e-ISSN 2320 –7876 www.ijfans.org

Vol.11, S Iss.1, 2022

Research Paper **UGC CARE Listed (Group -I) Journal**

Deep Learning for Elephant Behavior from Location and Rehabilitation in Captivity

Mrs. Bakhtawer Shameem, Research Scholar in MSIT, MATS University, Raipur, Chhattisgarh Email:saba7shameem@gmail.com
Dr. Bhavana Narain, Professor, MSIT, MAST University, Raipur, Chhattisgarh, Email: narainbhawna@gmail.com

Abstract

Today Elephant conflict is the most important problem. If we want to avoid this problem then it is very important for us to identify the elephant and understand the behavior that makes it easier to understand his moment. In such cases, individual elephant identification is one of the fundamental ingredients for the success of elephant conflict. Thus, in this paper, we shall explore and examine how image processing technologies can be utilized in analyzing and identifying individual elephant along with deep learning techniques. This system is mainly focused on the identification of individual elephant based on the color image of the elephant's body. In our system, firstly we detect the elephant's, Crop body reign, and then process a deep convolution neural network and the last one is to identify the elephant's name and behavior. Then, we crop the elephant's body region by using the predefined distance value. Finally, the cropped images are used as input data for training the deep convolution neural network for the self-collected elephant images are captured in the elephant rescue center at Tamor Pingla, Surguja, Distict, and Chhattisgarh, India. According to the experimental result, our system got an accuracy of 96.8% for automatic cropping in the elephant's body region and 97.01% for elephants' image identification. The result shows that our system can automatically recognize each individual elephant's images. Our data to train the CNN learning algorithms. However, behavioral observation synchronized with relocations and acceleration records are often missing or unattainable in many elephants, hindering the application of supervised learning, making unsupervised learning a suitable tool for behavioral annotation of, movement paths in secretive or less studied elephants. Environmental and behavioral annotation of animal movement paths by machine learning improves understanding of the effects of environmental condition on animal movements and behavioral decisions.

Keyword- Elephant identification, deep Learning, Edge detection, Behavioral classification, CNN, Movement.

I. INTRODUCTION

The demand for an automatic monitoring system for the elephant in prison is adding time by time due to the adding quantum of elephant's in large prisons and the difficulty of hiring labor for covering the elephant In recent times, numerous systems have been proposed for the automatic monitoring and identification of the elephant but the utmost of the systems need to put the detector bias on the body of the elephant which can beget a burden for the elephant. The identification of the Elephant's image Convolution Neural Network Technology (EICNNT) is an effective system for the recognition and identification of each individual elephant but it needs to attach the EICNNT to the elephant which can beget stress on the elephant. Indeed though the elephant was linked by the EICNNT, there's still a need for elephant monitoring. Another disadvantage of the traditional identification system is that they're precious and unreliable. The CNN-based automatic identifies the elephant and its behavior. A monitoring system for the elephant can break those problems by minimizing the elephant conflict and automatic monitoring from the image data. For the perpetration of an automatic image monitoring system for elephants, the recognition of each individual elephant plays an important part because it's necessary to cover the behavior of each elephant in long term similar to monitoring and changing the elephant behavior. Thus, our proposed system of individual elephant image identification is veritably useful for elephants. This paper is organized as follows some affiliated works are presented in section 2. The detailed proposed system is explained in section 3 followed by the experimental results in section 4. Eventually, in section 5, the conclusion and some unborn works are discussed.

