PugNet: A CNN Architecture to predict the Gender and Age of Blackbuck using Pugmarks

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Abstract

The identification of age and gender of Blackbuck from their pugmarks is a challenging task due to the unavailability of the dataset. Here, we present a dataset, contains two classes (age and gender) that have been further divided into three categories. The initial approach is inspired by existing pretrained models to train the RGB images of the pugmarks of the Blackbuck that were part of our generated dataset using Transfer Learning for multilabel classification. In this paper, PugNet has been discussed to improve the accuracy and abilities of large pretrained architecture with an optimized and improved Deep CNN architecture. The PugNet solves the problem of data imbalance, which is a reason for the failure of the pretrained architectures. It takes binary masks generated from annotated images as inputs and produces results better than transfer learning. The use of binary masks helped in reducing environmental noise. The PugNet lays down a foundation for animal footprint identification problems and can be extended to various other species.

Index Terms

Blackbuck, Deep CNN, PugNet, Pugmarks, Age, Gender, Identification.

I. Introduction

Blackbuck is a member of the antelope family and is listed in schedule 1 of the Indian wildlife protection act 1972 [1]. Blackbuck needs to be monitored for its protection and identification. Monitoring and identification wild animals are very hard and are a major concern to conservators because of declining in their population [2]. Major threat to wild animals are poaching and loss of their habitat. Every animal limb morphology is different, Therefore pugmarks of each animal are also different from elephant to tiger, deer, zebra, etc. have different pugmarks [3].

The pugmarks of animals are considered an indirect way of identifying animals. Determination of age and sex can be accurately calculated from pugmarks of an animal [4]. Pugmarks is used from ancient times to track animals different studies have shown the use of pugmarks for identifying animals at individual and species level [5] [6]. A footprint identification tool was made by a group of scientists to identify the different species of animals [7]–[11]. To identify pugmarks marking of points on pugmarks to select features is the most accurate approach to date to identify animals from their pugmarks [12]. It is a well standard method and is used in different fields e.g. radiology, and other medical examinations [13].

Most of the pugmarks identification is dependent on the classic machine learning approaches which usually dominated by the properties of the available dataset and requires the manual marking of the pugmarks. It needs human expertise, limiting the scope of the area [8]. The proposed work use the deep CNN networks to identify the pugmarks.

Recently, the convolutional neural networks overcome the automatic image classification. In 2014, a group of researchers proposed a CNN algorithm for identification of wild animals from the camera trap images, they collect data of 20 different species found in North America and trained them. But the accuracy of their model was only 38% [14].

Another study was done to identify wild species from the camera traps. In this the deep convolutional neural network was trained on the 26 of 48 species from the Snapshot Serengeti (SSe) dataset and got accuracy of 98.1% in single specie identification from 5 similar species [15].

Other study based on Snapshot Serengeti data. In which they train the deep convolutional neural network model to automatically identify, counting and animal behavior from the 3.2 million Snapshot Serengeti dataset and achieved accuracy rate of 93.8% [16].

Pugmark's identification can also be considered as pattern recognition task. Similar work has been done in different fields e.g. extraction of plant leaf features using deep learning [17]. Also in medical fields e.g. identification of different disease patterns from CT scans and MRI's [18]. This study is on the Blackbuck identification from pugmarks, using deep learning classification. The problem can be understood as a classification task handling altogether two subclasses which is age and gender. The initial approach for the problem was inspired from the existing state of the art pretrained models to train the colored images that were the part of our dataset using Transfer Learning for multi label classification.

In this paper we have come up with a novel approach to challenge the accuracy and abilities of large pretrained architecture with a an optimized and improved Deep CNN architecture (PugNet) which takes binary masks generated from annotated images as inputs and produces results better than transfer learning approaches in age prediction and a better accuracy in case of gender predictions. Thus overall, the use binary masks helped us in reducing the environmental noise in each image and generate results which are better than the pretrained architectures. The proposed architecture also solves the problem of class imbalance which was observed to be the point of failure for the various pretrained architectures.

The following are the specific contributions of the proposed work.

- We propose puglayer to design PugNet architecture for extraction of minute details. It has been proved that puglayer is capable to extract side edges and are able to reduce wild noise.
- It has been proved that pugnet is a light weight architecture, which reduce computational complexity of training process.

