# Computer Vision To Animal Footprint Classification Based On Deep Learning Model

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**Abstract—An emerging area in machine vision is a real dog biometric system that can identify and describe animal life in images and videos these programs offer methods for classifying animals using computer vision CNN features a well-liked deep learning technique are the foundation of the current system for classifying animal faces. Here, the suggested system analyses photos of animal footprints to categorise them using deep learning. Using a clever method, the footprint photos are pre-processed and turned into grayscale boundaries. Gabor filter are used to extract features of segmented image. The dimensionality reduction is carried out based on unsupervised model, Principal Component Analysis (PCA). Then reduced feature vectors are inputted into the classification model. Probabilistic Neural Network (PNN) is used for classification and identifying the animal class. Footprints 0 dataset of five different animal categories of 100 images is to be used for classification. The performance analysis of the system is evaluated using the measure accuracy, precision, recall and fl-measure**

**Keywords—Probabilistic Neural Network, precision, recall,F1score.**

## I. INTRODUCTION

A computer vision algorithm is used to extract features from a photo or video, and deep learning techniques are used to predict the labels of a given image in the field of animal recognition. There are various societal advantages to studying animal recognition: It enables the observation and preservation of wild animals, particularly in a setting where some species are in danger of going extinct. Also, it gives the general public an essential tool for examining and tracking long-term trends in the animal population. It enables ecologists and biologists to have a better understanding of how the abundance of animals affects their surroundings. Humanoid beings develop various algorithms and techniques to have a deeper understanding of animal behaviour. These applications can also be used to warn humanoids when dangerous wild animals are disturbed so that they can take immediate protective measures. An animal leaving its footprints on a ground surface, such as mud, snow, or dirt, is said to have left an animal track. Hunters use animal tracks to locate their prey, while naturalists use them to identify the creatures that inhabit a certain area. Animal footprints, which can appear differently according on the animal's weight and the type of strata they are made of, are frequently recognised using books. Over millions of years, tracks can become petrified. This explains why some types of rock formations have fossilised dinosaur tracks. Since these fossils are traces of an animal rather than the actual animal, they are known as trace fossils. In paleontology, tracks often preserve as sandstone infill, forming a natural mold of the track.

## II. RELATED WORK

Jonathan Li et al [1] in their work "Tree Classification in Complex Forest Point Clouds Based on Deep Learning" proposed that, In this work, We put forth a brand-new rasterization-based technique for categorising different tree species from TLS point clouds of intricate forest landscapes. Our approach entails individual tree extraction, noise removal, voxel-based rasterization of tree characteristics, and classification of tree species using a DBN model. Tests reveal that both data sets reach great accuracy. A potent way to represent information about 3-D objects is through rasterization. We'll keep thinking about better ways to represent 3-D objects in the future.

Junwei Han et al [2] in their proposed work "Object Detection in Optical Remote Sensing Images Based on Weakly Supervised Learning and High-Level Feature Learning" proposed that object detection issues using optical RSIs. Two key components of the proposed work are innovative, setting it apart from earlier efforts. First, this research established a WSL framework that can significantly reduce the human effort of annotating training data while attaining the excellent performance, as opposed to employing typical supervised or semi-supervised learning methodologies. Second, we created a deep network that can unsupervisedly learn high-level features, providing a more potent descriptor to capture the structural details of objects in RSIs. As a result, it can further enhance the performance of object detection. The usefulness of the suggested work has been shown by experiments on three separate RSI data sets.

Geoffrey E. Hinton et al [3] in their work titled “ImageNet Classification with Deep Convolutional Neural Networks” Our findings demonstrate that a large, deep convolutional neural network is capable of breaking records on a very difficult dataset when utilising only supervised learning. It is noteworthy that removing just one convolutional layer causes our network's performance to suffer. For instance, eliminating any one of the middle layers reduces the network's top-1 performance by around 2%. So, the depth is crucial for attaining our results. Although we anticipate that it will be helpful, especially if we are able to obtain enough computational power to significantly increase the size of the network without obtaining a corresponding increase in the amount of labelled data, we did not use any unsupervised pre-training in order to simplify our experiments. While our network has grown and been trained longer, our findings have thus far improved, but we still have a long way to go before we can match the infer temporal pathway of the human visual system. In the end, we want to deploy very big and deep convolutional nets on video sequences where the temporal structure offers very useful information that is absent or much less visible in static images.

Andrew Rabinovich et al [4] in their proposed work titled “Going deeper with convolutions” proposed that Our findings provide convincing evidence that optimising neural networks for computer vision can be accomplished by approximating the desired optimal sparse structure using easily available dense building pieces. In comparison to shallower and less wide networks, this method's key benefit is a large quality gain with a relatively small increase in processing needs. A further indication of the power of the Inception architecture is the fact that our detection work was competitive despite neither using context nor conducting bounding box regression.