II. SOME RELATED WORKS

In this review, the author aim to introduce animal behaviorists unfamiliar with machine learning (ML), to the promise of these techniques for the analysis of complex behavioral data. We start by describing the rationales behind ML and review a number of animal behavior studies where ML has been successfully deployed. (John Joseph Valletta et al., 2017). We also investigated how the classification would benefit from coarse-labeled training data, which alleviates the professional and expensive manual process of fine-grained annotation. Currently, it is necessary to have hierarchical labels in the training set, in order to train the RNN. CNN-RNN to boost the classification performance for general datasets. (Yanming Guo et al., 2018). In this paper, the segmentation method based on color segmentation accurately detects the fruit regions in the image. It outperforms the result of edge-based segmentation. In a color-based algorithm, the Clustering method has been applied to the images because of sharp differences between backgrounds (Pradeep Kumar Choudhary et al., 2017). Herein, we present a novel MAT that provides accurate high-throughput analyses of complex behaviors. Importantly, this user-friendly system is easy to operate and does not require prior programming skills. With a wide range of possible uses and the compatibility of studying various animal models, this MAT will serve as an important system for elucidating novel principles underlying complex behaviors. (Eyal Itskovits et al., 2017). This experiment gives 82.5% accuracy to analyze gender from speech; it shows that emotion doesn't affect the fundamental frequency range of human beings. The present era is extremely involved in speech recognition systems; this work can help a personal assistance application that used speech recognition, and automatic voice detection to make a machine intelligent. (Bhavna Narain et al., 2017). The objective of the study is to modify the activation function of the ANN to advance its performance. In this paper, we present the proposed modification of the activation function by integrating logsig and hyperbolic to propose SigHyper activation function. Comparative simulation analysis showed that the CSBP with SigHyper significantly performs better than the CSBP with logsig. The activation function proposed in this paper has added to the activation functions in the literature. This paper is a work in progress, the second phase of the research will involve further improvement of the SigHyper to enhance the computation time of the SigHyper. (Adamu I. Abubakar et al., 2014). Features from the VGG-16 model proved to be most effective when used alone, which resulted in a MAP score of 13.26%. Future efforts will focus on incorporating multi-modality fusion, i.e., model audio and text information. In addition, other CNN architectures will be tested by our current system (e.g. GoogleNet), along with CNN models that would complement multi-modal system features (e.g., video2Text-VGG). (Joseph P. Robinsona et al., 2016)

III. PROPOSED SYSTEM

The proposed system for individual elephant identification consists of two main components. The first one is the automatic detecting and cropping of the elephant's image. The second component is the training of a deep convolution neural network over the cropped elephant's pattern images for the identification of the individual elephant's pattern. The overall system flow of the proposed system is shown in fig. 1.

A. Automatic Detecting and Cropping

Elephant's Body Region the process flow of automatic detection and cropping of the elephant's body region is shown in fig.1. For detecting the elephant body region firstly, we perform the inter-frame differencing between two consecutive frames of the elephant's image in order to detect the elephant identification. Then we transform the inter-frame differencing result into the binary image by using the predefined threshold. The equation of inter-frame differencing method-based binary image creation is described in equation (1). 1 if threshold, 0 otherwise

$$Mt(x) = \begin{cases} 1, if \mid It(x) - \ It - 1(x)\mid \ \geq Threshold \\ \quad 0, \quad otherwise \end{cases} \qquad (1)$$

Where

$M_t(x)$ is the result binary image of frame t,

$I_t(x)$ is the cow's image at frame t and

$I_t - 1(x)$ is at the previous (t-1) frame

Then, we use the white pixel occurrences (350 pixels) as a Threshold in order to find the elephant images. If the horizontal histogram count is greater and less Threshold, we regard that location as pole location. If elephant image are two poles' locations are detected, we use the location which is located near the previous detected pole. For cropping, we use the copping height and width by the fixed value of 400 pixels and 840 pixels, respectively because the distance between two poles location and the length of the pole are the same for all frames. After getting the pole location, we check it for finding the cropped direction. If the value of y coordinate of detected pole plus the cropped height threshold of 400 is less than or equal to the height of the original image, then cropping is performed over the lower 400 pixels' area of the cow's image, otherwise, the upper 400 pixels' area is cropped. Count the frequency of the occurrence of pixels in the horizontal direction of each point along the vertical axis. As a result, we got the horizontal histogram of the binary image. The size of each frame is 1024×768.

