JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Efficient and reliable Monitoring of Animals using Machine Learning

[1]Mrs.A.Merry Ida, [2]Mr.S.Antony Mutharasan, [3]Siva T, [4]Chandru R

[1]Assistant Professor, [2]Assistant Professor, [3]Student, [4]Student
[1]Department of CSE, [2]Department of CSE, [3]Department of CSE, [1]Department of CSE
[1]Loyola Institute of Technology and Science, Nagercoil, India

Abstract : Reducing vehicle-animal collisions on roadways is one of the major difficulties, as these incidents lead to environmental imbalance and high costs for the public purse. In addition to outlining a methodology for identifying animals in camera-generated photos, this paper also outlines the parts of a basic animal detection system. This methodology allows the features extraction of regions of the image and the use of Machine Learning (ML) techniques to classify the areas into fifteen classes of animals: 'Beetle', 'Butterfly', 'Cat', 'Cow','Dog', 'Elephant', 'Gorilla', 'Hippo', 'Lizard', 'Monkey', 'Mouse', 'Panda', 'Spider', 'Tiger', 'Zebra'. This system classifies animals based on their images so we can monitor them more efficiently. Animal detection and classification can assist in preventing incidents involving animals and vehicles.

***Index Terms* - Animal detection, classification**

I. Introduction

Presently, extensive information and digital data about wild animal action and conduct can be easily acquired spanning more significant spaces and for long duration. Camera trap alongside the work of various researchers aids in observing and analyzing wild animals. With the increase in information on natural life, the researches on wild animals have turned out to be more advantageous and secure, for instance, deciding the effects of ecological changes on wild animal behaviour and activity, alterations in their living space and relocation exercises and the impact of human mediation on natural Wildlife. In camera traps network, many cameras are deployed on trees in a territory for monitoring wild animals activities. The network of such sensor cameras makes a camera trap network. The camera traps actuated whenever a movement is detected; they make short video or consecutive images of wild animal actions andtheir visual aspects alongside insights about the environment (light levels, moisture, temperature, and area). Such systems are necessary for gathering information about wild animals without having an uncomfortable impact.

Likewise, they are financially possible, simple to convey in more significant spaces and have low upkeep requirements; subsequently, they are broadly utilized for wild animalmonitoring. Additionally, the conduct and biometric components of species can be extracted alongside the details of the wildlife environment and surroundings. There is a basic need of automatic image processing tools to process camera-trap images obtained from the camera trapnetwork. The image processing tools for background segmentation and object detection are essential for the automatic analysis of images. The existing studies on object segmentation arebased on static scenes; however, the present methodologies are not practical with complex dynamic natural scenes. The brief videos produced by the camera trap network are intensely crowded with dense trees, water bodies, moving shadows, changing weather, downpours, and other factors. Likewise, the natural camouflage of wild animals represents another issue for dissecting particular scenes. The main goal of wild animal recognition is to set up a model that can effectively recognize animals in dynamic scenes and deal with complex backgrounds.

Checking on wild animals in their natural habitat is essential. The suggested work creates an algorithm to find animals in the outdoors. Because there are so many different kinds of animals, manually recognising them might be challenging. This algorithm[1] classifies animals based on their images so we can monitor them more efficiently. Animal tracking, animal accidents, and theft can all be avoided with the use of animal identification and classification. Effective deep learning algorithms can be used to achieve this.

[2]In this work a two-step classification is proposed to get closer to an automatic and trustfully camera trap classification system in low quality images. In order to differentiate images, first between sets of birds and mammals, then between sets of mammals, very deep convolution neural networks were employed. Using a camera trapping framework, it is feasible to observe animals in the wild without disturbing them. Automatically triggered cameras that capture a burst of photographs of animals in their natural habitat generate enormous amounts of data, but frequently yield images with poor image quality.This high volume data must be classified by a human expert The method reached 97.5% and 90.35% in each task. An alleviation mode using a confidence threshold of automatic classification is proposed, allowing the system to reach 100% of performance traded with human work.