The rest of the research paper is structured as follows: Section II gives data description, Section III describes the methodology used in the research work and presents the proposed architecture, Section IV shows the results of experiments and Section V discusses results, its applications and future scope.

Table I: Number of filters in each convolution layer of different PugLayers.

SN	PugLayer (Type)	Conv-1	Conv-2	Conv-3	Conv-4
1	PugLayer-A	32	64	64	128
2	PugLayer-B	256	128	512	128
3	PugLayer-C	256	128	256	128

II. The Proposed Methodology

A. Description of PugLayer

Three types of puglayer (PugLayer-A, PugLayer-B and PugLayer-C) have been used in the PugNet, as shown in Fig.1. Each puglayer contains four convolution (Conv-1, Conv-2, Conv-3 and Conv-4), three batch normalization and one max-pooling layer.

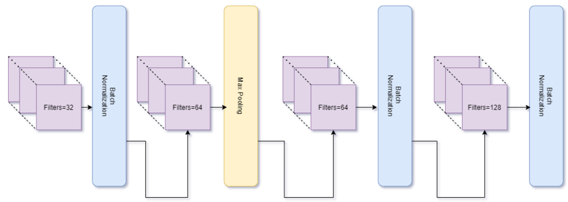
In each puglayer, the convolution layers have used different size of filter, as indicated in Table I. The number of filters in each PugLayer defines amount of local and global features to be extracted from Pugmark, as indicated in Table I. The PugLayer-A is used to extract minute details of the pugmark whereas PugLayer-B and PugLayer-C extracts global features of the pugmark.

Further, combination of convolution, batch-normalization and convolution in each PugLayer helped to understand the larger features of the images like the size differences and the internal attributes (such as the distance between hoofmarks). The combination of convolution, normalization, convolution and max-pooling helped to consider the corresponding smaller and finer features of the input images (such as the edges of the footprints, their shape, and concavity in the lower half of the pugmark). The use of batch-normalization also helped in avoiding exploding and vanishing gradient problem.

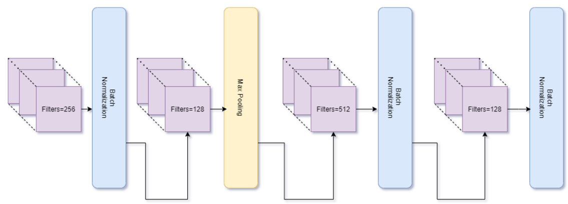
Next, each convolution layer in the pugNet used a filter of 3×3 to extract minute details. Table II represent the performance of the PugNet with varying size of the filters. It can be observed that the accuracy of the PugNet reduces with increased size of the filter. But the PugNet achieves high accuracy with filter of size 3×3. Thus, the proposed Puglayer has used a filter of size 3×3.

B. Introduction to PugNet

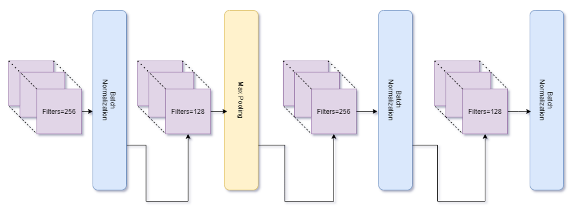
PugNet has been inspired by the concept of spatial exploitation models like LeNet and AlexNet and depth based CNNs such as ResNet and Inception. The motivation of the PugNet is to come



(a) PugLayer-A



(b) PugLayer-B



(c) PugLayer-C

Figure 1: The block diagram of the puglayer.

Table II: The performance of puglayer with varying filters.

SN	Filter Size	Accuracy
1	3×3	59.00%
2	5×5	17.63%
3	7×7	32.69%

up with a model, which could analyze the Blackbuck footprint boundaries and understand key features. They can be used to distinguish various age and gender. Hence, the PugNet is designed using PugLayers, which are capable to extract boundaries of the Pugmark.

The proposed PugNet composed of three PugLayers (PugLayer-A, PugLayer-B, and PugLayer-C) with input and output layers, as shown in Fig. 1. The PugNet begins with an input layer, which takes an input image of resolution 180×180. The input image is processed by three types of PugLayers, as shown in Fig. 1. The PugNet used ReLU as activation function to focus on non-linearity of the model.

