A Mini Project Report on

Wild Animal Detection in Public Places Using Footprints

A Dissertation submitted in partial fulfilment of the requirements for the award of the degree of B.Tech

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DECLARATION

We hereby declare that the Report entitled **"Wild Animal Detection in public places using footprints"** submitted for the award of Bachelor of technology Degree is our original work and the Report has not formed the basis for the award of anydegree, diploma, associate ship or fellowship of similar other titles. It has not been submitted to any other University or Institution for the award of any degree or diploma.

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CERTIFICATE

This is to certify that the Dissertation entitled **“Wild Animal Detection in public places using footprints”** that is being submitted by **Mr. P Phanindra Varshit** bearing the Hall ticket number **20EG105430**, **Mr. T Abhinav Reddy** bearing the Hall ticket number **20EG105444**, Mr. **P Sidhartha** bearing the Hall ticket number **20EG105436** in partial fulfillment for the award of B.Tech in **Computer Science Engineering** to the Anurag University is a record of bonafide work carried out by him under our guidance and supervision.

The result embodied in this Report have not been submitted to any other University or Institute for the award of any degree or diploma.

Signature of The Supervisor

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ABSTRACT

This project presents an innovative approach to identify animal species through their footprints, aiming to prevent unwarranted entry into human dwelling areas. The proposed methodology comprises a sequential process involving image processing, the Canny edge detection algorithm, Probabilistic Neural Network (PNN) classification, and a warning system.

In the initial phase, footprints collected near dwelling places undergo image processing to enhance their quality and extract relevant features. Subsequently, the Canny algorithm is employed to detect edges and highlight distinct patterns within the footprints. These processed footprints serve as inputs to the PNN, a robust classification technique capable of recognizing intricate patterns and making accurate species predictions.

The PNN is trained on an extensive dataset of known animal footprints, learning to associate specific features with distinct species. Upon encountering a new footprint, the PNN swiftly analyses its unique attributes and provides a species classification. This classification is then utilized to trigger a warning system, alerting inhabitants to the potential presence of a specific animal species near their dwelling.

This comprehensive approach offers a proactive strategy to prevent human-wildlife conflicts, allowing homeowners to take pre-emptive measures and avoid accidental encounters. By harnessing image processing, edge detection, machine learning, and real-time warnings, this study contributes to the development of a harmonious coexistence between humans and wildlife, promoting safety and preserving the sanctity of both habitats.

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1.INTRODUCTION

1 Introduction

Animals are one of the sentient and intellectual organisms of Mother Nature. They were considered as cardinal spiritual beings during the early civilization. They play a significant role in the healthy maintenance of the ecological balance. Every animal, both domesticated and wild, plays a crucial role in the food chain. Unfortunately, humans have pushed most of the animal species to the brink of extinction, although humans are directly dependent on animals. The cruel treatment of animals has started to backfire on humans. Strong evidence for the same is the ongoing global Coronavirus pandemic. The novel contagion is a karmic result of the way humans treated animals all the while. Now, humans have together hit the snooze button and is thinking of the ways to save the animals, at least from the live-animal market, where the novel Coronavirus is believed to be originated. Over the decades, animals have continuously faced threats in various forms. Some of the most prominent threats include habitat fragmentation or destruction, over-exploitation of natural resources, culling, climate change, pollution, and illegal activities such as poaching, smuggling, etc. According to the 2019 biodiversity report, around 1 million species belong to the endangered category, and several species are going extinct every day. Hence, animal monitoring is an indispensable task to protect them from going extinct.

1.1 Animal monitoring system

Animal monitoring is the process of continuous observation of the animals, their behaviour, and their habitat. Animals are monitored not only as part of conservation but also to avoid Human-Animal Conflict (HAC) or Animal-Vehicle Collision (AVC). Subsequently, animal monitoring moves onto the problem of animal detection. Detecting animals beforehand can save them from numerous attacks and accidents due to HAC and AVC. Few other leading problems that require animal detection are; unnoticed accidents in cattle stations, smuggling animals into the live-animal market, detecting endangered animal species, etc. In all these cases, an efficient animal detection system can help detect the animals and thereby save them. Conversely, animal detection is not always sufficient, as there are cases when animals have to be accurately classified. For instance, when an animal intrusion detection system in a village border incorrectly identifies a Black panther as a cat, the consequence will be life-threatening for both humans and the animal. The point here is that certain animal species have huge inter-class similarities as in the case of Black Panther and black color cat. These animals look almost similar and classifying them is a problem of Fine-Grained Classification (FGC). Concerning the abovesaid instance, fine-grained animal classification is as vital as an animal detection system.

Wildlife researchers developed various animal monitoring techniques like animal-mounted video monitoring system, very high-frequency radio-tracking, Global Positioning System (GPS) tracking, satellite tracking with radio collars (Venkataraman et al., 2005), pyroelectric sensors, Wireless Sensor Networks (WSN). However, these techniques were of little success, as they are mostly applicable only for a small geographic area. With the rapid technological advancement, the camera trap technology has matured and reached a point where they are readily available for the researchers. They have been successfully employed in several animal monitoring applications.

1.1.1 Animal monitoring

An effective animal monitoring system depends on various factors, as represented in Fig. 1.1. Animal monitoring systems require continuous observation of animals all through the day. Visible imaging cameras were initially used for this purpose. Over time, thermal cameras were used for their night vision capabilities. Both visible and thermal cameras are complementary to each other, and so they are used together in several monitoring devices. For surveying animal species, unmanned vehicles were employed. While Unmanned Aerial Vehicles (UAV) are used for surveying large areas from aerial; recently, Unmanned Ground Vehicles (UGV) are being used for monitoring animals over the terrestrial level. In general, animals are monitored using images, or videos. Earlier researchers focused on video-based animal detection; however, recently the shift has turned towards the images. Certainly, when compared to video-based animal monitoring, camera trap images are more challenging because of its background clutter, low illumination, low frame rates, occlusions, pose variations, scaling and more. Unlike humans or other objects, animals are too shy to be directly captured. Hence, capturing images of animals is itself a tedious task, given the nature of animals. Various technologies for capturing animals include motion or infrared based camera traps, UAV, and UGV to name a few. Among all, camera traps are predominantly used for data collection.

However, for monitoring larger area, either UAV or UGV can be employed. Image modality is yet another important factor in animal monitoring. Different scenarios require different type of images like visible/colour, thermal/infrared, and fusion of both visible and thermal images. Both visible and thermal images find uses in contradictory applications, where visible images are used during daytime and thermal images are used for night vision applications. On the other hand, fusion images are used when the information from both visible and thermal is insufficient. Animals are monitored from different areas, as well, based on their type of application. By and large, animals are monitored from ground/terrestrial, aerial/ remote sensing, satellite/ hyperspectral. Remote sensing or satellite imaging is usually used in case of monitoring or counting the endangered species over a larger area.