[3] Wildlife monitoring and analysis is an active research field since last many decades. In this research, we concentrate on wildlife monitoring and analysis using camera-trap networks' natural scene animal detection. The high levels of congestion in the image sequences produced from camera-traps make it difficult to spot animals, leading to low detection rates and significant false discovery rates. We have employed a camera-trap database with possible animal suggestions utilizing multilevel graph cut in the spatio temporal domain to address this issue. The verification process that determines if a certain patch is an animal or a background is made using these suggestions. Utilizing Deep Convolution Neural Network (DCNN) features that are self-learned, we have created an animal detection model. This efficient feature set is then used for classification using state-of-the-art machine learning algorithms, namely support vector machine, k-nearest neighbour, and ensemble tree. Our intensive results show that our detection model using DCNN features provides accuracy of 91.4% on standard camera-trap dataset.

[4] In this paper, the Convolution Neural Network (CNN) for the classification of the input animal images is proposed. This method is compared with well-known image recognition methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA),Local Binary Patterns Histograms (LBPH) and Support Vector Machine (SVM). The main goal is to compare the overall recognition accuracy of the PCA, LDA, LBPH and SVM with proposed CNN method. The database of wild animals is compiled for the experiments. This database consists of 500 different subjects (5 classes / 100 images for each class). Different numbers of test photos and training images were used to determine overall performances. The experimental results show that the proposed method has a positive effect on overall animal recognition performance and outperforms otherexamined methods.

[5] The components of a basic animal detection system are discussed in this article, along with a methodology for finding animals in images taken by cameras placed along highways. With the use of Machine Learning (ML) techniques, this methodology enables the features extraction of specific image regions and the classification of those regions into two categories—animal and non-animal. By applying five different methodologies to navigate the image's pixels, two ML systems were tested using synthetic images. Results indicate that the KNN learning model is more accurate at identifying animals on highways than Random Forest. Reducing vehicle-animal incidents on roadways, which contribute to environmental imbalance and high costs to the public purse, is one of the current concerns.

II PROPOSED SYSTEM

The main objective here is to design an efficient automatic Animal detection system. The captured images are trained and then extracted by using the segmentation process. Our model is easy to build and can be trained immediately on whole photos. Here fifteen classes ofanimals are trained namely 'Beetle', 'Butterfly', 'Cat', 'Cow', 'Dog', 'Elephant', 'Gorilla', 'Hippo','Lizard', 'Monkey', 'Mouse', 'Panda', 'Spider', 'Tiger', 'Zebra'. In this proposed system ResNet50V2 Algorithm is used for detecting the animal from the given set of images. ResNet50V2 pushes the state-of-the-art in real-time object detection. It also generalizes well to new domains making it ideal for applications that rely on fast, robust object detection .Thistype of system is widely used in wildlife animal monitoring. This system is mainly designed for the purpose of security system in wildlife.

ADVANTAGES OF PROPOSED SYSTEM

- These systems are specifically aimed at animals that can cause human death, injuryand property damage.
- This algorithm classifies animals efficiently with a great number of accuracy.
- Prevent wildlife poaching and even human animal conflict.

III ALGORITHM SPECIFICATION

ResNet50v2 is a convolutional neural network architecture that was introduced as an improvement over the original ResNet50 architecture. It has 50 layers and is commonly used for image classification tasks.