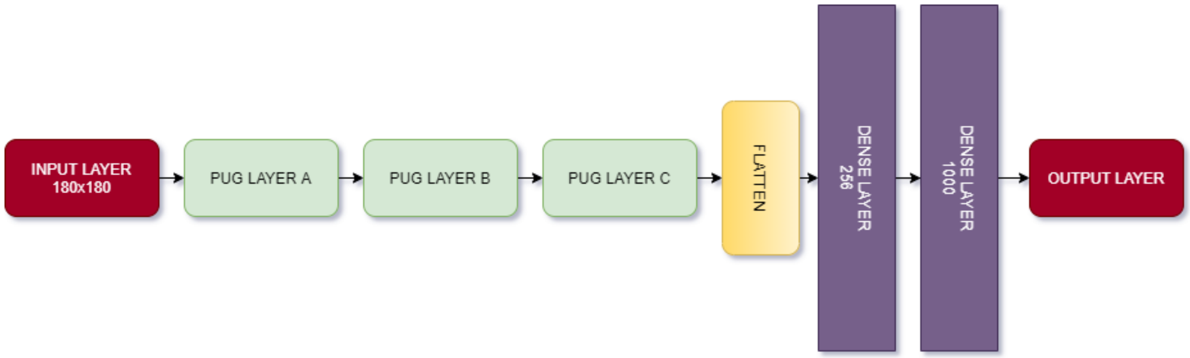


Figure 2: Detailed architecture of the PugNet.

Table III: The performance of the PugNet with varying number of Puglayers.

SN	Number of Layers	Accuracy
1	3	59%
2	4	47%
3	5	33%

The number of filters in each layer have been increased gradually, as mentioned in Table I. These varying size of filters helped in learning more levels of global features. Initially, smaller filters have been used to collect local information, then the larger filters extacted concavity of the Pugmark. Two fully connected dense layers (of 256 and 1000 neurons, respectively) have been used to provide accurate results. The use of two consecutive dense layers with decreasing number of neurons has proved to be effective. The use of the combination of three different types of PugLayers helped in the identification of boundary cases like the adult and young.

Next, Table III presents the performance of the PugNet with varying puglayers. It can be observed that performance of the PugNet is best with 3 puglayers and the performance reduces with increased number of puglayers. Hence, the proposed pugNet has used 3 puglayers to obtain the best results.

III. Description of the Experimental Data

The images of the Blackbuck's pugmarks are collected from Abohar wildlife sanctuary, Punjab and MC zoological park, Chhatbir, Punjab. The written permission was taken from the Chief wildlife warden, Punjab, Forest department Punjab. In Abohar wildlife sanctuary we selected 10 major areas from where the pugmarks of Blackbucks have been collected. In MC zoological park, the samples are collected from the deer safari. In the Table V, the sample collection location is mentioned with the number of male and female samples collected from the zoological parks. These images have been captured using a digital SLR camera with a multi functional adjustable scale to capture the color footprints images along with a tag slip. The images are captured in with a resolution of 6000×4000 pixels. All the images have been captured from same height at the angle of 90°. Total 10 to 15 images are clicked of every animal's pugmark, out of which the best ones are selected for annotation.

Further, the samples of male and female Blackbuck pugmarks images of different age group are collected from Abohar wildlife sanctuary, Punjab and Deer safari MC zoological park, Chhatbir, Punjab. Total 226 different Blackbuck pugmarks images have been collected from these two zoological areas out of which the 150 pugmarks images are of female and 76 of male. The maximum age of the Blackbuck is 15 years. These samples have been divided into six different classes; three for males and three for females. According to maximum age of the Blackbuck the classes are defined. The pugmarks images with age from 0-3 years are defined as young, from 3-6 years is defined as adult and from 6-9 years is defined as old (both for male and female pugmarks). The marked images are compared with original image of the pugmark to see any imperfections in the annotations. Next, the generated annotations are further processed to generate binary masks, which acts as the input for our proposed architecture.

A. Data Analysis

The generated binary masks are preprocessed using erosion and dilation. Six different state-of-the-art architectures (ResNet50, InceptionV3, InceptionResnetV2, VGG16, VGG19, NasNet) are implemented on pugmark images in TensorFlow via Keras.