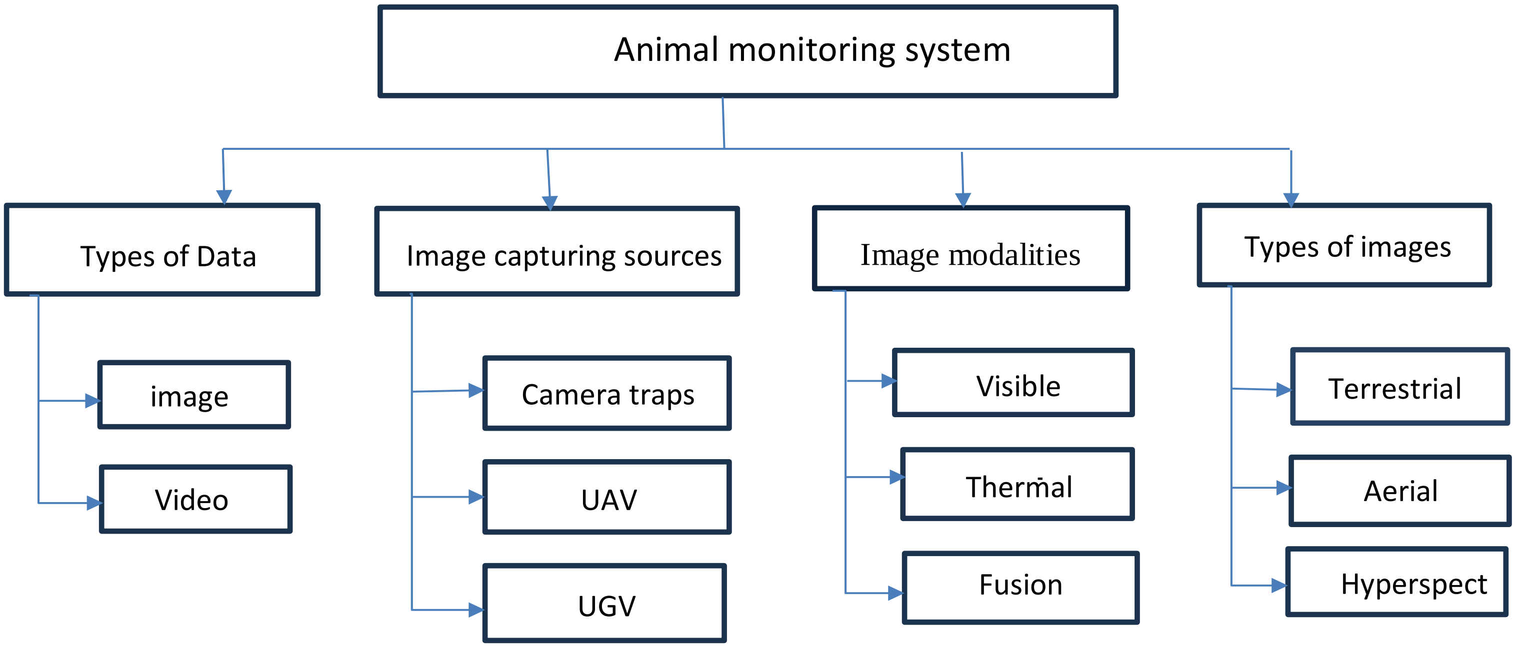

Fig 1.1 Animal Monitoring System

1.2 Animal detection system

Animal detection system detects the animals from images or videos and localizes them with bounding box. Animal detection has been approached through various techniques like animal motion, threshold segmentation, adaptive threshold segmentation, animal face detection , texture description, Content-Based Image Retrieval (CBIR), Light Detection and Ranging (LIDAR), etc. Both threshold segmentation and motion-based animal detection work well only on a static background, which is often not the case. On the other hand, the adaptive threshold segmentation incorrectly detects other moving objects like animals and produces a large number of false detections. Detecting animals through face recognition is an inefficient technique, as animals do not see the camera and pose for recognition. The texture descriptors method matches the texture of the detected animal with the pre-defined database and detects the animal. However, this technique works best only when there is a single type of animal, and the background clutter is minimal. The content-based retrieval algorithm suffers from poor querying performance when the database is huge. With the introduction of Convolutional Neural Network (CNN), the focus shifted from conventional image processing techniques to state-of-the-art machine learning models. Besides, with transfer learning, the animal detection systems started achieving higher performance even with minimal datasets. For a real-time application like animal detection, the choice of feature learning is important. One common drawback with most of the CNN based models is that they were trained using a supervised learning technique, which is not appropriate for real-time applications, as they cannot adapt unlabelled classes. At the same time, unsupervised learning techniques also cannot be relied on realtime applications since it is difficult to validate the results. Unsupervised learning models are very few in literature; besides, the accuracy of such models is below par. To bridge the gap between these two techniques, semi-supervised learning techniques were introduced.

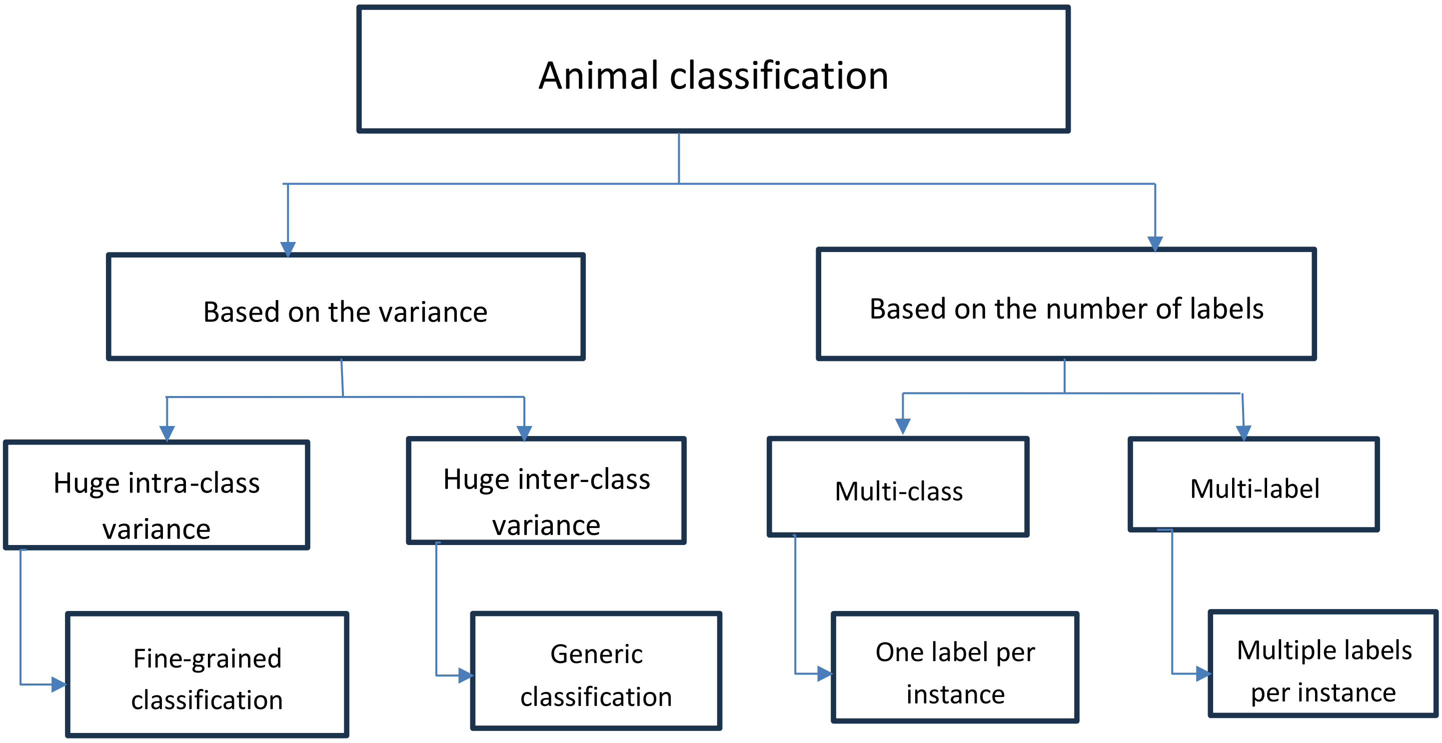

Fig. 1.2 Categorization of animal classification system

1.3 Animal classification system

In comparison to animal detection, animal classification systems are complex due to the huge inter-class similarity, intra-class variance and the large number of animal instances in each image. Animal classification models are further categorized into two. The primary factor that influences the complexity of the classification models is the similarity among the various classes. The similarity is expressed via inter-class and intra-class. Intra-class represents the similarity within the class. Higher the similarity, easier it becomes to classify. Inter-class represents the similarity between two different classes. When more than two classes are similar, then the classification becomes difficult. When the dataset has classes with huge intra-class variance, we say it as an FGC; else it is a generic classification. Classifying dog breeds is an instance of FGC. Classifying dog vs. cats is an instance of generic classification. Most of the existing works have focused on generic classification, and very few works have focused on FGC. In addition to the similarity factor, the number of labels also judges the complexity of the classification model. At large, we have two types of animal classification.

At large, we have two types of classification namely (i) multi-class and (ii) multi-label classifications. When the animals in the test image belong to only one class, then it is multiclass classification. In contrary, when the animal belongs to more than one class, then it is multi-label classification. Besides, there is yet another type of classification called multiclass – multi-label classification. The combination of multi-class with generic classification has a vast literature, however multi-label classification for animals is hardly studied.

1.4 Applications

Animal detection and classification systems are required in several real-time applications as discussed below:

1.4.1 Human animal conflict

HAC is the direct interaction between animals and humans. It often results in a negative impact on human or the animal or both. It is one of the major threats to the continued survival of animal species and has significantly impacted the lives of humans. HAC started when humans entered the wild animal's habitation and settled there for materialistic benefits. While HAC cannot be stopped completely unless humans change their behaviour towards humans, it shall be prohibited by rigorously monitoring the wild animals in and around their habitation for any possible entry to the adjacent villages or cities. Careful monitoring of wild animals cannot only help alleviate HAC but also save field and property damage due to animals, besides saving the animals from being killed out of retaliation.