The architecture of ResNet50v2 is divided into several blocks, each of which has a different number of layers. The blocks are connected in such a way that the output of one block is used as the input for the next block. The following essential elements are part of the architecture:

1. Input Layer: The input layer of ResNet50v2 takes an image of size 224 x 224 x 3(height, width, and depth).
2. Convolution Layers: The first layer of ResNet50v2 is a convolution layer with 64filters of size 7x7 and a stride of 2. A batch normalization layer and a ReLU activation function are then applied. There are several convolution layers in ResNet50v2, each with different filter sizes and numbers of filters.
3. Residual Blocks: ResNet50v2 uses a residual block architecture, where the output ofone block is added to the input of the next block. This allows the network to learn residual mappings, which can improve the accuracy of the network.

   a. The first residual block contains two convolution layers with 64 filters of size 3x3and a stride of 1, followed by a batch normalization layer and a ReLU activation function.

   b. The following residual blocks are divided into two types: identity blocks and projection blocks. Identity blocks are used when the input and output of the block have the same dimensions, while projection blocks are used when the input and outputdimensions are different.
4. Global Average Pooling: The output of the final residual block is passed through a global average pooling layer. This layer averages the output of each feature map in theprevious layer, resulting in a single value for each feature map.

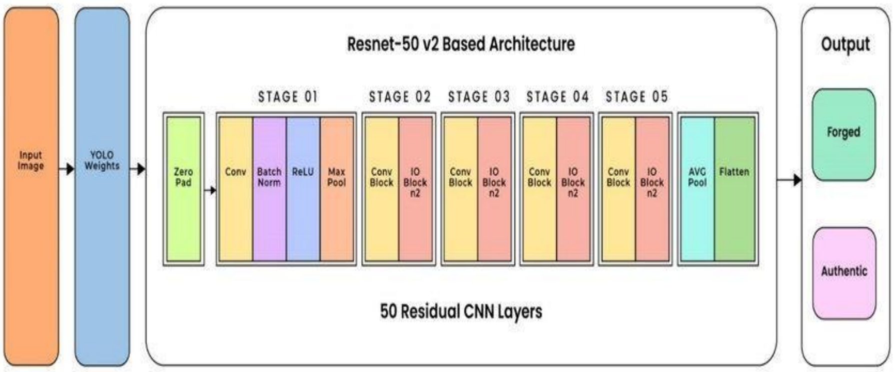


FIGURE : ARCHITECTURE OF RESNET50V2

5. Fully Connected Layers: The global average pooling layer is followed by a fully connected layer with 1000 nodes, which corresponds to the number of classes in the ImageNet dataset.
6. Softmax Activation: The output of the final fully connected layer is passed through a softmax activation function, which converts the output into a probability distributionover the 1000 classes in the ImageNet dataset.

Overall, the architecture of ResNet50v2 is designed to improve the accuracy of the original ResNet50 architecture by introducing several new features, such as the use of pre-activationresidual blocks and improved skip connections.

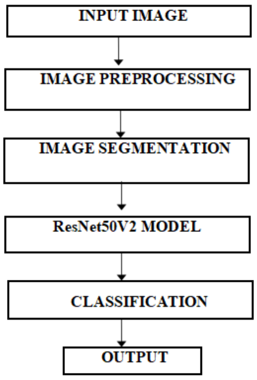


Figure:Architecture of proposed Design

IMAGE ACQUISITION

The first step is the capture of image. The image is captured by electronic device like Digital Camera or Webcam. JPEG format is used to save the captured image. It is characterized as the activity of recovering a picture from some source.

DATA PRE-PROCESSING

Pre-processing the image comes after the image has been captured. When an image is taken, there are several distractions and noises that prevent it from being used efficiently. In order to get an accurate result, it is necessary to clear the image noise in this phase. Then the image is resized in a particular resolution.

Fig preprocessing

SEGMENTATION

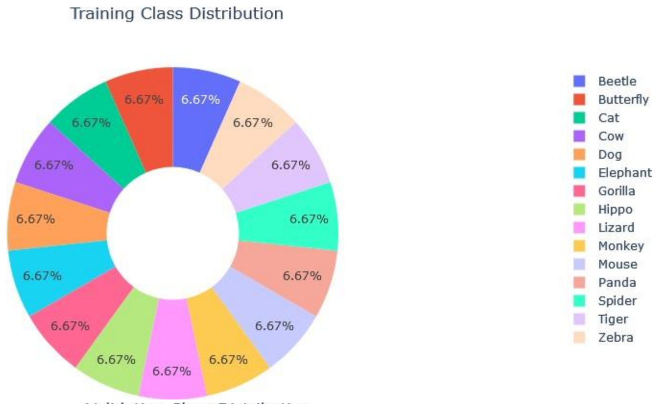
The process of segregating the digital image into numerous parts, so as to use the information retrieved and identify the objects easily from the segmentation process effectively is Image Segmentation. To perform segmentation on an image there are different techniques including, thresholding is using S-ROI Method. The thresholding methods are more efficient, user-friendly, and popular.