Albrecht Fehske et al [5] in their proposed title “The Global Footprint of Mobile Communications:The Ecological and Economic Perspective” discussed the global carbon footprint of mobile communication networks and its consequences for the environment and the economy. We project that CO2 equivalent emissions will rise by a factor of three between 2007 and 2020, from around 86 to 235 Mto CO2e, using the most recent data and life cycle assessment models. This suggests a sharper rise than that indicated in the well-known SMART2020 report.In cellular business models, the energy bill associated with network operation will become more and more significant.Taking into account several scenarios of technological advancement and rollout, we analyze the overall energy consumption of global radio access networks and illustrate the saving potential green communication technologies.

N. kljun et al [6] in their proposed work titled “Comparison of the langrangian footprint model lpdm- b with an analytical footprint model” The results of an analytical footprint model developed by Kormann and Meixner are compared with the flux and concentration footprint estimations from a three-dimensional Lagrangian stochastic dispersion model that applies backward trajectories. The comparison is carried out for various surface layer stability regimes as well as for various measurement heights. Excellent correspondence overall

H. P. Schmid et al [7] in their proposed work titled “A simple two-dimensional parameterisation for Flux Footprint Prediction (FFP)” said that In order to interpret flux tower observations, determine the location and size of surface source areas, and determine the proportional contribution of passive scalar sources to recorded fluxes, flux footprint models are frequently utilised. For any upscaling efforts from single site flux measurements to local or regional scale, accurate understanding of footprints is essential. Hence, in the end, footprint models are also very important for better greenhouse gas budgeting. With more flux towers being used in expansive monitoring networks like FluxNet, ICOS (Integrated Carbon Observation System), With the availability of airborne flux measurements and the expanding temporal range of observations from such towers (of the order of decades), such networks as NEON (National Ecological Observatory Network) or AmeriFlux have increased the necessity for accurate footprint assessment. Despite the recent development of various complex footprint models, the majority of them still cannot be applied to lengthy time series due to their high computing requirements.

Justin Kitzes et al [8] in their proposed work “Answers to common questions in Ecological Footprint accounting” said that Using current technology and resource management practises, the Ecological Footprint is a resource accounting tool that calculates the amount of biologically productive land and sea that is consumed by a specific population or activity and compares it to the amount of land and sea that is available (Rees, 1992; Wackernagel et al., 1996). The needs of humans for food, fibre, timber, energy, and space for infrastructure are supported by productive land and marine environments. Also, these areas take in the waste products of the human economy. Wherever they physically reside on the earth, the total of these areas is measured by the ecological footprint. These physical areas are frequently expressed in global hectares and weighted based on their relative productivity.

## III. PROPOSED METHODOLOGY

The proposed model is presented to eliminate all the drawbacks of the current system. With the use of a deep learning algorithm to categorise the animals from a picture collection, this system will improve the accuracy of the neural network findings. The performance of the overall classification results is improved. Finding the accuracy more trustworthy is to predict and recognise the animal image..

The proposed system consists of the following modules,

- Data selection
- Data pre-processing
- Data splitting
- Classification
- Performance Analysis

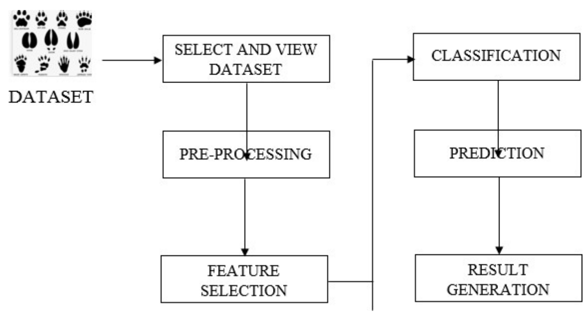



Fig .1 System Architecture

Fig.1 explains about the system architecture and themodules of the proposed model.

*A.DATA SELECTION*

The data selection is the process of selecting the data for Animal Foot Print dataset.In this project, forest animal digital images is used to find the scene.The dataset which contains the information about the elephant, dog etc.

*B.DATA PREPROCESSING*

Shape is an attribute of an image matrix that returns the shape of an image, consisting of the number of rows, columns, and planes. It is returned by the imread() and imshow() functions. One plane is all that is required for a grayscale image.

*C. DATA SPLITTING*

The act of breaking available data into two pieces, typically for cross-validator needs, is known as data splitting. Data are necessary for machine learning in order for learning to occur. In addition to the data needed for training, test data are also necessary to assess the algorithm's performance and determine how well it performs. With our method, we divided our dataset into training and testing portions, with the remaining 30% serving as training data. The act of breaking available data into two pieces, typically for cross-validator needs, is known as data splitting. A predictive model is created using a portion of the data, and its effectiveness is assessed using another portion of the data. A crucial step in reviewing data mining algorithms is dividing the data into training and testing sets. The majority of the data is often used for training, while a smaller portion of the data is utilised for testing when you divide a data set into a training set and testing set. You must separate the dataset into training and testing data in order to train any machine learning model, regardless of the type of dataset being utilised.