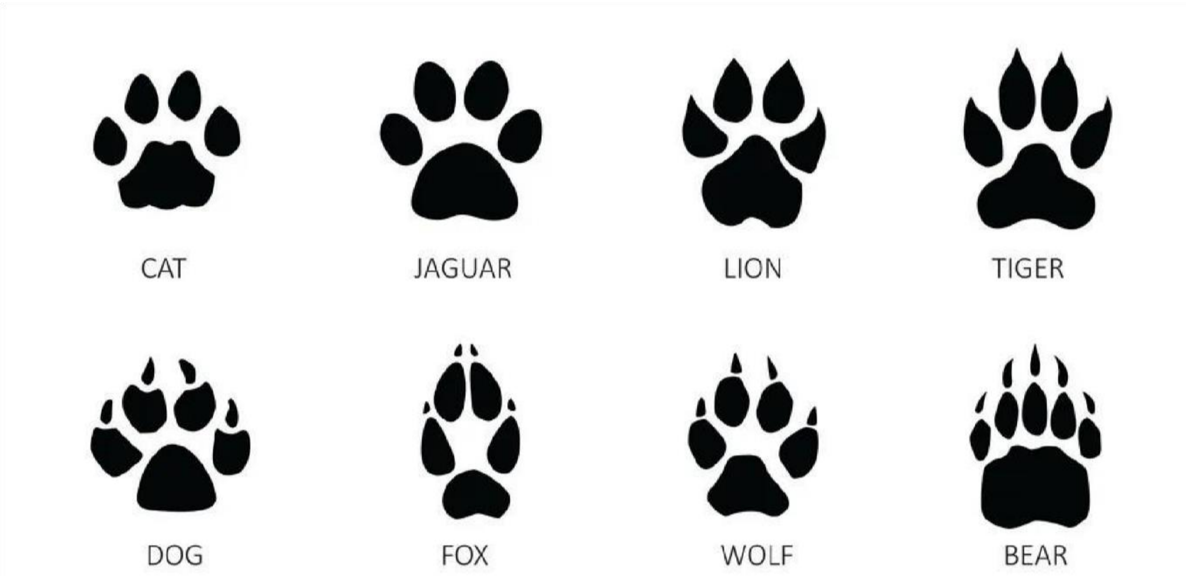

Fig. 1.3 Animals with huge inter-class similarity

Fig. 1.4 Monitoring animals with drones

1.4.2 Endangered animal species monitoring

Wildlife monitoring is the continuous observation of animals, their populations, habitation, and their interaction with the surrounding. With continuous observation, illegal activities such as poaching, and animal breakouts can be detected.

However, without a proper intervention mechanism, animal monitoring process is a mere waste of time and resources. A comprehensive animal monitoring system is a step towards the effective conservation of animals. Usually, wildlife is monitored using camera traps; however, they produce a large amount of data that must be manually analysed. With the latest advancements in technology, conservation drones are employed for monitoring animals (see Fig. 1.5). The drones are equipped with onboard analytics and can make informed decisions. Besides, with the advances in remote sensing, wild animals sprawling over a vast area can be easily and quickly captured using low-cost UAV. In Chapter 4, we present an aerial imaging-based animal detection and counting system for monitoring the animals.

1.5 Conclusion

This chapter concludes about how animal are monitored and also how animal detection system works. This chapter also includes animal classification system

2. LITERATURE SURVEY

2.1 Introduction

In this chapter we will discuss about Literature survey of the Dataset of the footprints of animal species and also about the Oxford dataset.

2.2 Literature survey

Hsu (2015) proposed an animal classification model using two CNN architectures, namely Google Net and LeNet, that achieved an accuracy of 90.5% and 91.1%, respectively. Later, **Yang et al.** (2012) proposed an unsupervised learning method for fine-grained recognition. The method learns shapes that commonly occur in all the images and consider them as templates. The template matching approach has achieved an accuracy of 38% on the SD dataset. This accuracy is further increased by **Kanan** (2014) by using Gnostic fields. With pattern identification units and image descriptors, the author developed a shape-size invariant model that can tackle animals with varying shapes and sizes. Further, the model is not affected by the bias in the dataset. The model has improved accuracy of 47%. Later, **Chen** et al. (2015) proposed Selective Pooling Vectors (SPV) for the FGC problem. SPV encodes the image descriptors into vectors and selects the best by setting a threshold value based on the quantization error. Further, the codebook is used as an approximation function for obtaining an approximate non-linear function f that determines the likelihood of classification for the various classes of dog breeds. SPV achieved an accuracy of 52% on the SD dataset. **Ra´duly** et al. (2018) proposed a multi-class dog breed classification model using NASNet-A and Inception-ResNet-v2. The architecture was developed by the Google team; however, the former is based on Neural Architecture Search (NAS). The model achieved an accuracy of 85.27% and 93.86% on both the architectures, proposed by Ahmed, A., **Yousif, H.,**

Kays, R. and **He, Z**, ‘Semantic region of interest and species classification in the deep neural network feature domain’, Ecological Informatics

Gavves et al. (2019) proposed a FGC model with alignments. The images are segmented and aligned in an unsupervised fashion and from which the features are extracted. However, this model requires ad-hoc modifications in the individual components, and the accuracy was 50.1%. **Chai** et al. (2013) proposed a fine-grained categorization model using symbiotic segmentation for segmenting the foreground from the background, since the background is uncorrelated and distracts the classification task. After segmenting, the model employs part localization through manual bounding box annotation to highlight the discriminative parts. This supervised approach achieved an accuracy of 45.6% on the SD dataset. An unsupervised part discovery model using Neural Activation Constellations (NAC) was proposed by **Simon** and **Rodner** (2015). The intuition is to use the activation maps of deep neural networks for exploiting the CNN channels. The activation maps of the neural network will act as a part detector and thus, a part model can be obtained without any supervised bounding box. The part model is then used to extract the discriminative parts of the animals through weakly-supervised classification. Besides, the NAC serves as a data augmentation technique. NAC achieved an accuracy of 68.61%.

Sermanet et al. (2019) proposed a novel fine-grained categorization model based on Recurrent Neural Networks (RNN). The model imposes an active visual network and pre-trains on a largescale dataset at the outset of RNN attention. Without any supervision, the model can easily identify the most discriminative region with high-resolution attentions. Besides, the model works equally well on low-resolution images like poor facial features and fur patterns. The proposed RNN achieved an accuracy of 76.8% in classifying the dog breeds. **Krause** et al. (2016) proposed a novel fine-grained recognition technique that uses noisy data to achieve decent performance and scalability. The model deliberately introduces two types of noise, namely the cross-domain noise (including images of a cat in a dog's class) and cross-category noise (mislabelling cat as a dog). For data collection, the authors employ active learning techniques with confidence-based sampling and Inceptionv3 network for classification. The model has achieved an accuracy of 80.8% on classifying Stanford dogs. **Liu** et al. (2016) proposed a fine-grained recognition model with a Fully Convolutional Attention Network (FCAN), a kind of reinforcement learning method to identify the local discriminative parts of the animals. FCAN has faster convergence with the greedy reward approach. On the SD dataset, the model achieved 88.9% accuracy.

Lin et al. (2020) proposed a bilinear CNN model for the fine-grained recognition task. The model is based on bilinear pooling that combines the pairwise local feature vectors. This model achieved 84.10% accuracy on the SD dataset. Later, **Dubey** et al. (2018) also proposed a pairwise confusion model for an FGC system. The model is trained on end-to-end CNN with a novel optimization technique. The model hosts intentional confusions in the activations of the neural network, to reduce the overfitting. Then the pairwise confusions are regularized to attain decent performance and achieved 83.75% accuracy. **Zheng** et al. (2017) proposed multi-attention-based CNN for fine-grained recognition model. The model identifies a discriminative or informative region with the class labels. Later, Sun et al. (2018) also proposed a multi-attention neural network with multiclass labels. So, this model was able to learn multiple informative regions through multiple channels. While **Zheng** et al. (2017) achieved 87.3% accuracy, Sun et al. (2018) achieved 85.2% accuracy. Sun et al. (2019) proposed a fine-grained recognition model with two key components, namely the diversification block and gradient boosting. These components force the network to identify the minute differences among classes having huge intra-class variance. The diversification block highlights the most salient features and forces the classification to use these features. On the other hand, the gradient boosting is a loss function that works on resolving the ambiguities among the classes. The co-operation between these two components helps the network in learning the most efficient features. With comprehensive experiments, the model achieved 87.7% accuracy on SD dataset.

Hu et al. (2019) proposed a weakly supervised data augmentation network for the FGC problem. The model uses attention maps to identify the most discriminative parts through weakly supervised learning. Through attention cropping and dropping, the images are augmented and trained. The model provides better performance as it extracts the discriminative features in the first stage, and the second stage, the accurate locations of the animals are found with attention maps. The model has achieved an accuracy of 80.8%. **Zhuang** et al. (2020) proposed an attentive pairwise interaction model for FGC. Unlike the models discussed so far, this model tries to learn the contrastive clues among the highly confusing classes, whereas other models focus on highly discriminative features.

This pairwise attentive model learns a pair of fine-grained images through continuous and repeated interaction. The model first identifies the semantic difference through mutual feature vector, which then generates gates for each of the images in the pair. This gate helps in spotting the contrastive clues through pairwise interaction. On the SD dataset, the model achieved 90.3% accuracy.