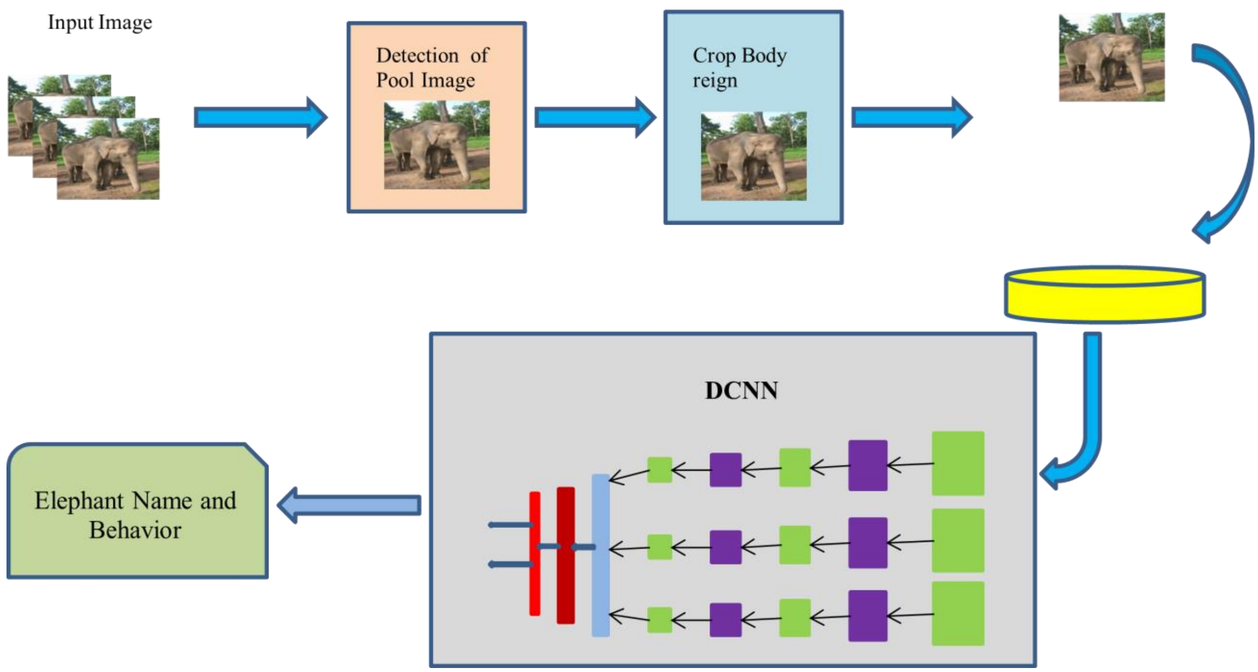

Fig. 1. Overall system for individual Elephant pattern identification

B. Deep Convolution Neural Network

After cropping the elephant's body region which includes the elephant images for identification, we train them into a deep convolution neural network which is a famous method for visual object recognition (Krizhevsky et al., 2012) and hand-written digit recognition (LeCun et al., 1998) with superior performance among state-of-the-art methods. We apply the deep convolution neural network (DCNN) over the elephant's image of RGB color input images. The architecture of the deep convolution neural network (DCNN) is shown in Fig.2. In this architecture, there consists of 1 input layer, 3 convolution and max-pooling layers, 1 fully connected layer, and 1 output layer. The elephant's image of size 64×32×3 is used as input. In our work, there are three main activation functions in each hidden layer such as max pooling sigmoid and convolution is used. The initialization of the elephant image value of the layers is done by the initialization with a random number. The weight initialization methods, the filter size, and the output feature maps of each convolution and max-pooling layer are shown in Table. 1. We also applied the randomly

e-ISSN 2320 –7876 www.ijfans.org

Vol.11, S Iss.1, 2022

initialized weight vectors of size 100 at the fully connected layer and the soft-max function is used at the output layer in order to calculate the probability of each possible elephant's name. The neural network is trained by using the back propagation algorithm with the stochastic gradient descent method. We used the learning rate as 0.0001 and the momentum value as 0.9. The network is trained with 1000 iteration by using the images DCNN framework (Jia, Y et al., 2014) is used for the implementation of experiments.

IV. EXPERIMENTAL RESULTS

For performing the experiments, we create our own elephant image dataset which consists of 13 different elephant images taken from the elephant rescue center for Tamor Pingla, Surguja District, and Chhattisgarh, India. The elephant images of the first 20 images per elephant are used as the training data and all elephant image data are used as the testing data.

