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Animal Identification And Detection Of Species

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Abstract: **Animal identification and species detection play crucial roles in wildlife conservation, ecological research, and biodiversity monitoring. In recent years, convolutional neural networks (CNNs), a type of deep learning algorithm, have shown remarkable success in various computer vision tasks, including animal identification and species detection. This paper comprehensively reviews current state-of-the-art animal identification and species detection techniques using CNN. The paper discusses the challenges associated with animal identification and species detection, including variations in animal appearance, complex backgrounds, and limited availability of labeled training data. In this study, we propose a deep learning solution based on Convolution Neural Networks (CNN) predict whether the animal belongs to which classes and their species. It also uses a pre-trained model and develops a solution to the same problem. We then explore a variety of CNN-based approaches that have been developed to address these challenges, including transfer learning, fine-tuning, and data augmentation techniques. This paper also describes, for example, various CNN architectures and their applications for animal identification and species discovery.**

Index Terms **- Animal detection; species identification; Convolutional neural Network (CNN);**

I. Introduction

Numerous different animal species inhabit the planet, each with its own traits, mannerisms, and ecological functions. The animal world includes a huge diversity of life forms that have developed and adapted to different settings over millions of years, ranging from the microscopic to the enormous, from the familiar to the exotic. Animal species are categorised into different taxonomic categories based on their evolutionary ties, physical traits, and genetic makeup. Species serve as the fundamental unit of taxonomy's hierarchical classification scheme. Animal species are incredibly diverse, which is one of their most amazing characteristics.

Animals can be found almost anywhere in the world, including the deepest oceans, highest mountains, icy tundra, scorching deserts, dense forests and vast grasslands. Animals are surprisingly diverse in shape, size, and ecological function. Animals come in all sizes, from tiny insects like ants and beetles to giant whales and elephants. Some species have various behavioural traits. Some animals are solitary, while others are part of social structures.

There are many types of animal communication, including speech, body language, smell, and sight. All animals are divided into five groups: mammals, birds, reptiles, amphibians and insects.

In wildlife conservation, ecological study, and biodiversity monitoring, animal identification and species detection are essential tasks. Understanding wildlife populations, migratory patterns, ecological relationships, and conservation efforts, require the accurate and effective identification of animals and the determination of their species. Convolutional neural networks (CNNs) are emerging as a potential method to automate these activities as a result of recent developments in computer vision and deep learning. CNNs have demonstrated outstanding performance in object identification, picture classification, and object detection and have the capacity to learn complex visual properties. The input provided by the user will be in the form of JPG or PNG images. The CNN algorithm will then convert these images into thumbnail images with a resolution of 64x64 pixels. These thumbnail images will be utilized to train the model. The trained model will subsequently be capable of detecting animals and identifying their species based on the input images. As a result, this study aims to thoroughly evaluate the most recent methods for animal identification and species detection that use CNNs.

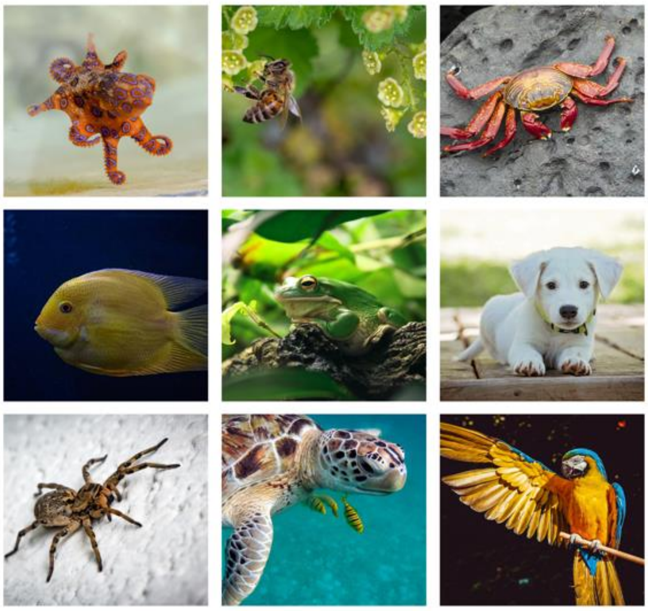

fig. 1. Types of animals.

The figure (Fig 2) illustrates different species of dogs, such as the domestic dog, dingo, grey wolf, Mexican wolf, golden jackal, coyote, and African wild dog. These species belong to the family Canidae and are domesticated mammals. Dogs display a wide diversity in terms of size, shape, and temperament, as they have been selectively bred by humans for various purposes. The use of CNN (Convolutional Neural Network) can be employed for species detection and evaluation of these dogs based on their visual characteristics.

fig. 2. species of dog.

