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A Deep Learning approach for Animal Breed Classification - Sheep

Prateek Dutta
B.Tech Artificial Intelligence, G.H. Raisoni College of Engineering, Maharashtra, India

Abstract: In the field of Husbandry, its little difficult to detect the breed of animals in order to estimate the commercial value production. Usually it can be classified with the help of DNA testing but its expensive and sometime not affordable. Lameness in sheep is one of the concerns which is to be taken care. It usually happens due to inadequate of healthcare and welfare among the country serving sheep industry. This paper aims to classify the sheep according to their respective breed. Basically 4 breeds have been taken into consideration and by applying neural networks, the sheep breed has been classified. Throughout the task the accuracy of 99.97% was achieved while training the CNN model & 87.1% was achieved while testing the model. With the help of this classifier, sheep farmer can identify the breed more accurately and efficiently.
Keyword: Deep Learning, Convolution Neural Network (CNN), Accuracy, Classification, Lameness

I. INTRODUCTION

For the purpose of milk, wool, meat, skins, manure & many more, even today sheep is an important part of society. Majority of the inhabited world and to many civilizations sheep husbandry been practised. Many British Isles, South American nations, Australia and New Zealand are associated with sheep production even in 21st century. In dry land farming system, sheep is considered to be important species.

The definition of animal genetic resources includes all activities associated with the identification, estimated value and quality of biodiversity and the natural environment and production systems that have been modified or altered. The Food and Agricultural Organization (FAO) estimates that industrial livestock activities are twice as fast as traditional farming systems and six times as many traditional food systems. Sheep seem to have received little attention in all areas of management, breeding healthy and healthy food even though they have more benefits than other livestock categories. Sheep's are often seen grazing during the day in many rural areas and animals from different households mingle together in unknown records. Livestock production is a major factor in agriculture and contributes significantly to meeting food needs, providing drought energy, compost to maintain soil fertility and composition and income, especially for farmers in the northern part of the country [1].

Considering the weaknesses of breed classification, studies related to sheep breed classification combine appearance and geometry information together to infer the class [2]. Although these works use geometry information [3], appearance features still play a major role in the final classification result. As we know, appearance differences between various sheep breeds are not easy to capture, Not only for computers, but even for human beings.

Object recognition is a comprehensive research topic located in the field of computer vision and image processing. A lot of potentially powerful applications that include automatic robotic navigation and deception, location understanding, etc. There were many proposed methods over the past few years. Recently, many works have been focused on the subordinate-level categorization. This problem involves categories of similar objects within the same class, such as different breeds of dogs or cats. In this paper, our work focuses on the classification of sheep.

Deep learning is a subset of machine learning that deals with algorithms that promote the structure and function of the brain called artificial neural networks. The Deep Learning Specialization is a series program that helps to understand the capabilities, challenges, and consequences of deep learning and prepare to participate in the development of leading-edge AI technology.

In this Specialization, will build neural network architectures such as Convolutional Neural Networks, Recurrent Neural Networks, LSTMs, Transformers, and make them better with strategies such as Dropout, BatchNorm, Xavier/He initialization, and more. Deep Learning tackles some real-world case studies such as autonomous driving, sign language reading, music generation, computer vision, speech recognition, and natural language processing.

AI is transforming many industries. The Deep Learning Specialization provides a pathway to gain the knowledge and skills to apply machine learning to our work, level up technical career, and take the definitive step in the world of AI.

With the help of Deep Learning we can achieve the following tasks: -

1) Build and train deep neural networks, implement vectorized neural networks, identify key parameters in architecture, and apply deep learning to your applications.
2) to train and develop test sets and analyze bias/variance for building DL applications, use standard neural network techniques, apply optimization algorithms, and implement a neural network in TensorFlow.
3) Diagnose and use strategies for reducing errors in ML systems, understand complex ML settings, and apply end-to-end learning, transfer learning, and multi-task learning.
4) Build a CNN, apply it to visual detection and recognition tasks, use neural style transfer to generate art, and apply these algorithms to image, video, and other 2D/3D data.
5) Build and train RNNs, GRUs, and LSTMs, apply RNNs to character-level language modelling, work with NLP and Word Embeddings, and use Hugging Face tokenizers and transformers to perform NER and Question Answering

Normalization is a commonly used method as part of data preparation. The normalization aims to convert numerical column values from the database to the same scale, without distorting the difference in the ranges of values. The technique which provides linear transformation on original range of data is called Min-Mix Normalization [4]. The technique which keeps relationship among original data is called Min-Mix Normalization. Min-Max normalization is a simple technique where the technique can specifically fit the data in a pre-defined boundary with a pre-defined boundary [5].