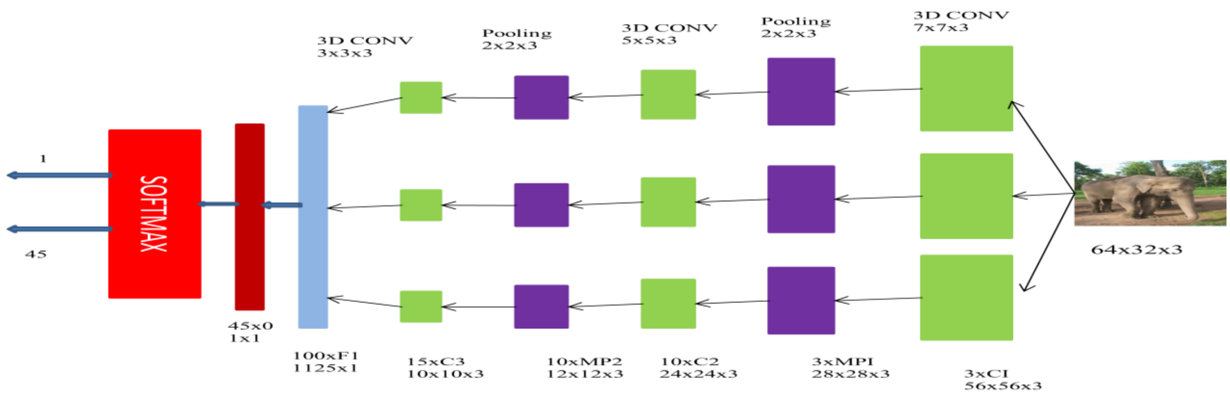

Fig. 2. Architecture of Deep Convolution Neural Network

The sample image of 13 different elephant images are shown in Fig. 3. The elephant's images dataset consists of two challenges such as the rotation variation of the elephant's body and the day-by-day illumination changing condition. In our proposed system, we handle those two kinds of challenges in order to be able to apply the system under the rotation invariant and various illuminations changing environment.

TABLE 1. Parameters of DCNN

Layer	**Filter Size**	**Weight Initialization Method**	**Feature Map**
C1	7×7×3	Normalization Uniform	3
MP1	2×2×3		3
C2	5×5×3	Normalization Uniform	10
MP2	2×2×3		10
C3	3×3×3	Normalization Uniform	15
MP3	2×2×3		15

Fig. 3. Sample image of 13 elephant' images (IDs are assigned from left to right and top to bottom order)

Training

Additional preprocessing is not required in the CNN-RNN model. To train the networks, we choose a wildly used adaptive learning rate algorithm, called Adam. The CNN-RNN model will bring the problem of model overfitting due to the addition of an additional network structure to reduce the over-fitting problem. At the output of the RNN layer, we have applied the normalization term imposed on the batch normalization and RNN weights.

A. Rotation Variation

The elephant's image can include rotation because the elephants can move at the time of staying on the other field and location. The rotated image of elephants is shown in Fig. 4. In order to get the rotation-invariant feature from the DCNN, we use the 30 continuous frames of each elephant's image as the input for training the DCNN.

B. Illumination Changing Condition

The illumination can change time by time, so the image data of the elephant's image include the effect of the illumination changes. It means that the images of the same elephant's elephant can be different depending on the illumination condition at the time of recording the video. The example images of the same elephant image under different illumination conditions.

C. Performance Evaluation

We evaluate the performance of the system for both automatic detecting and cropping of the elephant's body region and the individual elephant's identification accuracy. The average cropping accuracy for elephant image data is 97.8%. The accuracy of the identification on the training data set of all elephant images is 98.97% and on the testing data set of elephant, image is 97.01%. The identification accuracy of each elephant's image for both training data and testing data.

V. CONCLUSION AND FUTURE WORK

In this paper, we proposed the individual elephant's image identification using the rehabilitation differencing and horizontal histogram-based method for automatically detecting and cropping of elephant's body region and the DCNN (Deep Convolution Neural Network) for training and recognition of the elephant's image. We also create the elephant's image dataset of 13 different elephant images and perform the experiments on that dataset. The proposed system got an accuracy of 96.8% for automatically detecting and cropping an elephant's body region and 97.01% for individual elephant identification. In the future, we will try to improve the accuracy of automatic detection and cropping of elephant's body region by using enhancing histogram-based approach and we will also analyze the performance of the system under the various evaluation methods.

CRediT authorship contribution statement

Bakhtawer Shameem: Conceptualization, Methodology, Software, Validation, Investigation, Writing-original draft, Visualization, Validation.