II. RELATED WORKS

CNN has attracted the attention of numerous experimenters in the field of beast recognition due to its enormous capacity in terms of delicacy rate. Research works have been developed grounded on deep literacy, A study has been conducted on the impact of noisy markers on beast species bracket, performing in the development of an accurate categorization network. The study employed deep neural network features and k- means clustering to produce different groups of beast species for training. Maximum voting was used to determine real markers of noisy data. The proposed system has implicit operations in wildlife monitoring by citizen scientists, where inaccurate reflections are common. The study highlights the significance of network diversity for bettered sample marker estimation. farther exploration could have counteraccusations for wildlife conservation and other fields taking accurate brackets of noisy data. the authors proposed a face recognition system in the case of the presence of occlusion or noisy faces that are grounded on deep literacy using a deep neural network (DNN), for this the features are uprooted in a waterfall from the images independently also reused to elect the most applicable also these are used by a DNN for a bracket. Experimental results showed that this system achieved a delicacy of 92.3. Another system has been proposed for face recognition under inimical conditions (delicate lighting, blur, and low resolution) which uses CNNs to project the covariance matrices of Gabor swells into a point vector of the Euclidean space. This system effectively excerpts fine features from an image and has been shown to perform better than DNN. Another face recognition system was developed for use in a Big data terrain by who optimized a face recognition algorithm that combines two point birth ways which are the original double pattern (LBP) algorithm and two- dimensional principal element analysis (2DPCA) these features are latterly intermingled to pass them to a CNN as input data. In the environment of big data, the delicacy of this fashion could exceed 90.

III. METHODOLOGY

In the First step, the user has to give input in the form of an image that is any animal image including land, aquatic and birds. Pre-process is the stage where the raw image given by the user has to be processed before it is fed into learning purposes, to enhance the image for accurate prediction. The entire image is divided into tiny objects for which features are extracted using CNN. Then, The input provided by the user will be in the form of JPG or PNG images. The CNN algorithm will then convert these images into thumbnail images with a resolution of 64x64 pixels. These thumbnail images will be utilized to train the model. The trained model will subsequently be capable of detecting animals and identifying their species based on the input images. As a result, this study aims to thoroughly evaluate the most recent methods for animal identification and species detection that use CNNs. The resulting CNN algorithm will help to find out the category of Animal. In the next step, we will Apply that to the category-wise Animal Identification and Species Detection Model. CNN compares the input and training datasets and accurately predicts the animal species' output. In general, there are Eight main steps in completing Animal identification which can be seen in Figure 3, namely An, where the system must understand whether the detected image has a face or not, then which CNN algorithm step is to recognize distinctive features or characteristics that exist on the animal that whether it is animal or not. Finally, the prediction Animal Species step consists of identification and verification by comparing it with existing data. In the last step, the output will show the Category of animals and their Species.

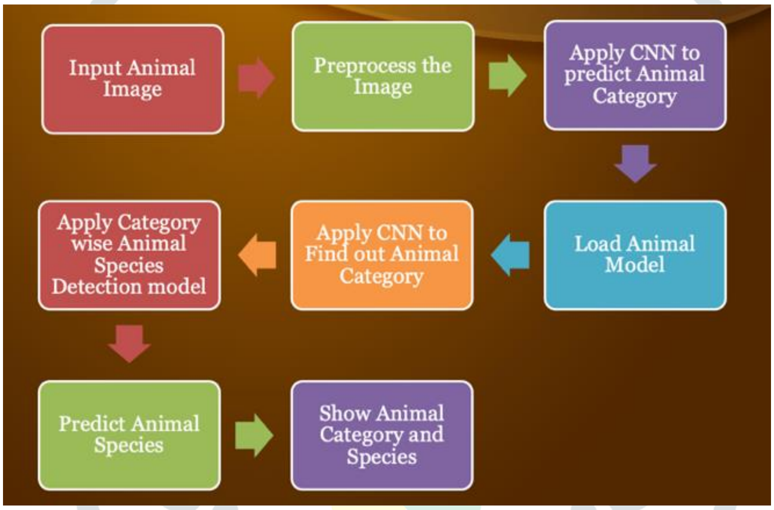

fig. 3. working of animal identification and species detection

IV. DATABASE DESIGN

Designing a database for animal images can be a complex task that requires careful consideration of various factors, including the size of the database, the quality and diversity of the images, and the specific requirements of the research or application. The database of animal images was collected from the trained model, or already trained dataset images and species. The images have different backgrounds, where some of them were taken in shadow conditions, lightening background, and some of them have other objects in the images as a background. This has added a huge challenge to the researchers to extract features and to provide high accuracy.