II. METHOD

This part of the study describes in detail the various methods used in data analysis. The analysis method considers the most discriminatory analysis method and the analysis of items as flexible selection options (e.g. data reduction tool). For curious minds, a model that helps to identify the type of sheep is helpful. From the last count to the observation of their movements, this helps to reduce the time and effort required of the task. Here, it has been tried to divide the facial images of sheep into four types of Marino, Poll Dorset, Suffolk, White Suffolk.

III. COMPARISON WORK

While there were other methods too to classify the breeds of animals such as Turaga et al., who performed a comprehensive analysis of applications using the Grassmann and Stiefel manifolds in computer vision, with applications such as action recognition, video-based face recognition [6]. Hamm and Lee [7] proposed a unifying view on subspace-based learning. Every subspace was treated as a point in the Grassmann space and a kernel was used in their work. In [8], Chang et al. illustrated that face images can be well represented using the Grassmann manifold, which is invariant to pose, illumination and expression. Wu et al. [9] used the Grassmann manifold to model the facial shapes for age estimation and cross age face recognition.

IV. DATA

Sheep from four sheep breeds were recorded while being drafted on farm. Individual frames capturing sheep are grouped by breed. There is a main folder for aligned sheep images, inside which there is a folder for each of the four breeds' images. The dataset has 1680 images of sheep, focussed on their faces, belonging to 4 classes — Marino, Poll Dorset, Suffolk, White Suffolk. Throughout the data, 1344 of these are used for training and 336 are used for testing.

V. ALGORITHM USED

For the approached task, Convolution Neural Network (CNN) has been used. The sector's agenda is to enable machines to view the world the way people do, to see it in the same way and to use information for a wide range of activities such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. Computer Vision and Deep Learning advances have been developed and implemented over time, especially over one algorithm - the Convolutional Neural Network.

A Convolutional Neural Network (CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a CNN is much lower as compared to other classification algorithms.

The objective of the Convolution Operation is to extract the high-level features such as edges, from the input image. CNN need not be limited to only one Convolutional Layer. Conventionally, the first CNN Layer is responsible for capturing the Low-Level features such as edges, color, gradient orientation, etc.

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VI. PROPOSED WORKING

Firstly, Dataset has been imported which was in 4 different categories. Different Libraries has been imported such as pandas, numpy, matplotlib, skimage, keras etc. As in next step I have imported data and processed it. Throughout the task it has been observed that images are different in size, so it will be little difficult to pre-process it. In the next step images are resized to 150x150. Then sequential model has been created with convolution layer, flatten layer and, dense layer along eith relyu and softmax as activation function. Adam is used as an optimizer. Refer to fig(1) for summary.

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 45, 78, 64)        640
_________________________________________________________________
flatten_4 (Flatten)          (None, 224640)            0
_________________________________________________________________
dense_10 (Dense)             (None, 64)                14377024
_________________________________________________________________
dense_11 (Dense)             (None, 32)                2080
_________________________________________________________________
dense_12 (Dense)             (None, 4)                 132
=================================================================
Total params: 14,379,876
Trainable params: 14,379,876
Non-trainable params: 0
_________________________________________________________________
```

Figure:- 1 Model Description

In the next step model has been fitted by taking batch size of 128 and epochs of 20 and 10 instances in each epoch. These calculations have been settled in order to avoid overfit or underfit of model. At last of 20th epoch, a training accuracy of 99.97% was achieved. Refer in Fig (2) for brief detail.

The algorithm is iterative means that we need to get the results multiple times to get the most optimal result. The iterative quality of the gradient descent helps a under-fitted graph to make the graph fit optimally to the data. One Epoch is where the entire database is transmitted back and forth via the neural network only once. Batch size is the total number of training models available in one batch. We need terms such as epochs, batch size, iterations only if the largest data occurring all the time in machine learning and we cannot transfer all data to a computer at once. Therefore, in order to overcome this problem, we need to break the data down into smaller sizes and give it to our computer individually and then update the weights of the neural networks at the end of each step to match the data provided.