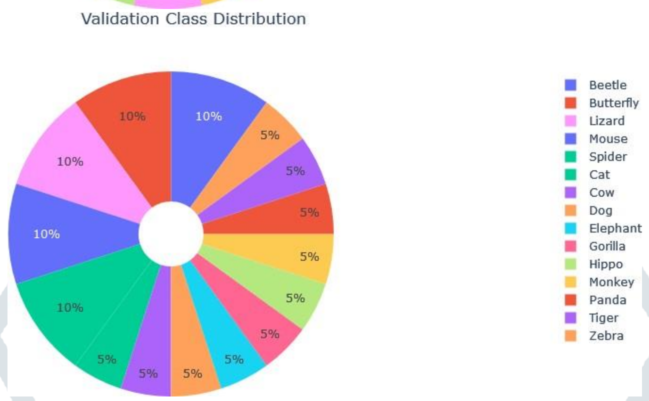
ACCURACY

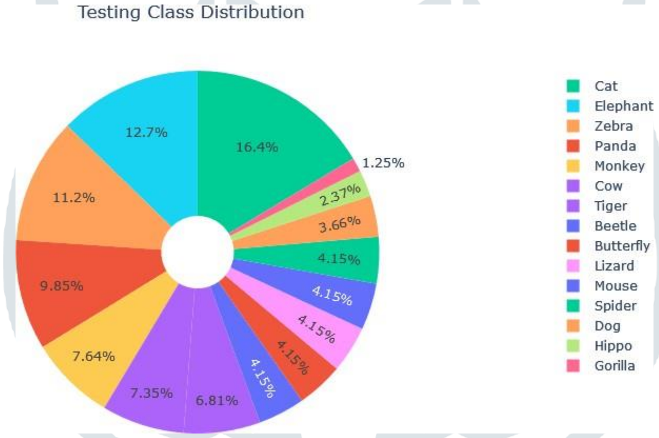
At this stage an image is given as an input .Our model classifies the given input animal imagesas elephant or pig.

Figure: Detected Elephant

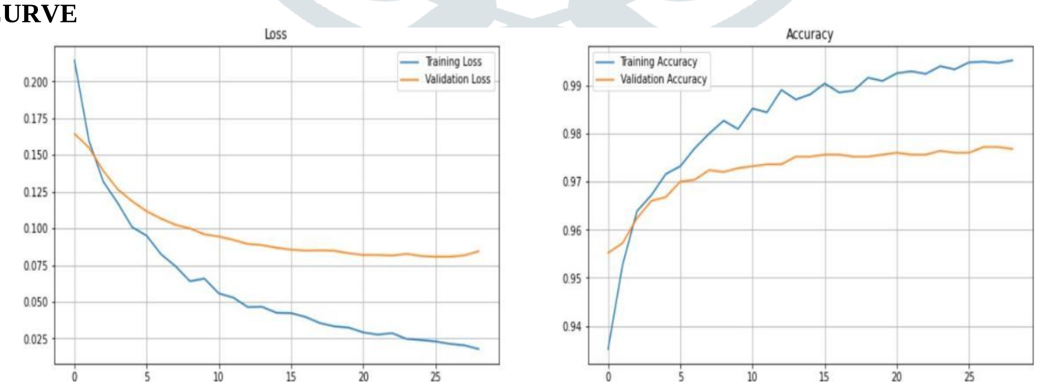
IV OUTPUT







LEARNING CURVE



V CONCLUSION

Thus this project uses a Neural Network, ResNet50V2 algorithm to detect animals. The algorithm classifies animals efficiently with a good number of accuracy and also the image ofthe detected animal is displayed for a better result .so that it can be used for other purposes such as detecting wild animals entering into human habitat and to prevent wildlife poaching and even human animal conflict. We have introduced a verification step in which the proposed region is classifies animal in two classes as pig or elephant. We applied ResNet50V2 machine learning algorithm to achieve better performance.

