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

Animal Detection in Farms Using Deep Neural Networks in Deep Learning

Indumathi R, Rajalakshmi T. G, Shanmugalakshmi Rand Sneha M
Computer Science and Engineering, Manakula Vinayagar Institute of Technology, Puducherry, India

Abstract. In this paper, issues related to the development of an effective and efficient animal detection, classification, and tracking system are addressed. Successful attempts towards the development of algorithmic models for animal segmentation, animal detection, classification, and tracking are made. To support the effective classification of animals, we propose two different methods to segment an animal from its background. Evaluation of the proposed animal segmentation algorithm is carried out by the use of region-based performance measures. We also provide a classification model based on several classifiers and features. In addition, we offer a method to identify animals in both photos and videos using a deep learning approach. The various characteristics, including as colour, Gabor, and LBP, are retrieved from the segmented animal images.Initially, features are extracted from images/frames using AlexNet pre-trained Probabilistic neural network. Lat, the extracted features are fed into a multi-class Probabilistic neural network classifier for classification.

Keywords: Animal recognition system,CNN,SVM, PCA,LBP

1 Introduction

At present, there is no one approach that offers a reliable and effective answer to all seat scenarios, making animal detection and recognition a challenging problem. Animal detection is really implemented by the binary pattern classification used by the animal detection methods problem [1]. This implies that an input picture is split into chunks, with each block being converted into a feature. A specific classifier is trained using animal characteristics that fall into a specific class. When presented with a new input picture, the trained classifier will be able to determine whether a sample is an image or not. The following fundamental applications may be made use of using the animal recognitionsystem.

- Identification - All other animals' characteristics that is stored in the databasewhich is then compared with the provided animal's image to and returns a one-to-N matchingwhich is a ranked list of matches.
- Authentication -Entails comparing with the provided animal image to the actual animal and certifying or disputing the authenticity of the discovered animal (one-to-one matching).

Despite identification and verification frequently use the same classification techniques, they both focus on different applications [1]. The following elements, which can seriously impair the performance of animal detection and identification systems, must be taken into account in turn to better comprehend the animal segmentation and classification job and its challenges:

Exposure conditions and other aspects of picture capture lighting variations, also including source distribution and intensity, or features of cameralike sensor responsiveness and lenses can all have an impact on the input animal imagery.Occlusions - both other items and other animals have the ability to partially obscure the animal pictures.
The following is how this document is structured. The most recent developments in object identification are briefly described in Section 2. The feature extraction and classification-based animal recognition system is covered in Section 3. The outcomes of the experiments are given in Section 4. Sec. 5 ends and makes suggestions for more research.

2 Literarure Survey

In the research article published by Fang, Y., et al[1],. discussed a method for improving animal detection by exploiting commonplace motion patterns in pixels worldwide. Using optical flow techniques, the motion vectors of each pixel were estimated in the dataset, which contains images of animals moving visibly against a static background. The majority of the unwanted foreground is then removed using a pixel-by-pixel coarse segmentation.a certain speed, or velocity, is required. With the help of the segmented regions, a second threshold was applied to eliminate false positives that could be part of the background..

G. Jaskó and coworkers [2] demonstrated a system that can distinguish between a variety of large wild animals in traffic scenes. Visual data was obtained from a camera that detects colors only through one eye. The image of the traffic scene was analyzed with the goal of locating and correctly classifying the regions of interest so that it could be used to identify the animals on the road that could potentially cause an accident. The image of the traffic scene was used to generate a saliency map, which included features like intensity, color, and orientation. It was assumed that the regions that stood out the most on this map were the most interesting. The source material for the creation of a database was a large number of photographs depicting a wide range of wild four-legged animals. These were used to extract relevant features, which were then extracted and used to train classifiers with Support Vector Machine.

Research was carried out by Nguyen, H., et al. [3] on a primary obstacle encountered by ecologists and scientists when attempting to monitor wildlife in an open environment. A framework has been presented with the goal of developing automated animal recognition in the wild, with the end goal of developing an automated wildlife monitoring system. This framework takes advantage of recent developments in deep learning approaches in computer vision. The framework's goal is to establish anself operating wildlife monitoring system.

Parham, J., et al. [4] proposed the method of enabling a 5-component detection pipeline in a computer-vision-based animal recognition system. This pipeline would be used to identify animals. Researchers were successful in compiling a new set of AOIs using this method, and authors labeled them according to species and perspective. The development of this methodology was motivated by the desire to improve the ecological data available to conservationists and to enhance the studies' reliability as well as their level of automation.

A novel method for object recognition using hybrid local descriptors was discussed by Matuska, S., et al. [5]. The methods SIFT - Scale-invariant feature transform, SURF - Speeded Up Robust Features were combined to form this strategy. A small subset of the images in the dataset were used to illustrate the effectiveness of the hybrid methods presented. The large mammals of the Slovak countryside are represented in the dataset by species like wolf, fox, brown bear, deer, and wild boar.

