy while comparing other techniques to detect animals as 99.2%.

5.2.2 Sensitivity

Generally, sensitivity is the capability of tests to predict animals in a correct way and the calculation of sensitivity is measured from the positive results of the developed framework. The sensitivity of the developed framework is identified using eqn. (12)

$$Sensitivity = \frac{C_p}{C_p + W_n} \tag{12}$$

The achieved sensitivity rate of developed technique is compared with other existing techniques such as IWCTI, WSDL, and WAD. Moreover, the IWCTI replica attained 98.5% and WSDL technique gained 82.2% in sensitivity. Also, WAD techniques gained sensitivity as 91.4% and the developed framework attained sensitivity as 99.5%. Furthermore, a comparison of sensitivity with other existing techniques is detailed in fig.9.

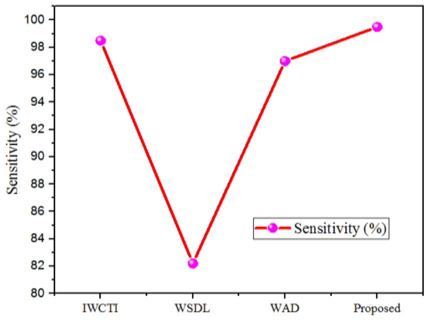

Fig.9 Sensitivity comparison

5.2.3 F-measure

F-measure is the harmonic mean of recall and precision, while the optimized classifier increase and disfavour automatically decrease the harmonic mean. The good F1 score represents the low false negative and low false positive thus perfectly detecting the animal in the input images.

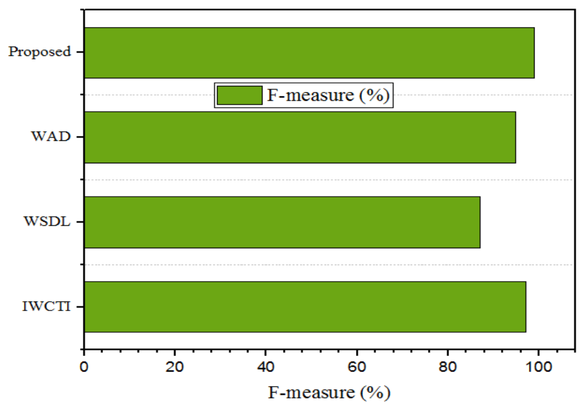

Fig.10 F-measure comparison

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Initially, the developed wildlife surveillance framework gained 99% in F-measure and WSDL replica achieved 87%. Moreover, the WAD and IWCTI methods gained a 94.9% and 98.6% in F-measure. Here, the existing approaches have achieved lower F-measure of almost 97% only. Thus the comparison of precision rate is detailed in fig.10.

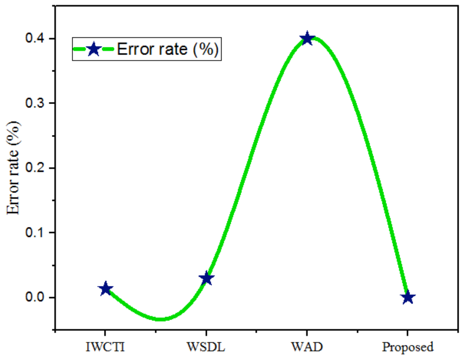

Fig.11 Error rate comparison

5.2.4 Error rate

Error rate is calculated depending upon the frequently occurred errors which are defined as the ratio of the total amount of data units to the total amount of transmitted data units. By increasing error rate, the reliability of data transmission is decreased. Furthermore, the gained error rate is compared with other existing techniques which are shown in fig.11.

The existing techniques of IWCTI replica achieved 0.014% in error rate for using 300 sample datasets. Moreover, WSDL and WAD methods gained 0.04% and 0.4% in error rate. Moreover, the developed technique gained an error rate of 0.001%. Here, the existing approaches achieved a high error rate and the proposed model has attained a low error rate of 0.001% than other methods.

5.3 Discussion

The proposed model has shown good performance by attaining the best results in accuracy, sensitivity, F-measure, and error rate. Thus, the developed scheme analyses any animals present in the input image in the initial stage. At next, extract the features based on colours, size, edges, nodes, weight, and length. Moreover, classification is processed to predict animal animals in the dense layer. Thus the developed technique enhances the performance of detection accuracy.

Table.2 Overall performance metrics

	Performance assessment			
Methods	**Accuracy**	**F-measure**	**Sensitivity**	**Error rate**
IWCTI	98.5	98.6	98.5	0.014
WSDL	97.58	87	82.2	0.03
WAD	91.4	94.9	97	0.4
Proposed	99.2	99	99.5	0.001

The outstanding metrics comparisons are tabulated in table.2, in all parameter validation, the proposed wildlife surveillance framework has gained the finest results. Moreover, the gained less error rate as 0.001% and high sensitivity as 99.5% also high detection accuracy as 99.2%. Hence, the robustness of the proposed technique is verified and it has the capability to detect animals.

VI. CONCLUSIONS

A novel wildlife surveillance framework is developed for predicting the wild animal in the input frame. Generally, 2700 sample datasets are collected from the net source and trained to the system, and then significant frames are retrieval using background subtraction. Furthermore, feature extraction is performed using HOG which helps to extract the significant features. Additionally, the classification layer classifies the animal with the help of the optimized weight of DCNN through SOA. Moreover, the developed framework is imported in the python tool and gained better detection accuracy. In addition, the developed technique has achieved better outcomes in sensitivity, F-measure, accuracy, and error rate. Thus it achieved 99.2% of accuracy for predicting wild animals.

ETHICAL STATEMENT:

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

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