Table IV: Summary of the proposed Blackbuck Pugmarks Dataset

SN	**Classes**	**Samples per class**	**Resolutions (pixels)**	**Types of Images**
1	Male Young	37	6000×4000	RGB
2	Male Adult	25		
3	Male Old	14		
4	Female Young	71		
5	Female Adult	69		
6	Female Old	10		

Male Young Male Adult Male Old

Figure 3: The pugmarks of three classes of male.

Female Young Female Adult Female Old

Figure 4: The pugmarks of three classes of female.

Table V: Showing the data collection locations in India.

SN	Area	Latitude	Longitude	Male	Female
1	Sukhchain	30°02’20.9”	74°20’41.3”	8	12
2	Dutaranwali	30°04’14.9”	74°17’13.6”	11	24
3	Rajanwali	30°04’12.7”	74°15’41.9”	9	18
4	Raipura	30°06’28.2”	74°17’32.7”	3	10
5	Sardarpura	30°04’23.9”	74°19’39.2”	5	12
6	Mehrana	30°02’29.0”	74°23’40.1”	3	8
7	Sitto Gunno	30°01’30.9”	74°21’52.1”	6	16
8	Narainpura	29°57’57.8”	74°20’36.3”	4	8
9	Rampura	29°57’45.9”	74°19’08.1”	7	14
10	Bazidpur Bhoma	29°57’19.3”	74°22’52.5”	8	14
11	Deer safari, MC zoological park	30°36’13.1”	76°47’32.4”	12	14
			Total (226)	76	150

IV. Result Analysis

The PugNet follows the principle of analysing the binary masks and predicting the corresponding label for the image. On the other hand, the transfer learning models applied to the BP dataset for predicting the gender and age of Blackbuck were ResNet50, InceptionV3, Inception-Residual

NetworkV2, NasNet, VGGNet16, and VGGNet19 which took resized coloured images as input for carrying out classifications. For the PugNet, binary masks had been resized to 180×180. All pretrained transfer learning models were trained on 35 epochs and PugNet was trained on 140 epochs.

For multilabel classification, the experimental results showed that with the increase in the size of images the model faced an increase in the variance towards the 'young' class of both females and males. The experimentation was carried out on size 150×150, 200×200, 224×224, 250×250, 256×256 however this gradual experimental increase failed to yield any significant improvement. Eventually, 180×180 came out as the best model with more diverse inferences as well as performing at the edge cases which were a big challenge in the case of the pretrained model as they failed to significantly distinguish between the samples for classes like Female Young and Adult as well as Female old and Male Adult. On carefully observing Table VII we can infer that all the pretrained models fail to predict the class 'old' for any gender i.e., having an F1 score of 0 whereas PugNet has an F1 score of 0.33 which solidifies the performance of our proposed architecture. The pretrained models like VGG16, VGG19, and NasNet showcased high variance for the 'female adult' class and failed to learn the global features like pugmark size and shape which were major points in confirming the gender and age of a Blackbuck.

From Table IV we can focus on the performance of PugNet which outperforms other architectures by a margin of 19-30% in terms of 'gender' accuracy which proves its reliability over the BP dataset and helps us in benchmarking our results. Further observing Table VII the PugNet shows better results than other models by achieving 65% accuracy in case of age classification thus proving its merit in understanding the concavity of the lower part of pugmarks, the distance between the two hoofs, and also the size of the footprint which are the major indicators in gender prediction for a human being.

The introduction of convolutional layer in fixed format and the combined use of set1 and set2 helped the model majorly as in the earlier stage of architectural design our model was also getting overfitted on the 'female adult and young' class because of the presence of more training samples of these particular labels. The introduction of PugNet not only improves the result manifold but also helped in handling class imbalance in the BP dataset which was the major achievement altogether. It is to be noted that the introduction of the 2 dense layers before the output layer brings about significant growth in the training accuracy. The dense layers helped in understanding higher levels of intrinsic features that belong to the respective pugmark. The introduction of binary masks by manually annotating the images brought about a reduction in the level of environmental noises and the region of interest could be identified easily. Since the data was affected by the natural lightings and varying ground terrain the use of binary masks played the pivotal role of identifying only the key point necessary for predictions and reduced any types of errors that could be detrimental in the determination of classification labels. Thus, the testing accuracy achieved by PugNet on the BP dataset fixates a baseline for the other architectures that could be used for predictions.