3 Proposed System

Various image processing algorithms have been incorporated to optimize the footprints. The algorithms include conversion of the input image to grayscale, detection of image edges, and others.. Before the input image is categorized and raw data is added, every picture in the dataset is read, edited, and its features are extracted before the input image is categorized. As part of this research, a Gabour filter response was developed in order to both extract features of a picture's texture and keep the properties of that texture intact in frequency. The input picture is given a filter that is selective in its scale and orientation in order to obtain the characteristics of the texture. Isolating the picture from the background is a necessary step for segmentation to achieve its intended purpose of producing an accurate classification. The subsequent step involves the extraction of the templates for the Animals. Both the procedure for updating the template and the procedure for matching templates are specified.

A CNN-based solution for object recognition is proposed. The proposed RGB-D object recognition architecture employs two distinct CNN processing streams, each of which is sequentially coupled with a late fusion network. In order to create the final image, an RGB image and the depth image that corresponds to it are combined. The CNNs' training had been done in the past by ImageNet. After the depth images have been rendered into RGB images and the depth data has been distributed across all three RGB channels, For the identification process, a conventional convolutional neural network (CNN) is used. CNNs that have been trained on ImageNet [4] are used instead of large-scale labeled depth datasets because there are not many of them. It has been suggested that an innovative data augmentation strategy be utilized in order to improve recognition in chaotic real-world environments. Two different datasets are utilized in an experimental evaluation of the method, which is as follows: RGB-D Object Dataset for the Washington.

Another method for object recognition that makes use of deep CNN is suggested in. Additionally, CNN is used, which has been taught to classify images and offers a wealth of semantically rich features. By drawing objects from a canonical viewpoint and colouring the depth channel in accordance with the object's centre distance, the depth information is included.

4 Animal Recognition System

The image (or a portion of the image) is input into the image recognition algorithm, which is also referred to as a "image classifier". The algorithm then generates an output that contains the contents of the image. To phrase it another way, What we receive as a result is a class label (fox, wild boar, mongoose, bear etc.).

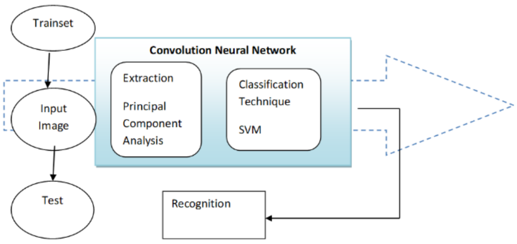

Fig. 1:Animal Intrusion Recognition system

The following steps comprise the animal recognition system (see Fig. 1):

- The input picture can be processed using a variety of pre-processing techniques in the pre-processing block to reduce the impact of variables that
- The features utilized in the recognition phase are calculated in the feature extraction block.
- The learning algorithm (classification) uses training data with features and class labels to create a prediction model. The predictive models estimate their class labels using the characteristics learnt from the training data on the fresh (previously unobserved) data. Discrete output classes are used. Among the many different kinds of categorization algorithms are decision trees and Support Vector Machines (SVM).

It is noteworthy to notice that many classification methods from the traditional computer vision era follow this pipeline, but Deep Learning-based algorithms completely skip the feature extraction stage (see Fig. 1).

In each of our tests, test animal photos will be classified using SVM and proposed CNN and feature extracted using PCA, LDA, and LBPH (fox, wild boar, mongoose, wolf, bear, hog, and deer).

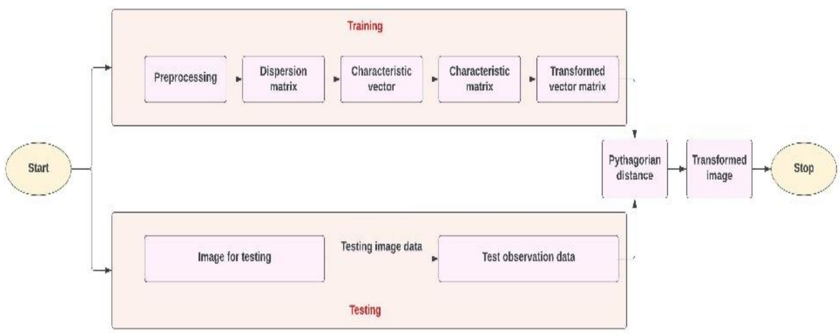

Fig. 2 Extraction of images with PCA

A variable-reduction approach called principal components analysis (PCA) is used to highlight variance and highlight clear patterns in a dataset. The primary goal of principal component analysis (PCA) is to condense a larger number of real variables into a smaller set of fictitious variables known as principle components that together explain the majority of the variance in the initial variables (see Fig. 2).

The general steps for performing a principal component analysis, To execute a principal component analysis the following steps to be followed

- Ignore the class labels and use the entire dataset of d-dimensional samples. The d-dimensional mean vector be calculated (i.e., Every dimension of the whole dataset mean is to be calculated).
- Calculate the scatter matrix (or matrix if you choose) for the entire set of data.
- Calculate the associated eigen values (e1, e2, e3, e4, e5,..., d) and eigenvectors (e1, e2, e3, e4, e5,..., d).