2.3 Oxford IIIT pet dataset

In this section, we discuss the benchmark OX and the various models that have used it. The OX dataset was released in an article titled "Cats and Dogs" by **Parkhi** et al. (2012). The dataset includes both dogs and cats breeds accounting to 37 classes. Each animal class had around 200 images approximately.

The baseline model for the OX dataset was proposed by **Parkhi** et al. (2012). The authors proposed a novel animal breed classification system using a deformable parts model for capturing the shape features of the animals. The shape features here refers to the face of the animals. Further, the authors used the Bag-of-Words (Bow) model with Scale-Invariant Feature Transform (SIFT) descriptors for capturing the appearance of the animals, which refers to the animals' fur. Before this, the animals were segmented from the image using the Grab-cut segmentation technique. Finally, two different classification approaches are proposed (i) Hierarchical model, where the animal is first classified either as dog or cat and then its breed is identified. (ii) Flat model, where the animal breed is directly identified. On the test data, the baseline model achieved an accuracy of 59%.

The OX dataset was used in CNN concepts like auto augmentation, fixing the resolution discrepancy in train and test data, bit transfer based visual representation learning, and performance improvement in CNN with assembled techniques. As part of a challenge, the above 4 CNN concepts were introduced and tested on OX dataset, in addition to a few other datasets. **Lee** et al. (2020) achieved an accuracy of 94.3% with Assemble-ResNet-FGVC-50. Xie et al. (2020) proposed a technique called Big Transfer for up scaling the task of transfer learning of large-scale datasets and achieved an accuracy of 96.62%. Touvron et al. (2019) proposed a technique for fixing the resolution discrepancy between the train and test data.

According to the authors, the model trained with high-resolution images faces difficulties when the test data is of a low quality than the train data. To tackle this problem, the authors proposed a technique named FixResNet that is based on the ResNet model. The model achieved an accuracy of 94.8%. Finally, Cubuk et al. (2019) also used this dataset to validate the proposed auto augmentation technique. It is a novel data augmentation technique, where the augmentations are chosen automatically based on the policies stored in the search space. The policies are updated for each mini-batch to yield better augmentation. The novel augmentation technique achieved 89% accuracy on the OX dataset.

2.4 Conclusion

This chapter concludes about Literature survey of the Dataset of the footprints of animal species and also about the Oxford dataset.

3. PROPOSED METHODS

3.1 Canny algorithm

The Canny edge detection algorithm is a widely used technique in image processing for detecting edges in digital images. It was developed by John F. Canny in 1986 and remains one of the most popular edge detection methods due to its effectiveness at accurately identifying edges while minimizing false detections and preserving edge continuity. steps involved in the Canny edge detection algorithm:

1. Noise Reduction

The first step is to reduce noise in the image using a Gaussian blur. This is done to ensure that the edges detected are not influenced by small fluctuations in pixel intensity.

The blurring operation is applied using a convolution operation with a Gaussian kernel.

2. Gradient Calculation

The gradient of the image is calculated to find the rate of change of intensity at each pixel. Typically, two filters (Sobel filters) are applied to the blurred image to calculate the gradients in the horizontal and vertical directions.

The gradient magnitude and direction are calculated as follows:

Gradient Magnitude: $\surd\,(Gx^2 + Gy^2)$

Gradient Direction: atan2(Gy, Gx), where Gx and Gy are the gradient components in the horizontal and vertical directions, respectively.

3. Non-Maximum Suppression

This step helps thin out the edges to get a single-pixel width edge.

For each pixel, compare its gradient magnitude with the two neighbours along the gradient direction.

Keep the pixel's value if it's the maximum among the three; otherwise, set it to zero.

4. Double Thresholding

Define two thresholds: a high threshold and a low threshold. Pixels with gradient magnitudes above the high threshold are considered strong edge pixels.

Pixels with gradient magnitudes between the low and high thresholds are considered weak edge pixels.

Pixels with gradient magnitudes below the low threshold are suppressed and considered non-edges.

5. Edge Tracking by Hysteresis

The goal here is to connect weak edge pixels to strong edge pixels.

Start from a strong edge pixel and follow the weak edges in its vicinity along the gradient direction If a weak edge pixel has a strong edge pixel as a neighbour, mark it as a strong edge pixel. Repeat this process iteratively. This helps extend and complete edges that were previously considered weak.

The result of the Canny edge detection algorithm is a binary image where edges are represented by white pixels and non-edges are represented by black pixels.

It's important to adjust the threshold values based on the specific image characteristics and application requirements. The Canny algorithm provides a reliable way to detect edges in images and has been widely used in computer vision, image processing, and various fields where edge information is crucial.

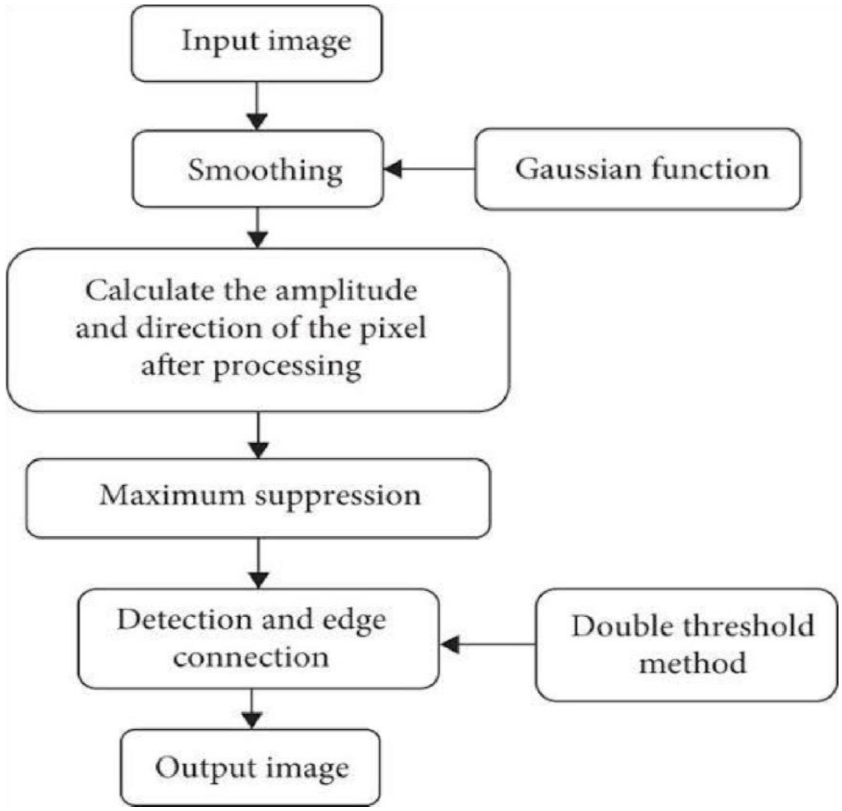

Fig 3.1 Canny algorithm

3.1.1 How Canny Algorithm Is Different

The identification of animals using their footprints through machine learning holds significant potential for the future. As technology advances and more data becomes available, this field could experience exciting developments and applications:

1. Improved Species Identification

More comprehensive and diverse datasets can lead to better-trained models capable of identifying a broader range of species accurately.

2. Real-time Tracking

Integration with real-time sensor data and AI can enable instant identification and tracking of animal movement patterns, aiding in wildlife conservation and research.

3. Rare and Endangered Species Monitoring

Machine learning models can help monitor and protect rare and endangered species by accurately identifying their footprints and habitats.

4. Behavioural Insights

By analysing footprints and movement patterns, machine learning can provide insights into animal behaviour, migration, and interactions with their environment.

5. Ecological Research

Footprint analysis can contribute to ecological research by offering non-intrusive data collection methods, helping scientists study ecosystems and biodiversity.

6. Automated Wildlife Surveys

Machine learning models could replace or supplement manual wildlife surveys, making data collection faster, more efficient, and less intrusive.

7. Human-Wildlife Conflict Mitigation

Predictive models can help communities anticipate animal behaviour and take preventive measures to minimize conflicts and damage to property.

8. Biosecurity Applications

Identifying invasive species through their footprints can aid in biosecurity efforts to protect native ecosystems.

3.2 Probabilistic Neural Network (PNN)

A Probabilistic Neural Network (PNN) is a type of feed-forward ANN in which the computation intensive backpropagation is not used It’s a classifier that can estimate the pdf of a given set of data. PNNs are a scalable alternative to traditional backpropagation neural networks in classification and pattern recognition applications. When used to solve problems on classification, the networks use probability theory to reduce the number of incorrect classifications.

The PNN aims to build an ANN using methods from probability theory like Bayesian classification & other estimators for pdf. The application of kernel functions for discriminant analysis and pattern recognition gave rise to the widespread use of PNN.