V. ALGORITHM

A CNN includes convolutional layers, pooling layers, activation functions and completely connected layers. In general, the upper layers are convolutional layers, and also one or further completely connected layers are protruded. All completely connected and convolutional layers are followed by an activation function, which is used as a non-linear transfigure. At the same time, the pooling subcaste is after the convolutional subcaste, which serves to reduce the quantum of data contained in the intermediate issues. In a convolutional neural network, the convolutional subcaste is the utmost introductory unit. Under the action of mapping, a well-trained convolutional subcaste automatically and efficiently excerpts features from the data and transfers the original data to the retired point space. The completely connected subcaste is the classifier in CNN, which maps the learned features to the sample data labelling space. At the same time, the substance of the operation in this subcaste is the addition of vectors and matrices. However, only the convolutional subcaste point chart can be input to the completely connected subcaste, If it's converted into vector form after the uncurling operation. The pooling subcaste differs significantly from the completely connected and convolutional layers. Because the upper branch recognition delicacy and recognition time issues for the four algorithms independently, with the vertical equals all representing the types of independently, while the delicacy of CNN is above 97 for all of them, and the recognition delicacy for the end is as high as 99.

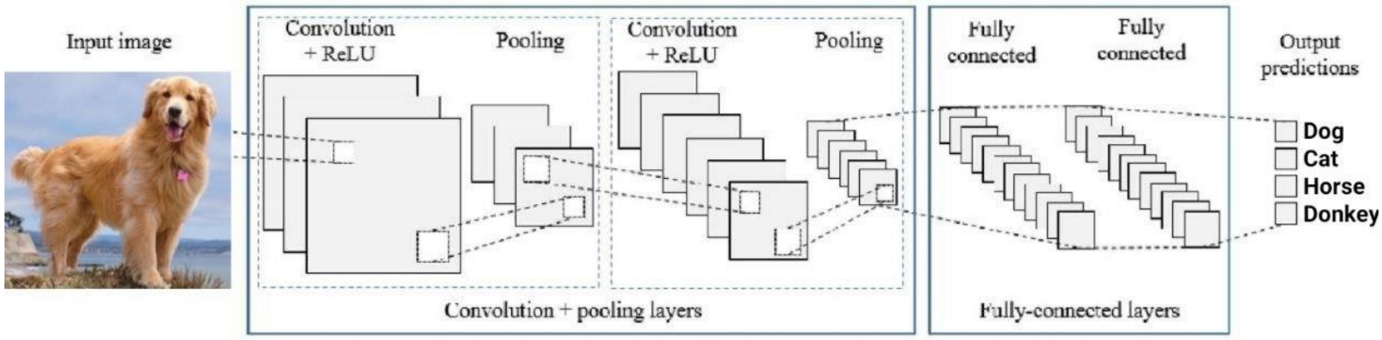

Fig. 4. typical convolutional neural network

VI. PROPOSED METHOD

Animal species identification and detection system is an application that uses machine learning algorithms to recognize animals from their images. The system involves several steps, including image preprocessing, CNN algorithm, and animal model training. The CNN algorithm is the system's most important component, and it is responsible for recognizing the animal category and species. The first step in the animal species identification and detection system is to input the animal image. The image is then preprocessed to enhance the quality of the image and reduce noise. The preprocessing step is important as it can improve the accuracy of the system. Once the image is preprocessed, it is passed through the CNN algorithm. The CNN algorithm is a deep learning technique that can automatically recognize patterns in the image data. CNNs have been successfully used in many applications, including image classification, object detection, and segmentation. The algorithm includes several layers, pooling, convolutional and fully connected layers. In the animal species identification and detection system, the CNN algorithm is used to predict the animal category. The CNN model is trained using a dataset of animal images. The dataset is collected from the internet, and it contains images of different animal categories, such as dogs, cats, lions, tigers, and bears. The images in the dataset are converted into 64*64 resolution images to train the model faster. The CNN model is trained by minimizing the loss function, which measures the difference between the predicted and actual outputs. The model is trained using backpropagation, which updates the weights and biases of the neural network to minimize the loss function. After training the model, the animal species detection model is created.