Bhavna Narain: Conceptualization, Formal analysis, Supervision, Writing- review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ashwini V Sayagavi, Sudarshan T S B, and Prashanth C Ravoor, (2021), Deep learning methods for animal recognition and tracking to detect intrusions, Smart innovation, System and Technologies vol-196,pp 617-626, DOI: 10.1007/978-981-15-7062-9_62.

Bae, Han Byeol Pak, Daehyun Lee, Sangyoun, (2021), Dog nose-print identification using deep neural networks. IEEE Access, vol-9, pp- 49141-49153, DOI: 10.1109/ACCESS.2021.3068517, ISSN: 21693536 2021.

Bakhtawer Shameem, and Bhavana Narain, (2021), An Elephant Identification by Trunk Using Digital Image Processing Using Convolution Neural Network, paper presented in IEEE International Conference on Technology, Research and Innovation for Betterment of Society (TRIBES - 2021), 17-19 dec 2021, DOI: 10.1109/TRIBES52498.2021.9751664 Raipur, Chhattisgarh, India

Bakhtawer Shameem, and Bhavana Narain, (2021), Identification of Elephant Age Using CNN Classification Model in Deep Learning, paper presented in 3rd International Conference on Innovative Research in Science Management and Technology (ICIRSMT 2021) Dee 27-28, 2021, Bilaspur, Chhattisgarh, India, *India*, Vol. 02, No. 01, January 2022, ISSN- 2767-1933, https://gjcet.gkfusa.org/current-issue/, pp-60-67.

Bakhtawer Shameem, Bhavana Narain, 'Suitability of Location for Rehabilitation of Elephants in Chhattisgarh', Paper presented in International Conference on SPAST-2021Nov 2021, Japan.
Banupriya, N. Saranya, S. Jayakumar, Rashmi Swaminathan, Rashmi Harikumar, Sanchithaa
Bhavana Narain, Purnima Saha, and Manjushree Nayak, (2018), Impact of Emotions to Analyze Gender Through Speech, Publication in 4th International Conference on Signal Processing, Computing and Control (ISPCC), Proceeding IEE Xplore 25 jan 2018, DOI: 10.1109| ISPCC. 2017.8269645.

Cassytta Dhiya, Imtiyaaz Amir, Syarifuddin Joko, Triwanto Rosyid, Ridlo Al Hakim, ((2021), Analysis of welfare levels, ecology, and animal management in Seblat Elephant Training Centre, Bengkulu−Indonesia, Journal of Biotechnology and Natural Science, Vol. 1, Issue-2, pp. 1-11, 2021, url://http://journal2.uad.ac.id/index.php/JBNS/issue/view/378/12, (Accepted 20 dec 2021)
Chen, Hui Hui Hwang, Bor Jiunn Wu, Jung Shyr Liu, Po Ting, (2020), The Effect of Different Deep Network Architectures upon CNN-Based Gaze Tracking, Algorithms, MDPI, 2020, Vol-13, Issue-127; doi: 10.3390/a13050127, (Accepted 17 may 2020)

Chiranjib Nad (2018), Conflict with wild giant (Elephant Maximus) and Us in Northen West Bengal: A Review, vol-23, Issue-1, ver.-7, pp. 13-22, e-ISSN: 2279-0837, p-ISSN: 2279-0845. www.josrjournals.org, ISOR Journal of Humanities and Social Science (IOSR-JHSS).

Cioffi, Raffaele Travaglioni, Marta Piscitelli, Giuseppina Petrillo, Antonella De Felice, Fabio, (2020), Artificial Intelligence and Machine Learning Applications in Smart Production: Progress, Trends, and Directions, Sustainability 2020, Vol- 12, Issue- 492; doi:10.3390/su12020492, (5 jan 2020).
Devipriya, G Keerthi Chandana, E Prathyusha, B Chakravarthy, T Seshu, (2019), Image Classification using CNN and Machine Learning, Vol-5, Issue-2, ISSN: 2456-3307, DOI: 10.32628/CSEIT195298575 I, Pp 575-580.