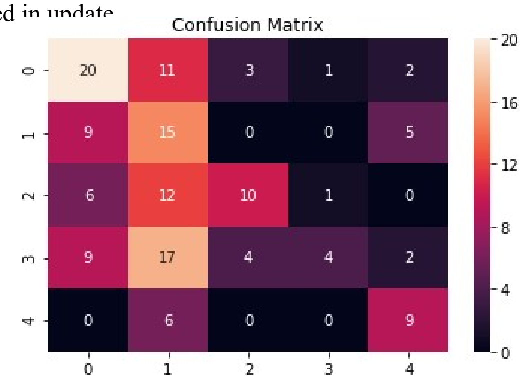
*D. CLASSIFICATION*

PNN When one input characteristic has larger values than the other, the network is sensitive to these situations. Before to training, input data needs to be standardised. The range of the input features must match the standard deviation. For more details, see the description. The slower the forecast, the larger the training dataset. For tiny datasets, the algorithm is substantially more effective. The network employs lazy learning, thus it doesn't require iterative training. It only keeps the variables and uses them to generate predictions..

**Step 1:** We use the PNN algorithms for segmentation.

**Step 2:** The following variables are utilised in the PNN classification algorithm max depth: The default setting is 5. A tree's maximum depth must be specified. The scale is from 1 to.

The value of colsample bytree is set to 0.3. When building each tree, you must give the subsample ratio of columns. It ranges from 0 to 1. Rate of learning: The default setting is 0.1. To avoid overfitting, you must specify the step size shrinkage utilised in update




*E. PERFORMANCE ANALYSIS*

The performance of this proposed approach is evaluatedusing some measures like,

**Accuracy:** The classifier's capability is expressed in terms of accuracy. It accurately predicts the class label, and the predictor's accuracy measures how effectively it can estimate the value of a predicted attribute for new data.

AC= (TP+TN)/ (TP+TN+FP+FN)

**Precision:** Precision is calculated by dividing the total number of true positives by the total number of true positives + false positives.

Precision=TP/ (TP+FP)

**Recall:** Recall is defined as the number of true positives divided by the number of true positives plus number of falsenegatives.

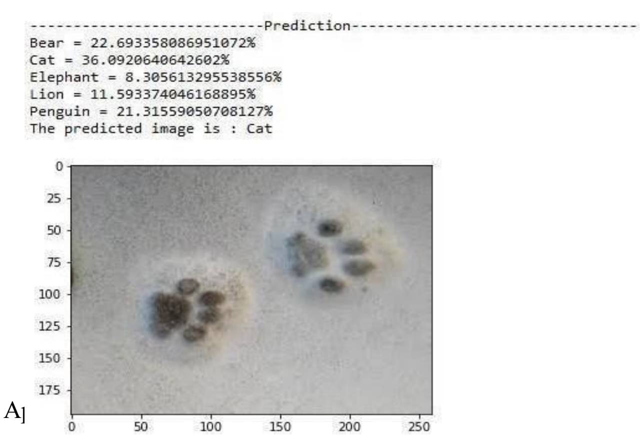


Fig.3 Test Dataset

This Fig.3shows the processed output of the testing datasetwith the process of Data Splitting.

Recall=TP/(TP+FN)

**F1-score:** Binary classification F1 score for the positive class, or the weighted average of the F1 scores for each class in the multiclass problem. Precision is undefinable when true positive plus false positive equals 0. Recall is undefinable when true positive plus false negative equals 0.

F1-score= 2*((precision*recall)/(precision+recall))

## IV.RESULTS

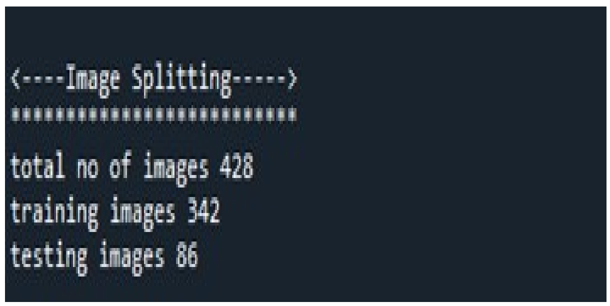



Fig.2TrainDataset

This Fig.2 shows the processed output of the training datasetwith the process of Data Splitting.

## V. CONCLUSION AND FUTURE WORK

The deep learning classifier in this approach is used to identify animal footprint photos in the dataset. The data on forest animals is used in the pre-processing procedure as input data. The photos are shrunk and arrayed in the pre-processing phase. The dataset is divided into a training dataset and a testing dataset in the feature selection technique that follows. All of the photos are then downsized and converted to an array. Lastly, the study of the forest creatures from photos is done using the classification method. The implementation of the PNN deep learning algorithm predicts the outcome based on accuracy, precision, recall, and f1-measure. To use alternative accuracy methods in the future to accomplish the improvement of accuracy for Animal Footprint utilising Probabilistic Neural Network Algorithm and obtain a better accuracy.

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