This model is trained to detect the animal species based on the animal category predicted by the CNN algorithm. The animal species detection model is trained using a dataset of animal images of different species. The images in the dataset are labelled with the corresponding animal species. Once the animal species detection model is trained, it can be used to predict the animal species based on the animal category predicted by the CNN algorithm. The predicted animal category and species are then shown to the user. In summary, an animal species identification and detection system is an application that uses machine learning algorithms to recognize animals from their images. The system involves several steps, including image preprocessing, CNN algorithm, and animal model training.

The CNN algorithm is the system's most important component, and it is responsible for recognizing the animal category and species. The CNN algorithm is a deep learning technique that can automatically recognize patterns in the image data. The algorithm is trained using a dataset of animal images, and the model is trained to minimize the loss function by updating the weights and biases of the neural network using backpropagation. The animal species detection model is trained to detect the animal species based on the animal category predicted by the CNN algorithm. The predicted animal category and species are then shown to the user. After obtaining the basketball pose data features, a CNN is used to downscale and identify the features.

VII. CONCLUSIONS AND FUTURE WORK

In conclusion, the animal species identification and detection system is a powerful application that uses machine learning algorithms to recognize animals from their images. The system involves several steps, including image preprocessing, CNN algorithm, and animal model training. The CNN algorithm is the system's most important component, and it is responsible for recognizing the animal category and species. The CNN algorithm is a deep learning technique that can automatically recognize patterns in the image data. The algorithm is trained using a dataset of animal images, and the model is trained to minimize the loss function by updating the weights and biases. The animal species detection model is trained to detect the animal species based on the animal category predicted by the CNN algorithm. Animal species identification and detection system has many potential applications, such as wildlife monitoring, conservation, and research. The system can be used to identify and track different animal species, which can help researchers and conservationists understand the behaviour and habitat of animals. The system can also be used to monitor endangered species, which can help prevent extinction. In addition, animal species identification and detection system can be used in agriculture to detect and prevent animal diseases. The system can identify and track animal species that are susceptible to diseases, which can help farmers prevent the spread of diseases. Overall, animal species identification and detection system are powerful application that has many potential applications in various fields. The system can help researchers, conservationists, and farmers to identify and track different animal species, prevent the spread of diseases, and protect endangered species. The development of such systems is a step forward towards the advancement of technology and the protection of our planet's diverse wildlife.

VIII. REFERENCES

[1] E. Beigman, B.B. Klebanov, Learning with annotation noise, in: In Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP vol. 1, Association for Computational Linguistics, 2009, pp. 280–287 August.

[2] A.J.A. Fegraus, E.T. Birch, N. Flores, R. Kays, T.G.O. Brien, J. Palmer, S. Schuttler, J.Y. Zhao, W. Jetz, M. Kinnaird, S. Kulkarni, A. Lyet, D. Thau, Wildlife insights : a platform to maximize the potential of camera trap and other passive sensor wildlife data for the planet, Environ Conserv page 2014 (2019), https://doi.org/10.1017/ S0376892919000298.

[3] R. Fergus, L. Fei-Fei, P. Perona, A. Zisserman, Learning object categories from internet image searches, Proc. IEEE 98 (8) (2010) 1453–1466.

[4] B. Han, Q. Yao, X. Yu, G. Niu, M. Xu, W. Hu, I. Tsang, M. Sugiyama, Coteaching: robust training of deep neural networks with extremely noisy labels, Adv. Neural Inf. Process. Syst. (2018) 8527–8537.

[5] L. Jiang, Z. Zhou, T. Leung, L.J. Li, L. Fei-Fei, Mentornet: Learning Data-Driven Curriculum for Very Deep Neural Networks on Corrupted Labels, 2017 arXiv preprint arXiv:1712.05055.

[6] I. Jindal, M. Nokleby, X. Chen, Learning deep networks from noisy labels with dropout regularization, in: Data Mining (ICDM). in: 2016 IEEE 1th, 2016, December.

[7] A. Krizhevsky, I. Sutskever, G.E. Hinton, ImageNet classification with deep convolutional neural networks, Adv. Neural Inf. Process. Syst. (2012) 1097–1105.

[8] N. Manwani, P.S. Sastry, Noise tolerance under risk minimization, IEEE Trans. Cybernetics 43 (3) (2013) 1146–1151.

[9] N. Natarajan, I.S. Dhillon, P.K. Ravikumar, A. Tewari, Learning with noisy labels, Adv. Neural Inf. Process. Syst. (2013) 1196–1204.

[10] D.F. Nettleton, A. Orriols-Puig, A. Fornells, A study of the effect of different types of noise on the precision of supervised learning techniques, Artif. Intell. Rev. 33 (4) (2010) 275–306.

[11] L. Niu, W. Li, D. Xu, Visual recognition by learning from web data: a weakly supervised domain generalization approach, in: Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2015, pp. 2774–2783.