The change in the accuracy and loss of the different pretrained CNN network models with increasing iterations and time are shown in the Figures 5 to 11. It can be observed that the accuracy for the gender prediction is much higher in the VGG16 model than all other transfer learning architectures. The accuracy of all other models ResNet50, Inception-Residual Network, NasNet, InceptionV3, and VGGNet19 for gender prediction lies only in the range of 47-59% as shown in Table VI.

For the age prediction, the accuracy is fairly higher in the VGG19 and NasNet having an accuracy of 59% however on close observation we can easily infer that overfitting on the BP dataset resulted in such a comparable result with PugNet and this can be confirmed on comparing the F1 scores. Besides these two models other failed in making any significant predictions regarding age classification. Inception ResnetV2 and VGGNet16 came as the least performing architectures.

For Gender Prediction, the key focus should be on the F1 score of female class since all the architectures except PugNet failed to cross even 0.50 score which actually shows the lack of adaptability of these models and strengthens the final outcomes of our proposed architectures. The evident difference between male and female hoofmarks lies in the shape of the pugmark and thus the pretrained models fail to perform on these real-life samples by not being able to learn the smaller features as well the observable global features while predicting the outcomes. Thus the binary masks usage by the PugNet helped in eliminating many corner cases which might have been difficult for the other neural network architecture to identify and understand.

Table VI and VII which evaluates the capabilities of PugNet in identifying both age and gender of sample in cumulation and the results showcase an accuracy of 59% which is a major indicator of establishing PugNet as the strongest contender for handling BP dataset and related data. The performance of other models lacks robustness and precision. In Table IX it can be observed that no other model except PugNet and Inception Resnet V2 have an F1 score not equal to zero for male adult class with PugNet outperforming Inception Resnet V2 with a F1 score of 0.80. In case of female samples, it can be observed from Table IX those other architectures fail to generate comparable results with PugNet as the F1 score of all the classes i.e., female adult old and young is highest for our proposed model. Also, another significant observation made is that beside PugNet no other architecture was capable enough to handle and learn features from male samples which were actually lesser in number in comparison to female samples. In wildlife the issue of class imbalance is always a significant one and can't be eradicated thus PugNet rises to the occasion and forms a foundation for further development of a dedicated architecture and a dedicated methodology to handle Animal Footprint identification tasks using Deep Learning.