Concepts of PNN

An accepted norm for decision rules or strategies used to classify patterns is that they do so in a way that minimizes the "expected risk." Such strategies are called "Bayes strategies" and can be applied to problems containing any number of categories/classes. In the PNN method, a Parzen window and a non-parametric function approximate each class's parent probability distribution function (PDF). The Bayes' rule is then applied to assign the class with the highest posterior probability to new input data. The PDF of each class is used to estimate the class probability of fresh input data. This approach reduces the likelihood of misclassification. This Kernel density estimation (KDE) is analogous to histograms, where we calculate the sum of a gaussian bell computed around every data point. A KDE is a sum of different parametric distributions produced by each observation point given some parameters. We are just calculating the probability of data having a specific value denoted by the x-axis of the KDE plot. Also, the overall area under the KDE plot sums up to 1. By replacing the sigmoid activation function, often used in neural networks, with an exponential function, a probabilistic neural network (PNN) that can compute nonlinear decision boundaries that approach the Bayes optimal is formed.

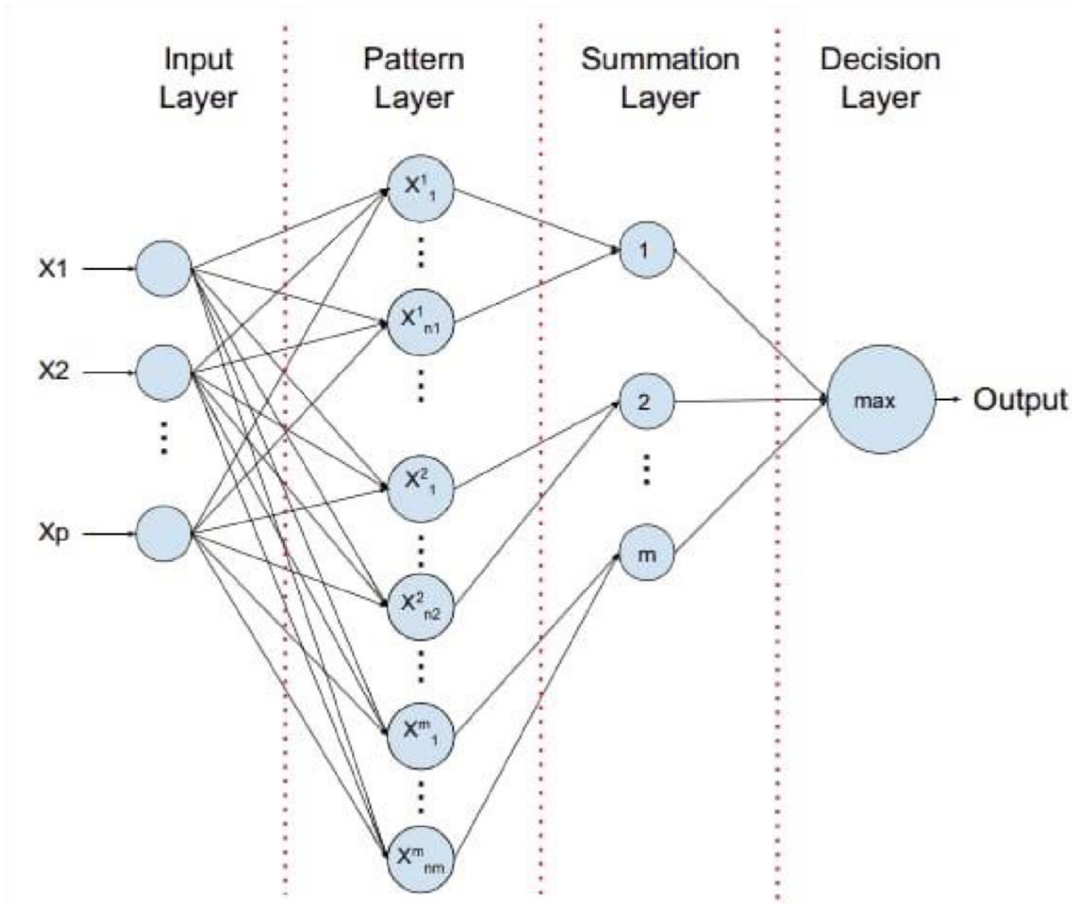

Fig 3.2 PNN architecture

Understanding Kernel Density Estimation

Kernel density estimation (KDE) is analogous to histograms, where we calculate the sum of a gaussian bell computed around every data point. A KDE is a sum of different parametric distributions produced by each observation point given some parameters. We are just calculating the probability of data having a specific value denoted by the x-axis of the KDE plot. Also, the overall area under the KDE plot sums up to 1. Let us understand this using an example.

3.3 Conclusion

This chapter concludes about machine learning and its working. Machine learning algorithms and also the classification of it is also explained. Overview of applications of the machine learning and its approaches is also explained.

4. IMPLEMENTATION

4.1 Introduction

In this chapter we will cover the different types of modules and model used for identification of animal species from animal footprint.

4.2 Modules description

4.2.1 Data Collection:

Online database of animal tracking data hosted by the Max Planck Institute for Ornithology. It is designed to help animal tracking researchers to manage, share, protect, analyse, and archive their data. Move bank is an international project with over 11,000 users, including people from research and conservation groups around the world.

4.2.2 Data Pre-processing:

Pre-processing animal footprint images are converted into gray-scale. Gray-scale image is an image consists of binary contents in the form of 0 and 1 pixels of the initial rgb image.

Gray-scale image consists of image pixel is a single sample representing only small amount of light, it carries only intensity information between (0 to 1). The converted grayscale for further processing, it should be further reduced in information which includes edge detection.

4.2.3 Feature Extraction Module:

Here we choose Gabor filters for the purpose of feature extraction. Gabor filters effectively preserves the texture characteristics of an image pattern in frequency domain. By applying the selective scale and orientation Gabor filter on an image where, the texture analysis is accomplished. Initially the images are segmented before extracting desired feature.

4.2.4 Classification Module

Classification after processing and feature extraction we have to determine the animal class by comparing the input image with trained data, trained data consists of 80 percent samples, probabilistic neural network is used for footprint classification.

4.2.5 Saving the Trained Model

Once you're confident enough to take your trained and tested model into production-ready environment, the first step is to save it into a .h5 using model.save() and to load the function named load_model("modelname.h5").

4.3 Conclusion

This chapter concludes about implementation of the project and also its modules. What the modules do and what work is done in these modules.

5. EXPERIMENT AND RESULTS

5.1 Introduction

In this chapter it includes the steps of operations and also discuss about the results of animal footprints which are gone through several processing and algorithm steps with a message and warning if humans have any risk.

5.2 Steps of operation

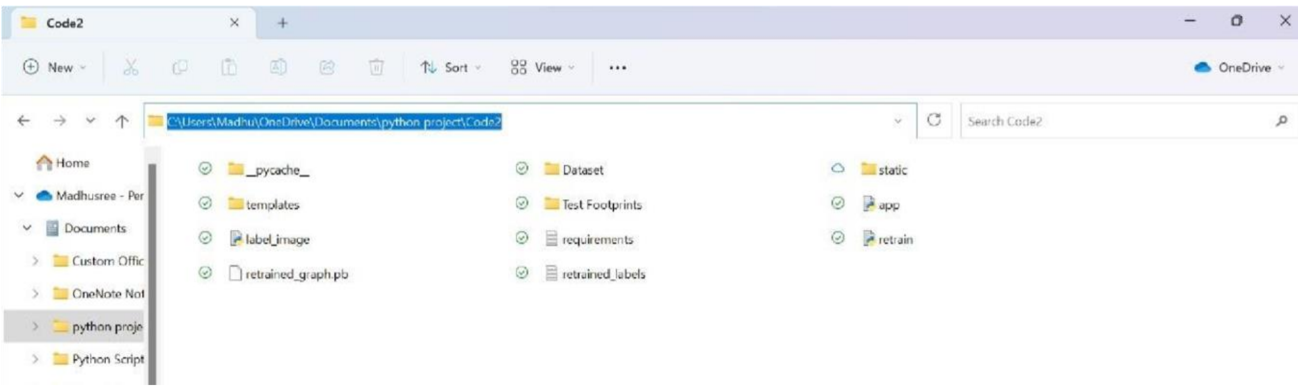

Fig 5.1 Path of the code

First the path of the code should be copied and then it should be pasted in.