[12] M. Ren, W. Zeng, B. Yang, R. Urtasun, Learning to Reweight Examples for Robust Deep Learning, 2018 arXiv preprint arXiv:1803.09050.

[13] D. Rolnick, A. Veit, S. Belongie, N. Shavit, Deep Learning Is Robust to Massive Label Noise, 2017 arXiv preprint arXiv:1705.10694.

[14] A. Swanson, M. Kosmala, C. Lintott, R. Simpson, A. Smith, C. Packer, Snapshot Serengeti, high-frequency annotated camera trap images of 40 mammalian species in an African savanna, Sci. Data 2 (2015).

[15] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, R. Fergus, Intriguing Properties of Neural Networks, 2013 arXiv preprint arXiv:1312.6199.

[16] G. Van Horn, S. Branson, R. Farrell, S. Haber, J. Barry, P. Ipeirotis, P. Perona, S. Belongie, Building a Bird Recognition App and Large Scale Dataset with Citizen, 2015.

[17] A. Veit, N. Alldrin, G. Chechik, I. Krasin, A. Gupta, S.J. Belongie, in: Learning from Noisy Large-Scale Datasets with Minimal Supervision, CVPR, 2017, July, pp. 6575–6583.

[18] T. Xiao, T. Xia, Y. Yang, C. Huang, X. Wang, Learning from massive noisy labeled data for image classification, Proc. IEEE Conf. Comput. Vis. Pattern Recognition (2015) 2691–2699.

[19] B. Yuan, J. Chen, W. Zhang, H.S. Tai, S. McMains, Iterative cross learning on noisy labels, in: In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), IEEE, 2018, March, pp. 757–765.

[20] N. Zhang, M. Paluri, M.A. Ranzato, T. Darrell, L. Bourdev, Panda: pose aligned networks for deep attribute modeling, in: Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2014, pp. 1637–1644.

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

[22] B. Zhou, A. Lapedriza, J. Xiao, A. Torralba, A. Oliva, Learning deep features for scene recognition using places database, Adv. Neural Inf. Process. Syst. (2014) 487–495.

[23] X. Zhu, A.B. Goldberg, Introduction to semi-supervised learning, Synth. Lect. Artif. Intell. Mach. Learn. 3 (1) (2009) 1–130.

[24] Ramdas Vankdothu, DrMohd Abdul Hameed, Husnah Fatima, A brain tumor identification and classification using deep learning based on CNN-LSTM method, Comput. Electr. Eng. 101 (2022), 107960.

[25] Ramdas Vankdothu, Mohd Abdul Hameed, Adaptive features selection and EDNN based brain image recognition on the internet of medical things, Comput. Electr. Eng. 103 (2022), 108338.

[26] Vankdothu Ramdas, Mohd Abdul Hameed, Ayesha Ameen, Raheem, Unnisa, Brain image identification and classification on Internet of Medical Things in healthcare system using support value based deep neural network", Comput. Electr. Eng. 102 (2022), 108196.

[27] Ramdas Vankdothu, Mohd Abdul Hameed, Raju Bhukya, Gaurav Garg, Entropy and sigmoid based K-means clustering and AGWO for effective big data handling, Multimed. Tool (2022) 1–18.

[28] Ramdas Vankdothu, Mohd Abdul Hameed, Brain tumor MRI images identification and classification based on the recurrent convolutional neural network, Measurement: Sensors Journal 24 (2022), 100412.

[29] Ramdas Vankdothu, Mohd Abdul Hameed, Brain tumor segmentation of MR images using SVM and fuzzy classifier in machine learning, Measurement: Sensors Journal 24 (2022), 100440.

[30] Ramdas Vankdothu, Mohd Abdul Hameed, COVID-19 detection and classification for machine learning methods using human genomic data, Measurement: Sensors Journal 24 (2022), 100537.

[31] Ayodeji Olalekan Salau, Nikhil Marriwala, Muzhgan Athaee, Data security in wireless sensor networks: attacks and countermeasures, Mobile Radio Communications and 5G Networks (2020) 173–186.

[32] Nikhil Marriwala, O.P. Sahu, Anil Vohra, 8-QAM software defined radio based approach for channel encoding and decoding using forward error correction, wireless personal communications Journal 72 (4) (2013).

[33] Nikhil Marriwala, Om Prakash Sahu, Anil Vohra, LabVIEW based design implementation of M-PSK transceiver using multiple forward error correction coding technique for software defined radio applications, J. Electr. Electron. Eng. 2 (4) (2014).