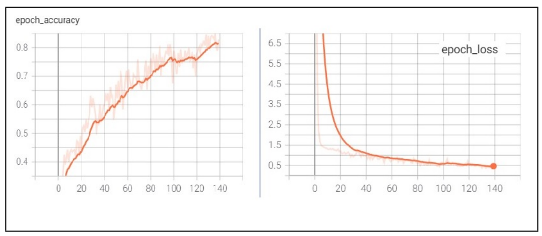


Figure 5: Accuracy and loss of PugNet during training

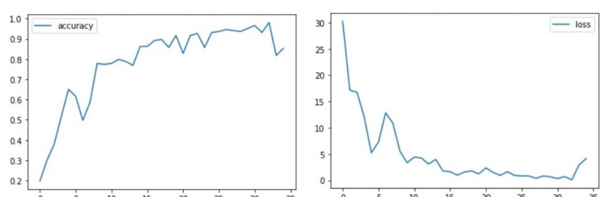


Figure 6: Accuracy and loss of InceptionResNetV2 during training

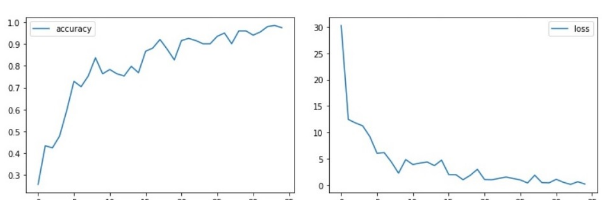


Figure 7: Accuracy and loss of InceptionV3 during training

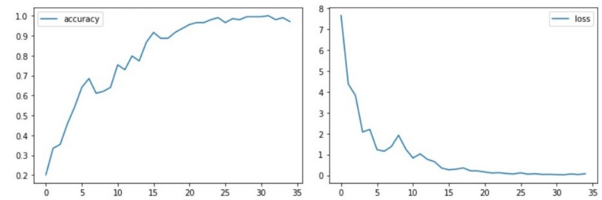


Figure 8: Accuracy and loss of NasNet during training

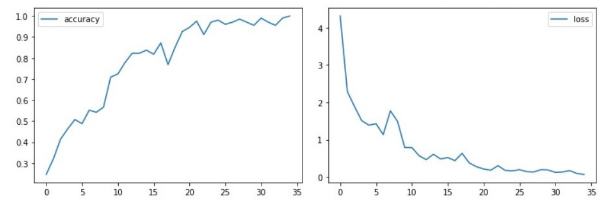


Figure 9: Accuracy and loss of ResNet during training

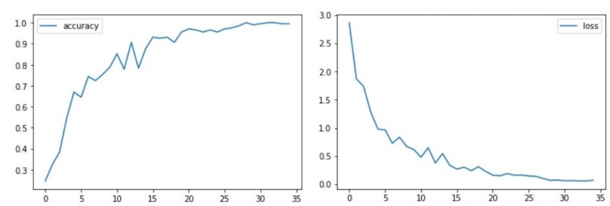


Figure 10: Accuracy and loss of VGG16 during training

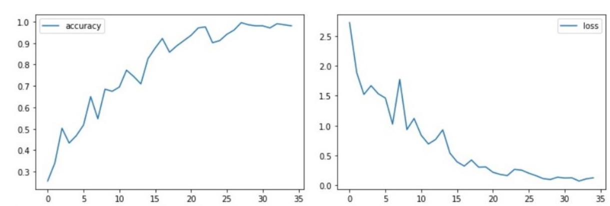


Figure 11: Accuracy and loss of VGG19 during training

V. Results and Discussion

Inspired from Tensor Flow deep learning structure via keras, a deep convolutional neural network architecture using 29 different layer following a specified scheme called Conv2d Set1 and Set2 as described above has been created in this research work to automatically identify the gender and age of the Blackbuck from their pugmarks. The research work was carried out on the binary masks of pugmark images of the Blackbuck and directly on pugmark images. The

Table VI: Precision, Recall, F1 Score and Accuracy of architectures in gender classification

SN	Architectures	P Male	P Female	R Male	R Female	F1 Male	F1 Female	Accuracy
1	PugNet	1.00	0.75	0.62	1.00	0.77	0.86	82%
2	VGG16	0.6	1	1	0.25	0.75	0.4	65%
3	VGG19	0.53	0	1	0	0.69	0	53%
4	InceptionV3	0.57	0.67	0.89	0.25	0.7	0.36	59%
5	ResNet50	0.53	0.5	0.89	0.12	0.67	0.2	53%
6	NasNet	0.58	0.6	0.78	0.38	0.67	0.46	59%
7	InceptionResNetV2	0.5	0.33	0.78	0.12	0.61	0.18	47%

Table VII: Precision, Recall, F1 Score and Accuracy of architectures in age classification

SN	Architectures	P. Young	P. Adult	P. Old	R. Young	R. Adult	R.Old	F1. Young	F1.Adult	F1. Old	Accuracy
1	PugNet	0.50	0.86	0.50	0.80	0.75	0.25	0.62	0.80	0.33	65%
2	VGG16	0.50	0.47	0.00	0.20	0.88	0.00	0.29	0.61	0.00	47%
3	VGG19	0.67	0.57	0.00	0.40	1.00	0.00	0.50	0.73	0.00	59%
4	InceptionV3	0.33	0.38	0.00	0.60	0.38	0.00	0.43	0.38	0.00	35%
5	ResNet50	0.67	0.50	0.00	0.40	0.88	0.00	0.50	0.64	0.00	53%
6	NasNet	0.50	0.64	0.00	0.60	0.88	0.00	0.55	0.74	0.00	59%
7	InceptionResNetV2	0.33	0.62	0.00	0.60	0.62	0.00	0.43	0.62	0.00	47%

Table VIII: Precision, Recall, F1 Score and Accuracy of architectures in Male gender and age classification