```
model.fit(X_train, y_train, batch_size=128, epochs=20)

Epoch 1/20
10/10 [==============================] - 7s 559ms/step - loss: 1.6770 - accuracy: 0.3055
Epoch 2/20
10/10 [==============================] - 6s 556ms/step - loss: 1.1311 - accuracy: 0.5118
Epoch 3/20
10/10 [==============================] - 6s 554ms/step - loss: 0.9243 - accuracy: 0.5860
Epoch 4/20
10/10 [==============================] - 5s 534ms/step - loss: 0.7427 - accuracy: 0.7021
Epoch 5/20
10/10 [==============================] - 6s 546ms/step - loss: 0.6493 - accuracy: 0.7059
Epoch 6/20
10/10 [==============================] - 5s 545ms/step - loss: 0.4813 - accuracy: 0.8434
Epoch 7/20
10/10 [==============================] - 5s 534ms/step - loss: 0.4222 - accuracy: 0.8434
Epoch 8/20
10/10 [==============================] - 5s 532ms/step - loss: 0.4109 - accuracy: 0.8689
Epoch 9/20
10/10 [==============================] - 5s 541ms/step - loss: 0.2756 - accuracy: 0.9403
Epoch 10/20
10/10 [==============================] - 5s 544ms/step - loss: 0.2302 - accuracy: 0.9467
Epoch 11/20
10/10 [==============================] - 5s 539ms/step - loss: 0.1722 - accuracy: 0.9628
Epoch 12/20
10/10 [==============================] - 5s 529ms/step - loss: 0.1409 - accuracy: 0.9720
Epoch 13/20
10/10 [==============================] - 5s 541ms/step - loss: 0.1226 - accuracy: 0.9826
Epoch 14/20
10/10 [==============================] - 5s 539ms/step - loss: 0.1095 - accuracy: 0.9835
Epoch 15/20
10/10 [==============================] - 5s 534ms/step - loss: 0.1111 - accuracy: 0.9778
Epoch 16/20
10/10 [==============================] - 5s 524ms/step - loss: 0.0791 - accuracy: 0.9915
Epoch 17/20
10/10 [==============================] - 5s 527ms/step - loss: 0.0524 - accuracy: 0.9973
Epoch 18/20
10/10 [==============================] - 5s 531ms/step - loss: 0.0484 - accuracy: 0.9973
Epoch 19/20
10/10 [==============================] - 6s 547ms/step - loss: 0.0279 - accuracy: 0.9989
Epoch 20/20
10/10 [==============================] - 6s 553ms/step - loss: 0.0246 - accuracy: 0.9997
<tensorflow.python.keras.callbacks.History at 0x7fdac1c3d748>
```

Figure:- 2 (Loss, Accuracy of the CNN model)

Then at the last stage, Normalization is being performed and created two separate Confusion Matrix for train and test. On normalization, the accuracy of 87.1% achieved on testing the model. Refer fig (3), (4) for brief explanation of normalization.

	Marino	Poll Dorset	Suffolk	White Suffolk
Marino	294.0	0.0	0.0	0.0
Poll Dorset	0.0	294.0	0.0	0.0
Suffolk	0.0	0.0	294.0	0.0
White Suffolk	0.0	0.0	0.0	294.0

Figure:- 3 (Confusion Matrix for training)

	Marino	Poll Dorset	Suffolk	White Suffolk
Marino	97.0	18.0	0.0	11.0
Poll Dorset	7.0	116.0	2.0	1.0
Suffolk	3.0	0.0	123.0	0.0
White Suffolk	12.0	11.0	0.0	103.0

Figure:- 4 (Confusion Matrix for testing)

VII. RESULT

Convolution Neural Network has been presented throughout this research. The algorithm has been applied over the image data in order to classify the breeds. The accuracy of 99.97% was achieved while training the model and 87.1% while testing the model. Hence Convolution Neural Network can be further developed by Generative Adversarial Networks (GAN) to extend the training dataset, using other loss function like centre loss [10].

VIII. CONCLUSION

The study was aimed at establishing a separator/discriminating function for separating the four known sheep breeds (Marino/Poll Dorset/ Suffolk/ White Suffolk sheep breeds). The derived discriminant functions provided maximum (canonical linear discriminant function) separation among the four known breeds. The study can therefore conclude that sheep breeds can be clearly separated based on the physical traits with minimum rate of misclassification without concentrating on only their genotypic features.

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