The top k eigenvectors with the highest eigen values should be chosen in order to form a d k dimensional matrix W, where each column represents an eigenvector.Apply the eigen vector matrix to transform the samples into the new subspace. This can be mathematically stated as follows:

y = WT x, (1) where y is the transformed k 1 dimensional sample in the new subspace and x is a d 1-dimensional vector in place of one sample.

The variance maintained is maximized when high-dimensional data are projected linearly into a lower-dimensional subspace, as found by PCA (maximizes the variance of projected data).

- Minimizing the least-square reconstruction error (minimizes mean squareddistance between data points).

4 Conclusion

The suggested CNN is compared in the research to popular image recognition, feature extraction, and image classification methods (PCA, LDA, SVM, and LBPH). The produced animal database was used to assess the proposed CNN. Different numbers of test photos and training images were used to achieve the overall performances. The experimental finding demonstrates that for the big training set, the LBPH method outperforms PCA, LDA, and SVM. SVM, on the other hand, performs better on short training data sets than PCA and LDA. Using the suggested CNN, the best experimental outcomes for animal recognition were attained. The gathered experimental data from the carried out studies demonstrate that the suggested CNN provides the optimum recognition rate for a larger number of input training pictures. More window divisions of the image should improve the categorization outcomes. However, the difficulty of calculation will rise.

To compare the provided methodologies with other available algorithms, we want to conduct trials and testing of more complicated algorithms in future work (deep learning). We also want to use bigger datasets of animal photos to test the validity of the methodologies that have been provided. The performance of many classifiers needs to be improved next employing a mix of local descriptors. Future projects may involve testing this methodology on datasets of additional animals.

References

1. Xie, Z., Singh, A., Uang, J., Narayan, K.S., Abbeel, P.: Multimodal blending for high-accuracy instance recognition. IEEE/RSJ International Conference on Intelligent Robots and Systems , pp. 2214-2221. IEEE Press, New York (2013)
2. Eitel, A., Springenberg, J.T., Spinello, L., Riedmiller, M., Burgard, W.:, September. Multimodal deep learning for robust RGB-D object recognition. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 681-687. IEEE Press, New York (2015)
3. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A.C.: Imagenet large scale visual recognition challenge. International journal of computer vision, vol. 115, pp.211-252. (2015)
4. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. Communications of the ACM, vol. 60, pp.84-90 (2017)
5. RGB-D Object Dataset. In: University of Washington [online]. (2014)
6. Schwarz, M., Schulz, H., Behnke, S.: RGB-D object recognition and pose estimation based on pre-trained convolutional neural network features. IEEE international conference on robotics and automation (ICRA), pp. 1329-1335. IEEE (2015)
7. Howley, T., Madden, M.G., O'Connell, M.L., Ryder, A.G.:. The effect of principal component analysis on machine learning accuracy with high dimensional spectral data. In Applications and Innovations in Intelligent Systems XIII: Proceedings of AI-2005, the Twenty-fifth SGAI International Conference on Innovative Techniques and Applications of Artificial Intelligence, Cambridge, UK, pp. 209-222. Springer London(2006)
8. Aburomman, A.A., Reaz, M.B.I.: November. Ensemble SVM classifiers based on PCA and LDA for IDS. In 2016 International Conference on Advances in Electrical, Electronic and Systems Engineering (ICAEES), pp. 95-99. IEEE (2016)
9. Hagar, A.A., Alshewimy, M.A., Saidahmed, M.T.F.: December. A new object recognition framework based on PCA, LDA, and K-NN. 11th International Conference on Computer Engineering & Systems (ICCES), pp. 141-146. IEEE (2016)
10. Kamencay, P., Trnovszky, T., Benco, M., Hudec, R., Sykora, P., Satnik, A.: Accurate wild animal recognition using PCA, LDA and LBPH. ELEKTRO. Pp. 62-67. IEEE (2016)
11. Stekas, N., Van Den Heuvel, D.: Face recognition using local binary patterns histograms (lbph) on an fpga-based system on chip (soc). IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW), pp. 300-304. IEEE (2016)
12. Faruqe, M. O., Hasan, A. M.: Face recognition using PCA and SVM. 3rd International Conference on Anti-counterfeiting, Security, and Identification in Communication, pp. 97–101.IEEE, Hongkong (2009)
13. Vapnik, V.: Statistical Learning Theory, John Wiley and Sons,New York (1998)
14. Wu, J.L., Ma, W.Y.: A deep learning framework for coreference resolution based on convolutional neural network. IEEE 11th International Conference on Semantic Computing (ICSC), pp. 61-64. IEEE (2017)
15. Le Ne Convolutional Neural Networksin Python.: PyImage- Search [online]. Available at:https://pyimagesearch.com/2016/08/01/lenet-convolutional-neural-network-in-python/
16. Understanding convolutional neural networks.: WildML [online].Available at: http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-NLP/ (2015)
17. Murphy, K.P.: Machine learning: a probabilistic perspective. MIT press (2012)