SN	Architectures	P. Young	P. Adult	P. Old	R. Young	R. Adult	R.Old	F1. Young	F1.Adult	F1. Old	Accuracy
1	PugNet	0.33	1.00	0.00	0.33	0.67	0.00	0.33	0.80	0.00	59%
2	VGG16	0.50	0.00	0.00	0.33	0.00	0.00	0.40	0.00	0.00	35%
3	VGG19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	35%
4	InceptionV3	0.33	0.00	0.00	0.33	0.00	0.00	0.33	0.00	0.00	29%
5	ResNet50	0.50	0.00	0.00	0.33	0.00	0.00	0.40	0.00	0.00	29%
6	NasNet	0.20	0.00	0.00	0.33	0.00	0.00	0.25	0.00	0.00	35%
7	InceptionResNetV2	0.00	0.33	0.00	0.00	0.33	0.00	0.00	0.33	0.00	12%

research work results for the gender prediction were 82% and 65.37% for the age prediction. There was very huge difference between the numbers of samples of different age groups of Blackbuck due to the inherent nature of the animal. Overall PugNet has very high accuracy for the gender prediction of the Blackbuck while for age prediction it was little low because of the less number of samples. The main issue encountered were in the edge case of adult and young category identification by the model for both male and female samples.

Table IX: Precision, Recall, F1 Score and Accuracy of architectures in Female gender and age classification

SN	Architectures	P. Young	P. Adult	P. Old	R. Young	R. Adult	R.Old	F1. Young	F1.Adult	F1. Old	Accuracy
1	PugNet	0.40	0.80	0.50	1.00	0.80	0.50	0.57	0.80	0.50	59%
2	VGG16	0.00	0.33	0.00	0.00	1.00	0.00	0.00	0.50	0.00	35%
3	VGG19	0.30	0.36	0.00	0.50	1.00	0.00	0.40	0.53	0.00	35%
4	InceptionV3	0.17	0.38	0.00	0.50	0.60	0.00	0.25	0.46	0.00	29%
5	ResNet50	0.00	0.29	0.00	0.00	0.80	0.00	0.00	0.42	0.00	29%
6	NasNet	0.00	0.45	0.00	0.00	1.00	0.00	0.00	0.62	0.00	35%
7	InceptionResNetV2	0.07	0.00	0.00	0.50	0.00	0.00	0.12	0.00	0.00	12%

Table X: Showing training accuracy and loss of models

SN	Architectures	Training Accuracy	Training Loss	Input size	Training time for per Epoch
1	PugNet	78.95%	0.5256	180×180×1	11.32 sec
2	VGG16	99.81%	0.0491	224×224×3	90.3 sec
3	VGG19	98.94%	0.1245	224×224×3	90.3 sec
4	InceptionV3	97.69%	0.2121	256×256×3	90.3sec
5	ResNet50	98.45%	0.1170	224×224×3	94.4 sec
6	NasNet	94.66%	0.0961	331×331×3	93.4 sec
7	InceptionResNetV2	80.57%	4.1757	299×299×3	89.25sec

In this work we also used 6 different state of the art architecture i.e. ResNet50, InceptionV3, InceptionResnetV2, VGG16, VGG19, directly on the pugmarks images of the Blackbuck. These popular architectures has been used evidently in different fields of science and thus helped us in benchmarking the results of PugNet. In pugmarks identification of Blackbuck the accuracy and F1 score of these architectures was lower than our model and therefore aided us in reaching to our inferences and deriving our final conclusions. The model was trained on Tesla P100 which had a RAM of 16 GB and the development environment used was Google Colab Pro.

To our knowledge, there is no study that has done identification of gender and age of Blackbuck. The major challenge with this type of research was in the case of data collection and data annotation. The Blackbuck is a very agile land animal and live on the grasslands. Collection of the pugmarks images of this type of animal was very hard task. There walk is so fast due to which the pugmarks distort from the sides and also it affects the depth of the impression. Blackbuck have only two toes in their foot called hoofs and the size of their foot is very small. The difference in the size of different age group Blackbuck pugmarks is also very minor due to small size of their foots which make it very hard to analyze and annotate the samples manually.

Most research on animal's pugmarks used manual features to identify the animals. In our work we used deep CNN for making the architecture innately understand the key feature points and predict the gender and age of the Blackbuck from their pugmarks. The limitation of our work is that the sample size of BP dataset was small. In future we will collect more samples to achieve better accuracy for age prediction. The PugNet could help in monitoring the Blackbuck population also the study can be laid down as a foundation for animal footprint identification problems and can be extended to various other species.

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