Dhouibi et al., (2021), Optimization of CNN model for image classification, 3rd IEEE International Conference on Design and Test of Integrated Micro and Nano-Systems, DTS 2021, Proceeding pp. 1-6, DOI: 10.1109/DTS52014.2021.9497988, ISSN: 9780738132631, 2021.

Diqi, Mohammad, Unriyo Yogakarta, Respati Wijaya, Nurhadi, Unriyo Yogakarta, Respati, (2022), Pooling Comparison in CNN Architecture for Javanese Script Classification, International Journal of informatics and computation (IJICOM), Issue-January, DOI: 10.35842/ijicom.

Duporge, Isla Isupova, Olga Reece, Steven Macdonald, David W. Wang, Tiejun (2020), Using very-high-resolution satellite imagery and deep learning to detect and count African elephants in heterogeneous landscapes, Remote sensing in ecology and conservation, doi: 10.1002/rse2.195,(Acceptance 4 dec 2020)

Feddewar, Palash Deshmukh, Bharti Science, Computer College, Prerna, (2022), Convolution Neural Processing : A Survey Network (CNN) for Video, Vol-8, Issue-01, pp 147-152, DOI: 10.46501/IJMTST0801025.

Ferreira, André C Silva, Liliana R Renna, Francesco Brandl, Hanja B Renoult, Julien P Farine, Damien R Covas, Rita Doutrelant, Claire, (2020), Deep learning-based methods for individual recognition in small birds, International Journal for Modern Trend in science and technology, Vol-9, Issue- may, pp 1072-1085, DOI: 10.1111/2041-210X.13436.

Grooms, D., Radio Frequency Identification (RFID) Technology for Cattle, Extension Bulletin E-2970, Michigan State University, Jan. 2007.

Guiming Wang (2021), Machine learning for inferring animal behavior from location and movement data, Ecology and evalution, vol-49, pp.69-79, doi.org/10.1016/j.ecoinf.2018, (Jan 2019)

Ilestrand, M., Automatic eartag recognition on dairy cows in real barn environment, 2017.

Itskovits, Eyal Levine, Amir Cohen, Ehud Zaslaver, Alon, (2019), A multi-animal tracker for studying complex behaviors, BMC Biology DOI: 10.1186/s12915-017-0363-9.

Jia, Y., Shelhamer, E. Donahue J., Karayev S., Long J., Girshick R., Guadarrama S., and Darrell T., Caffe: Convolutional Architecture for fast feature embedding, In Proceeedings of the 22nd ACM international conference on Multimedia, pp 675-678, Nov.- 2014.

Jimmy Borah, K. Thakuria, K. K. Baruah, Karabi Deka, (2005), Man-Elephant Conflict Problem: A Case Study, vol-XX, Issue-7, pp.22-24, 2005Man-Elephant Conflict Problem: A Case Study, vol-XX, Issue-7, pp.22-24.

K. Zeeshan, (2018) The Impact of Regularization on Convolution Neural Networks, 2018.

K.M.S. Madheswaran; K. Veerappan; V. Sathiesh Kumar, (2019), Region Based Convolution Neural Network for Human-Elephant Conflict Management System, International conference on computational intelligence in data science, DOI: 10.1109/ICCIDS.2019.8862006, 10 oct 2019.

Kavyashree, B S Navarathna, M Jain, Samyak V Vignesh, N P, Prof Vidyashree K, (2019), Virtual Fences, International Journal of Innovative Technology and Exploring Engineering (IJITEE) vol-9, Issue-25, pp. 526-529, DOI: 10.35940/ijitee.b1044.1292s19,(Dec 2019)

Kim, H. T., Choi, H. L., D. W. and Yong, C. Y., (2005), Recognition of individual Holstein cow by imaging body patterns, In Asian Australasian Journal of Animal Sciences, Vol.-8, no.-8, pp.1194, 2005.

Lai, Kenneth Tu, Xinyuan Yanushkevich, Svetlana, (2019), Dog Identification using Soft Biometrics and Neural Networks, International joint conference on neural networks (IJCNN), DOI:10.1109/IJCNN.2019.8851971, 978-1-7281-2009-6/19/$31.00, 30 (sep 2019)

Le Q V, Jaitly N, Hinton G. E. A simple Way to Initialize Recurrent networks of Rectified Linear Units [J]. Computer Science, 2015.