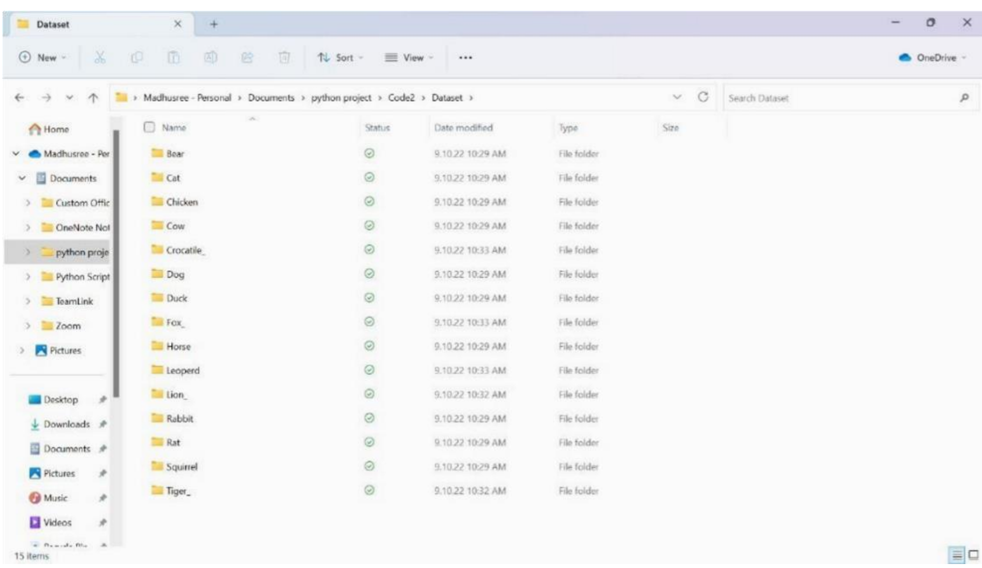

Fig 5.2 Dataset

The above window shows the data set of the animal footprints and this is the file from where the footprint is selected.

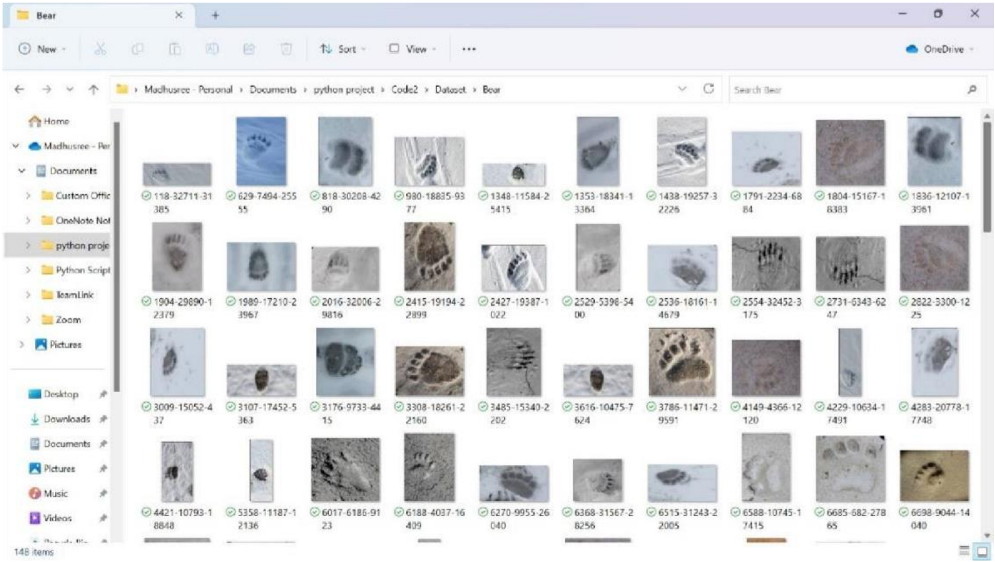

Fig 5.3 Animal Dataset

As shown in the above figure, the footprints are stored under their species names.

```
58/58 [==============================] - 70s 1s/step - loss: 0.5810 - accuracy: 0.8039 - val_loss: 1.6597 - val_accuracy
Epoch 90/100
58/58 [==============================] - 70s 1s/step - loss: 0.5561 - accuracy: 0.8192 - val_loss: 1.4665 - val_accuracy
Epoch 91/100
58/58 [==============================] - 72s 1s/step - loss: 0.5533 - accuracy: 0.8001 - val_loss: 1.5998 - val_accuracy
Epoch 92/100
58/58 [==============================] - 78s 1s/step - loss: 0.5075 - accuracy: 0.8296 - val_loss: 1.1143 - val_accuracy
Epoch 93/100
58/58 [==============================] - 71s 1s/step - loss: 0.5955 - accuracy: 0.8143 - val_loss: 1.0142 - val_accuracy
Epoch 94/100
58/58 [==============================] - 69s 1s/step - loss: 0.4863 - accuracy: 0.8454 - val_loss: 0.6857 - val_accuracy
Epoch 95/100
58/58 [==============================] - 70s 1s/step - loss: 0.4432 - accuracy: 0.8509 - val_loss: 2.1231 - val_accuracy
Epoch 96/100
58/58 [==============================] - 69s 1s/step - loss: 0.4516 - accuracy: 0.8449 - val_loss: 2.4016 - val_accuracy
Epoch 97/100
58/58 [==============================] - 71s 1s/step - loss: 0.4553 - accuracy: 0.8433 - val_loss: 1.5971 - val_accuracy
Epoch 98/100
58/58 [==============================] - 69s 1s/step - loss: 0.4666 - accuracy: 0.8362 - val_loss: 2.1058 - val_accuracy
Epoch 99/100
58/58 [==============================] - 71s 1s/step - loss: 0.4288 - accuracy: 0.8493 - val_loss: 3.8854 - val_accuracy
Epoch 100/100
58/58 [==============================] - 69s 1s/step - loss: 0.4252 - accuracy: 0.8558 - val_loss: 2.9260 - val_accuracy
Found 1831 images belonging to 14 classes.
```