VI REFERENCES

[1] [N. Banupriya et.al "Animal detection using deep learning algorithm" journal of criticalreviews ,2020

[2] Alexander Gomez et.al "Animal Identification in Low Quality Camera-Trap Images Using Very Deep Convolutional Neural Networks and Confidence Thresholds" Springer International Publishing AG 2016

[3] Gyanendra K. Verma et.al "Wild Animal Detection Using Deep Convolutional Neural Network "Proceedings of 2nd International Conference on ComputerVision & Image Processing 2018.

[4] Patrik kamencay et.al "Animal Recognition System Based on Convolutional Neural Network" DIGITAL IMAGE PROCESSING AND COMPUTER GRAPHICS, 2017

[5] William H. S. Antônio et.al "A Proposal of an Animal Detection System Using Machine Learning" APPLIED ARTIFICIAL INTELLIGENCE , 2019 Taylor & Francis

[6] Hung Nguyen et.al "Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring" 2017 International Conference on DataScience and Advanced Analytics

[7] Gyanendra K. Verma et.al "Wild Animal Detection from Highly Cluttered Images Using Deep Convolutional Neural Network" International Journal of Computational Intelligence and Applications, 2018

[8] Emmanuel Okafor et.al "Comparative Study Between Deep Learning and Bag of Visual Words for Wild-Animal Recognition" 2016 IEEE Symposium Series on Computational Intelligence (SSCI)

[9] Kamencay, P., T. Trnovszky, M. Benco, R. Hudec, P. Sykora and A. Satnik. Accurate wild animal recognition using PCA, LDA and LBPH, In: 2016 ELEKTRO. Strbske Pleso: IEEE, 2016, pp. 62–67.

[10] I. A. Hulbert and J. French, "The accuracy of GPS for wildlife telemetry and habitatmapping," Journal of Applied Ecology, vol. 38, no. 4, pp. 869–878, 2001.

[11] G. Chen, T. X. Han, Z. He, R. Kays, and T. Forrester, "Deep convolutional neural network based species recognition for wild animal monitoring," in Proceedings of the IEEE International Conference on Image Processing (ICIP), 2014, pp. 858–862.

[12] A. Gómez, A. Salazar, and F. Vargas, "Towards automatic wild animal monitoring: Identification of animal species in camera-trap images using very deep convolutional neural networks," arXiv:1603.06169, 2016.

[13] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv:1409.1556*, 2014.

[15] Zhi Zhang, Zhihai He, Guitao Cao, and Wenming Cao, Animal Detection From HighlyCluttered Natural Scenes Using Spatiotemporal Object Region Proposals and Patch Verification, in IEEE Transactions on Multimedia, vol. 18, no. 10, October 2016.

[16] Z. Zhang, Z. He, G. Cao and W. Cao, Animal detection from highly cluttered natural scenes using spatiotemporal object region proposals and patch verification, IEEE Trans. Multimedia 18(10) (2016) 2079–2092.

[17] A. Mammeri, D. Zhou, A. Boukerche and M. Almulla, An efficient animal detectionsystem for smart cars using cascaded classifiers, in IEEE Int. Conf. Communications (ICC) Sydney, NSW, 2014, pp. 1854–1859.

[18]A. Gomez., A. Salazar, F. Vargas, towards automatic wild animal monitoring: Identification of animal species in camera-trap images using very deep convolutional neuralnetworks,2016