Lecun Y., Bottou L., Bengio Y., and Haffner P., Gradient-based learning applied to document recognition, In proceedings of the IEEE, Vol.-86, no.-11, pp.- 2278-2324.

Lu Y., He X., Wen Y., and Wang P.S., A New cow identification system based on iris analysis and recognition, In International Journal of Biometrics, Vol.6, no.-1, pp.-18-32.

Miao, Zhongqi Gaynor, Kaitlyn M Wang, Jiayun Liu, Ziwei Muellerklein, Oliver Norouzzadeh, Mohammad Sadegh Mcinturff, Alex Bowie, Rauri C K Nathan, Ran Yu, Stella X Getz, Wayne M, (2019), Insights and approaches using deep learning to classify wildlife, Scientific report, 9:8137, pp. 1-9, doi.org/10.1038/s41598-019-44565-w, (31 may 2019)
Miao, Zhongqi Gaynor, Kaitlyn M Wang, Jiayun Liu, Ziwei Muellerklein, Oliver Norouzzadeh, Mohammad Sadegh Mcinturff, Alex Bowie, Rauri C K Nathan, Ran Yu, Stella X Getz, Wayne M Dhouibi et al., (2021), Optimization of CNN model for image classification, 3rd IEEE International Conference on Design and Test of Integrated Micro and Nano-Systems, DTS 2021, Proceeding pp. 1-6, DOI: 10.1109/DTS52014.2021.9497988, ISSN: 9780738132631, 2021

N. Banupriya, s. Saranya, rashmi jayakumar, rashmi swaminathan, sanchithaa harikumar, sukitha palanisamy, (2020), ISSN- 2394-5125 Vol 7, Issue 1, pp 434-439, DOI: 10.31838/jcr.07.01.85, ISSN: 23945125,

Neethidevan and M. V. Chandrasekaran, G, (2020), Image Segmentation for Object Detection using Mask R-CNN in Colab, Academia.Edu, vol-4, issue-5, pp. 15-19, 2020

Norouzzadeh, Mohammad Sadegh Morris, Dan Beery, Sara Joshi, Neel Jojic, Nebojsa Clune, Jeff, (2020), A deep active learning system for species identification and counting in camera trap images, vol. 2020;00:1–12., DOI: 10.1111/2041-210X.13504, (22 Oct 2019)

Palanisamy, Sukitha (2021), Animal Detection using Deep Learning Algothm, International journal of engineering science and computing, ISSN 2321 3361, Volume 11 Issue No.06, (Accepted 15/01/2020)

Raniah Zaheer and Humera Shaziya, (2019), A Study of the Optimization Algorithms in Deep Learning, Third International Conference on Inventive Systems and Control (ICISC), Proceeding ISBN: 978-1-5386-3950-4, DOI: 10.1109/ICISC44355.2019.9036442, pp. 536-539, 16 march 2020

Renu Khandelwal (2020), Convolution Neural Network: Feature Map and Filter Visualization, Published Towards data science, (18 may 2020)

Ruilong Chen, Ruth Little, Lyudmila Mihaylova, Richard Delahay, Ruth Cox, (2019), Wildlife surveillance using deep learning methods, vol-9, Issue-7, pp 9453-0466

Shruti kanga, a. C. Pandey, ayesha shaheen, suraj kumar sing, (2018), Resarch paper geospatial modeling tiger reserve, Jharkhand (India), vol-13, Issue-3, pp. 24-34, 2018, i-manager's Journal on Future Engineering & Technology.

Singh Sandeep Kumar and Carpio Francisco, (2018) Improving animal-human cohabitation with machine learning in fiber-wireless networks, pp-4-13, DOI: 10.3390/jsan7030035, 2018, Journal of sensor and actuator networks.

Songtao Guo, Pengfei Xu, Qiguang Miao, Guofan Shao, Colin A. Chapman, Xiaojiang Chen, Gang He, Dingyi Fang, He Zhang, Yewen Sun, Zhihui Shi, Baoguo Li, (2020), Automatic Identification of Individual Primates with Deep Learning Techniques, pp 1-32, https://dio.org/10.1016/j.isci.2020.101412, celpress open access, iscience article.