Fig 5.4 Training Model Accuracy

5.3 Result

Experiment 1: -

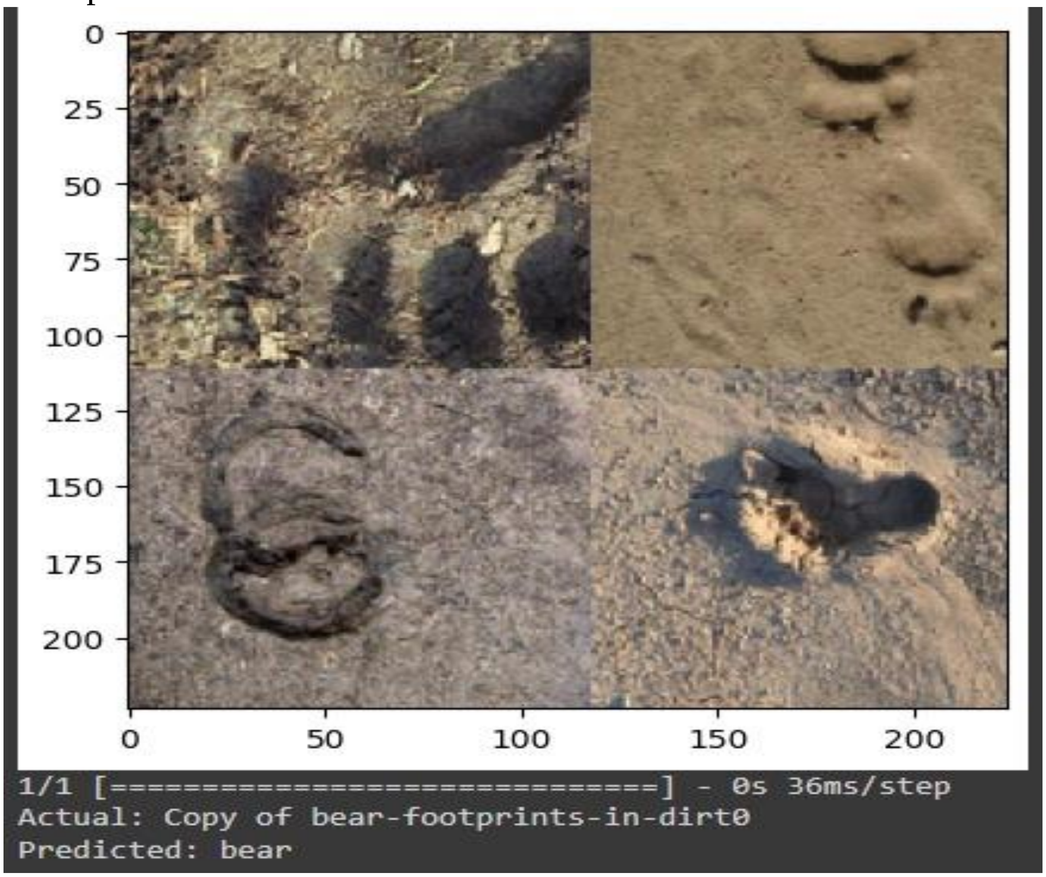

Fig: 5.5 Bear Footprint

Experiment 2:-

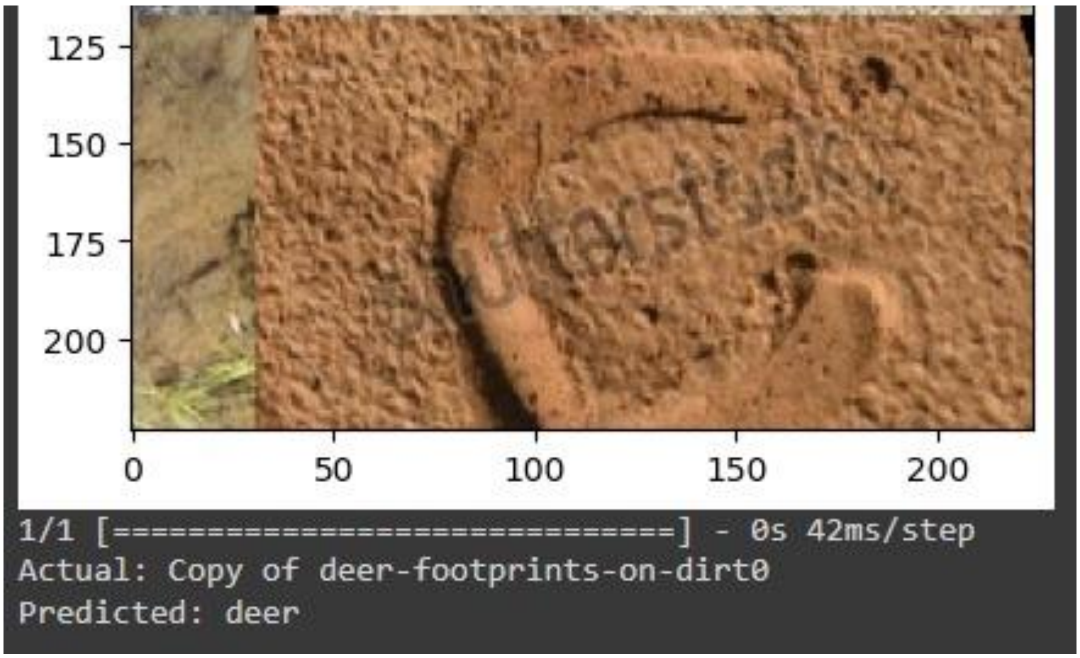

Fig: 5.6 Deer footprint

5.4 Parameters with Formulas

Pattern Layer: -

$$\phi_i = \frac{1}{(2\pi)^{d/2}\sigma^d} e - (x - x_i)^T (x - x_i)$$

Summation Layer: -

$$v_i = \frac{\sum_{j=1}^{M} \phi_{ij}}{M}$$

5.5 Conclusion

In this chapter we have seen the steps of operation and also the results of the footprints and also the message which is along the identification of the footprint.

6. DISCUSSION OF RESULTS

6.1 Memory efficiency

PNNs (Product Neural Networks) are a type of neural network that is more memory efficient than CNNs (Convolutional Neural Networks) for certain tasks. PNNs work by learning a product of input features, rather than a convolution of input features. This makes PNNs more efficient in terms of memory usage, as well as computational complexity.

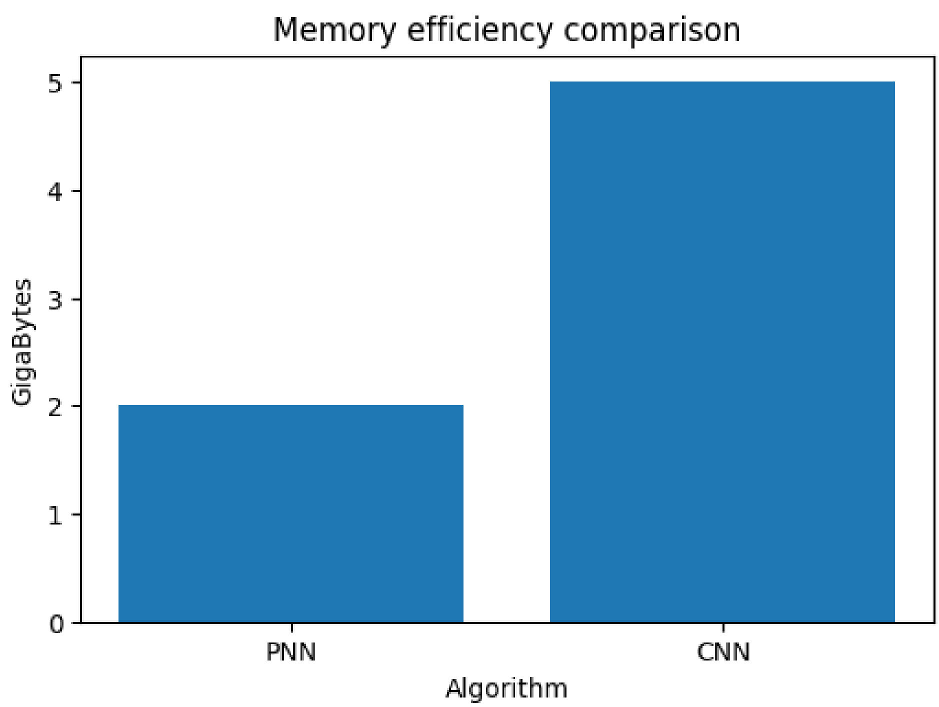

Fig: 6.1 Memory Efficiency Comparision

As we can see that PNN is more efficient than CNN. PNN only uses 2Gb of data for the storage of dataset while CNN uses 5Gb of data for the same dataset.

6.2 Training Speed

PNNs are faster to train than CNNs because they require fewer parameters. PNNs also use a simpler mathematical operation (product) to learn feature representations, which is faster than the convolution operation used by CNNs.

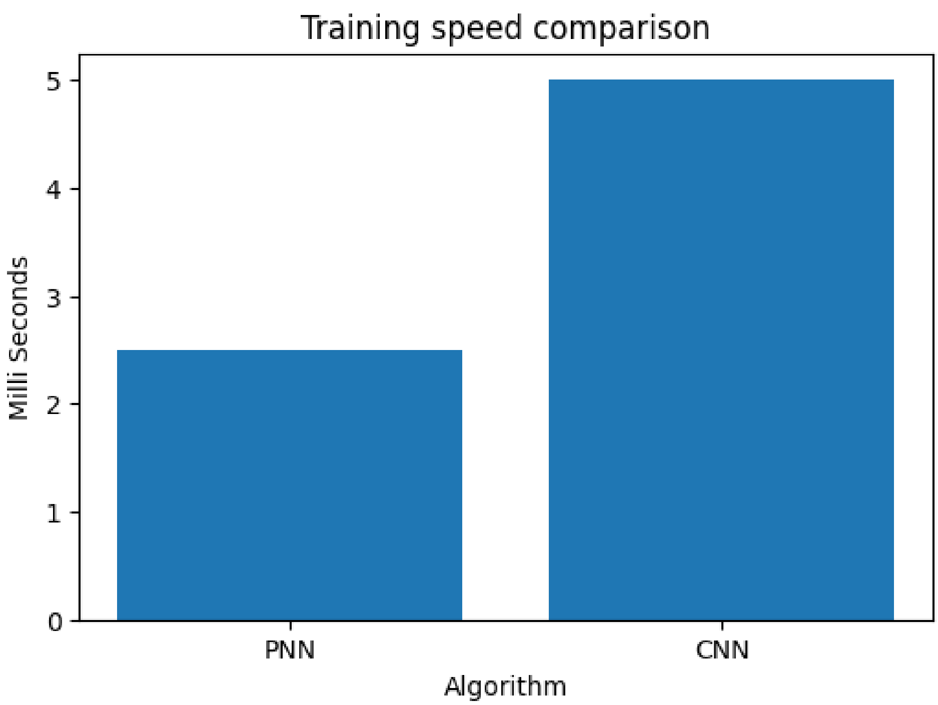

Fig: 6.2 Training Speed Comparision

Here the PNN model takes just around 2.5 milli seconds to train the dataset whereas CNN is taking 5 milli seconds to train the same dataset.

6.3 Loss

Loss is a metric where it determines the false positive values of the model. So, we need to ensure that the false positive values are less and need to decrease the loss. Which in turn specifies that the lesser the loss, better the model.

6.4 Accuracy

Accuracy is a metric that measures the proportion of correct predictions made by the model. It is a more intuitive measure of model performance, representing the percentage of correctly classified or predicted instances. In classification tasks, accuracy is often expressed as a percentage.

6.5 Loss and Accuracy

The loss function and accuracy are not always directly related, but they tend to move in opposite directions during model training. As the model learns and improves its predictions, it tends to reduce the loss. This is because when the model makes better predictions, the difference between the predicted values and the true target values becomes smaller, resulting in a lower loss. The point at which loss and accuracy "meet" or intersect is typically known as a decision boundary.

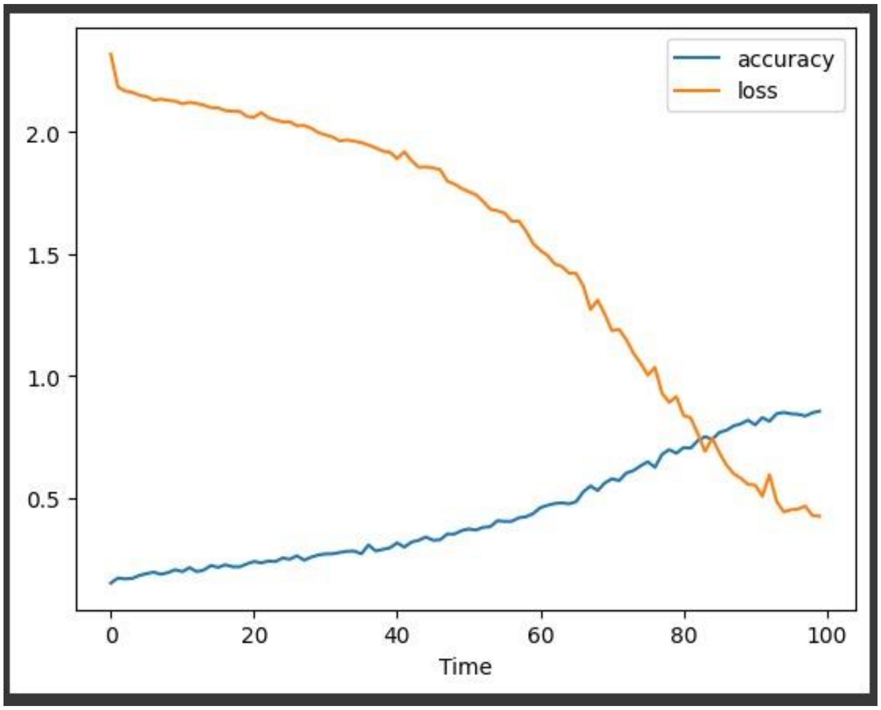

Fig: 6.3 Loss and Accuracy

6.5.1 Decision Boundary

The decision boundary is a critical concept in classification tasks. It's the boundary or threshold that separates data points belonging to different classes. For binary classification (e.g., distinguishing between two classes, such as "cat" and "dog"), the decision boundary could be a line or curve in the feature space that separates the two classes.

7. Summary, Conclusions and Recommendation

7.1 Advantages

1. Ecological Balance: Identifying animal species from footprints helps maintain ecological balance by preventing unnecessary human interference in natural habitats.
2. Conservation: Avoiding dwelling into human places reduces disturbances to wildlife, aiding in the conservation of vulnerable species.
3. Human-Wildlife Conflict: Identification of animal footprints enables humans to steer clear of areas prone to human-wildlife conflicts, reducing potential danger.
4. Research Integrity: Accurate identification of animal species helps maintain the integrity of research studies and wildlife monitoring efforts.
5. Tourism and Recreation: Avoiding animal habitats enhances the quality of ecotourism experiences and recreational activities, as visitors can appreciate animals in their natural settings.
6. Epidemiological Safety: Staying away from animal habitats reduces the risk of zoonotic disease transmission, benefiting both humans and animals.
7. Ethical Consideration: Respecting animal habitats showcases ethical considerations for the welfare and existence of other creatures on our planet.

7.2 Recommendation

1. Wildlife Monitoring: Tracking animal populations in specific areas without disturbing their habitats.
2. Ecological Studies: Studying animal behaviour, migration patterns, and interactions within natural ecosystems.

3. Conservation Efforts: Assessing the presence of endangered or threatened species to develop targeted conservation strategies.
4. Biodiversity Research: Understanding the diversity of animal species in a particular region without intruding on human settlements.
5. Habitat Assessment: Evaluating the health and suitability of ecosystems by observing the diversity of animal footprints.
6. Anti-Poaching: Identifying footprints in remote areas to detect illegal hunting activities and protect wildlife.
7. Scientific Research: Gathering data on animal distributions for scientific publications and wildlife management.
8. Natural Resource Management: Assessing the impact of animals on vegetation and landscapes for sustainable land use.
9. Education and Outreach: Engaging the public through educational programs about wildlife tracking and footprints.

7.3 Conclusion

The project has successfully developed a new system for detecting the presence of wild animals using footprints in real time. The system uses a probabilistic neural network (PNN) to learn the features of wild animal footprints and classify new footprints as belonging to a particular animal class. The system has been evaluated on a dataset of real-world wild animal footprints and has been shown to achieve high accuracy.

The system has the potential to be used in a variety of applications, such as protecting livestock from predators, preventing human wildlife conflicts and monitoring wildlife populations. The system can be deployed in a variety of environments such as forest, parks and farms.

Overall, the project has made significant progress towards developing a practical and effective system for detecting the presence of wild animals using footprints in real time. The system has a potential to be a valuable tool for protecting livestock, preventing human wireless conflicts and monitoring wildlife populations.

REFERENCES

[1] L. Lin, J. Jiakai, S. Guangwen, L. Weiwei, Y. Hongjie1, and L. Wenjuan, ``Hotspot prediction of public property crime based on spatial differentiation of crime and built environment," J. GeoInf. Sci., vol. 21, no. 11, pp. 16551668, 2019.

[2] X. Hong, R. Lin, C. Yang, N. Zeng, C. Cai, J. Gou, and J. Yang, ``Predicting Alzheimer's disease using LSTM," IEEE Access, vol. 7, pp. 8089380901, 2019.

[3] L. Mou, P. Zhao, and Y. Chen, ``Short-term traffic ow prediction: A long short-term memory model enhanced by temporal information," in Proc. 19th COTA Int. Conf. Transp. Prof. CICTP Transp. China-Connect.World, 2019, pp. 24112422.

[4] G. R. Nitta, B. Y. Rao, T. Sravani, N. Ramakrishiah, and M. BalaAnand, ``LASSO-based feature selection and Naïve Bayes classier for crime prediction and its type," Serv. Oriented Comput. Appl., vol. 13, no. 3, pp. 187197, 2019.

[5] L. Lin,W. J. Liu, andW.W. Liao, ``Comparison of random forest algorithm and space-time kernel density mapping for crime hotspot prediction," Prog. Georg., vol. 37, no. 6, pp. 761771, 2018.

[6] Y. Yang, J. Dong, X. Sun, E. Lima, Q. Mu, and Wang, ``A CFCC-LSTM model for sea surface temperature prediction," IEEE Geosci. Remote Sens. Lett., vol. 15, no. 2, pp. 207211, Feb. 2018.

[7] S. Favarin, ``This must be the place (to commit a crime). Testing the law of crime concentration in Milan, Italy," Eur. J. Criminol., vol. 15, no. 6, pp. 702729, Nov. 2018.

[8] A. Almehmadi, Z. Joudaki, and R. Jalali, ``Language usage on Twitter predicts crime rates,'' in Proc. 10th Int. Conf. Secur. Inf. Netw. (SIN), 2017, pp. 307310.

[9] W. H. Li, L.Wen, and Y. B. Chen, ``Application of improved GA-BP neural network model in property crime prediction,'' Geomatics Inf. Sci. Wuhan Univ., vol. 42, no. 8, pp. 11101116, 2017.

[10] X. Zhao and J. Tang, ``Modeling temporal-spatial correlations for crime prediction,'' in Proc. Int. Conf. Inf. Knowl. Manag. Proc., vol. F1318, 2017, pp. 497506.

[11] H. Tyralis and G. Papacharalampous, ``Variable selection in time series forecasting using random forests,'' Algorithms, vol. 10, no. 4, p. 114, Oct. 2017.

[12] L. Lin,W. J. Liu, andW.W. Liao, ``Comparison of random forest algorithm and space-time kernel density mapping for crime hotspot prediction,'' Prog. Geogr., vol. 37, no. 6, pp. 761771, 2018.

[13] C. L. X. Liu, S. H. Zhou, and C. Jiang, ``Spatial heterogeneity of microspatial factors' effects on street robberies: A case study of DP Peninsula,'' Geograph. Res., vol. 36, no. 12, pp. 24922504, 2017.

[14] M. I. Jordan and T. M. Mitchell, ``Machine learning: Trends, perspectives, and prospects,'' Science, vol. 349, no. 6245, pp. 255260, Jul. 2015.

[15] X. Zhao and J. Tang, ``Modeling temporal-spatial correlations for crime prediction,'' in Proc. Int. Conf. Inf. Knowl. Manag. Proc., vol. F1318, 2017, pp. 497506.