Susama Bagchi, Kim Gaik Tay, Audrey Huong, Sanjoy Kumar Debnath, (2020), Image Procesing and Machine Learning Techniques Used in Computer-Aided Detection System for Mammogram Screening – A Review Image Processing and machine learning techniques used in computer-aided detection system for mammogram screening –A review, Vol-10, no-3, pp 2336-2348, ISSN: 2088-8708, DOI: 10.11591/ijece.v10i3.

Tabak, Michael A., Norouzzadeh, Mohammad S.,Wolfson, David W., Sweeney, Steven J., Vercauteren, Kurt C.Snow, Nathan P.Halseth, Joseph M. Di Salvo, Paul A. Lewis, Jesse S. White, Michael D. Teton, Ben Beasley, James C. Schlichting, Peter E. Boughton, Raoul K. Wight, Bethany Newkirk, Eric S. Ivan, Jacob S. Odell, Eric A. Brook, Ryan K. Lukacs, Paul M. Moeller, Anna K. Mandeville, Elizabeth G. Clune, Jeff Miller, Ryan S., (2019), Machine learning to classify animal species in camera trap images: Applications in ecology. Methods in Ecology and Evolution. Vol-10, issu – 4, pp- 585-590, DOI: 10.1111/2041-210X.13120, ISSN: 2041210X year 2019.

Tej Bahadur Chandra, Kesari Verma, Bikesh Kumar Singh, Deepak Jain, Satyabhuwan Singh Netam, (2020), Corona virus disease (COVID-19) detection in Chest X-Ray images using majority voting based classifier ensemble, Expert syst Appl. 2021 Mar PMCID: PMC7448820.

Thangarasu, Rajasekaran Kaliappan, Vishnu Kumar Surendran, Raguvaran Sellamuthu, Kandasamy Palanisamy, Jayasheelan, (2019), Recognition Of Animal Species On Camera Trap Images Using Machine Learning And Deep Learning Models, international journal of scientific & technology research, volume 8, issue 10, ISSN 2277-8616, pp. 2613-2622, (oct 2019).

Thi Thi Zin, Member, IAENG, Cho Nilar Phyo, Pyke Tin, Hiromitsu hama, Ikuo Kobayashi, (2018), Image Technology based Cow Identification System using Learning, Proceedings of the International Multi Conference of Engineers and Computer Scientists 2018, Vol.- I, IMECS 2018, March 14-16, 2018, Hong Kong.

Vidal, Maxime Wolf, Nathan Rosenberg, Beth Harris, Bradley P. Mathis, Alexander, (2021), Perspectives on individual animal identification from biology and computer vision, pp. 1-12, arXiv: 2103.00560v1 [cs.CV], (28 Feb 2021)

Vishal Kumar Sharma and Vaskar Bera, (2021), Animal identification by using deep learning, ISSN- 2321 3361 © IJESC, vol 11, Issue no-06, International journal of engineering science and computing IJESC.

Vitaly Bushaev, (2018), Adam latest drand in deep learning optimization, published towards data science. https://towardsdatascience.com/adam-latest-trends-in-deep-learning-optimization-6be9a291375c.

Wang Guiming, (2018), Machine learning to infer animal behaviors from location and movement Ecological informatics machine learning for inferring animal behavior from location and movement data, vol-49, Issue- Dec, pp 69-76, DOI-10.1016/j.ecoinf.2018.12.002, ISSN- 1574-9541, Ecological Informatics.

Willi, Marco, Pitman, Ross T., Cardoso, Anabelle W. Locke, Christina Swanson, Alexandra Boyer, Amy Veldthuis, Marten Fortson, Lucy, (2019), Identifying animal species in camera trap images using deep learning and citizen science, vol-10, Issue-1, pp.80-91, Methods in Ecology and Evolution, DOI: 10.1111/2041-210X.13099, ISSN: 2041210X.

Y. Sun, Y. Liu, G. Wang, and H. Zhang, (2017), Deep Learning for plant identification in natural environment, Computer Intel Neurosis.

Yu Liang, Li Binbin, Jiao Bin, (2019), Research and Implementation of CNN Based on TensorFlow, IOP Conf. Series: Materials Science and Engineering vol. 490, Issue-4, DOI: 10.1088/1757-899X/490/4/04202, ISSN: 1757899X, (2019)