Animal Faces Classification using Transfer Learning: A comparative Analysis of AlexNet and VGG16 on High-Resolution

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ABSTRACT

Animal classification depends on the morphology of faces and is one of the important research areas due to supporting the automated smart system to detect the animal type classes. There is a high complexity of many types of animals in terms of facial hair, face color, head shape, eye size, ear size, nose size, mouth shape, and neck length. Using artificial intelligence can automate the detection and classification of the types of animals to support farmers, students, and vets' staff. It can also support the special needs of the blind by identifying types of animals without seeing them. Deep neural networks can support animal object detection and classify the categories with high accuracy. This research presents a proposed method for classifying animal faces with two pre-trained transfer learning methods with AlexNet and VGG16. The experiment is applied to the Kaggle dataset of Animal Faces, which includes 16,130 images with high resolution. The dataset is categorized into three classes: cat, dog, and wildlife of wild animals with similar facial features, such as fox, lion, cub, lioness, white tiger, golden tiger, and cheetah. The experimental classification accuracy results achieved 69.03% using AlexNet, although the VGG16 has more feature extraction and achieves 96.24%. The performance time using AlexNet is 20 minutes and 7 seconds, but VGG16 has 121 minutes with 20 seconds. The classification results show the accuracy classification results of VGG16 are better than the accuracy classification results of AlexNet on this animal face detection dataset.

Keywords: Artificial intelligence; Animal Learning; Deep learning; Detection; Classification; VGG16; AlexNet.

1 Introduction

Animal learning is one of the artificial neural network trends that can automate animal detection images and classify them Liu, (2021). Animal classification of animals depends on the morphology of face classification, and body classification is an important reach due to the support of the automated smart system to detect the animal type classes. Artificial intelligence can interpret machine intelligence to explore machines that simulate the cognitive tasks that humans relate to human-related (Bao, J., & Xie, Q., 2022), (Taheri, S., & Toygar, O., 2018). Using artificial intelligence can automate the detection and classification of the types of animals to support farmers, students, and vet staff. It also supports the special needs of the blind to identify types of animals without seeing them. Deep neural networks can support the animal object detection and classify the categorized with high accuracy. Capabilities of modern machines generally classified as artificial intelligence include understanding animal faces and body shape morphology, and they can also determine the behaviour of animals. Animal zoology is one of the branches of biology, which includes the study of the shape, structure, and functions of animals, methods of reproduction, and the transmission of their genetic traits in successive generations (Schmid, C., 2001). It also includes the study of various relationships between modern species and extinct species and between them. In addition, the surrounding environment can describe the zoography definition that is concerned with studying the description of animals in their geographical environment. Animal classification is a critical range that has not been examined quickly. Creature classification, which depends on the issue of recognizing pictures of diverse creature species, is a straightforward assignment for people, but proof proposes that indeed, in basic cases like cats and pooches, it is troublesome to recognize. The recognized have adaptable structures that may be structures, and ordinarily, they show up in complex scenes. Moreover, as with all objects, they can show up beneath diverse light conditions, perspectives, and scales. There are endeavours to apply acknowledgment strategies on pictures of creatures, but the particular issue of creature categorization has, as of late, pulled in limited interest. Traditional artificial intelligence in animal classification research shows animal recognition types and features a fusion of animal detection, tracking animal objects, and the ability to manipulate objects (Ramanan, D., et al., 2005). Globally, the usage of artificial intelligence in animal classification learning has several objectives. Methodologies contain statistical techniques, computational intelligence, and classical artificial intelligence. Recently, there are numerous devices that have been utilized in counterfeit insights, counting forms of inquiry, scientific optimization, counterfeit neural systems, and strategies based on measurements, likelihood, and financial matters. The trend of fake insights draws on computer science, informatics designing, science, brain research, phonetics, logic, and numerous other areas. The field was established on the presumption that human insights can be depicted so precisely that a machine can be built to mimic it. This raises philosophical contentions approximately the intellect and morals of making counterfeit creatures with human-like insights. These issues have been investigated through mythology, fiction, and logic since olden times. Few individuals consider artificial intelligence used for animal determinants. This research presents animal classification comparative anatomy based on studying the face structure of animals. Animals acquire the characteristics of the characteristics that possess these characteristics. Land animals are split into diverse kinds concerning their taxonomic categories, containing class, objective, order, and family, and are further subdivided into classes such as invertebrates. The most important aspects related to wild animals. The term wild animal is applied to every animal that lives on its own without needing help, where it finds its food, housing, and all its other needs in a specific natural habitat, and the forms of the habitat extend to a field, forest, pond, garden, etc., and wild animals are found in cities and countryside Liu, (2021). It is worth noting that wild animals are predators and difficult to tame. These animals are often mammals that feed on meat and are known to be dangerous animals. Recently, there has been an awareness of the importance of wild animals for the continuation of human existence. Wildlife is one of the most important pillars of tourism, as people are attracted to the beauty and life of wild animals. This reflects positively on the economy and creates new jobs, and this also reflects positively on the environment and the preservation of these animals. Wildlife has played a huge role in the daily lives of several cultures; as part of religious ceremonies, organism events, and community bonding, wild animals still play a large role in several third-world nations. Wildebeest migration patterns, distribution, and behaviour can be a vital indicator of ecosystem health and the deeper impacts of climate change. Lion, cat, dog, Tigris tiger: It is believed that there are less than 4,000 of them left, and China has banned the use of tiger bones and other organs that have great healing powers since 2014. Asian medicine is the biggest threat to these tigers. Snow leopards: It is likely that less than 6,500 tigers likely remain; the largest numbers are found in China and Mongolia, with some others in Kyrgyzstan. For this purpose, we construct a proposed animal classification solution using two classification models to extract features and compare them for classifying the animals based on animal faces. We tested our proposed solution with the Animal Faces dataset that contains 3 classes, 2 classes of training, and validation for different animals. It is challenging to discern the similar features of tigers, lions, leopards, and other wild types that have similar features: face colour, facial hair, head shape, eye size, ear size, nose size, mouth shape, and neck length. We utilized these experimental properties to apply state-of-the-art techniques. Our experimental results prove that the VG16 classifier has deeper extraction features and enhances classification accuracy. The outline of organizing follows: per is as follows, an overview of the literature the view is given. Section 3 shows a proposed animal classification method. Section 4 shows the experimental dataset and results, and Section 5 shows the conclusion and future works.

2 Literature Reviews

This section includes two sections of related works of animal classification and feature extraction prior to methods of deep neural networks. A) Animal Classification Animal classification is one of interpreting animal images of faces or body shapes. When interpreting the complex image database, it is very critical to utilize a technique capable of capturing data via diverse classes (Liu, et al., 2021), (Taheri, S., & Toygar, O., 2018). The result analysis presents the animal classes using smooth skin texture and hard background. In addition, animal classification shows the expert systems that can be used for detecting wild animal's migration corridors. Animals' classification is one of the patterns of object classification that is utilized in the literature for object recognition. The powerful rate of object classification relies on great object representation and characterization. Object characterization could be reached by visual identifiers, shape identifiers, or texture representation. Animal classification can interpret several features such as facial hair, face painting, head shape, eye size, ear size, nose size, mouth shape, and neck length as shown in Figure 1.

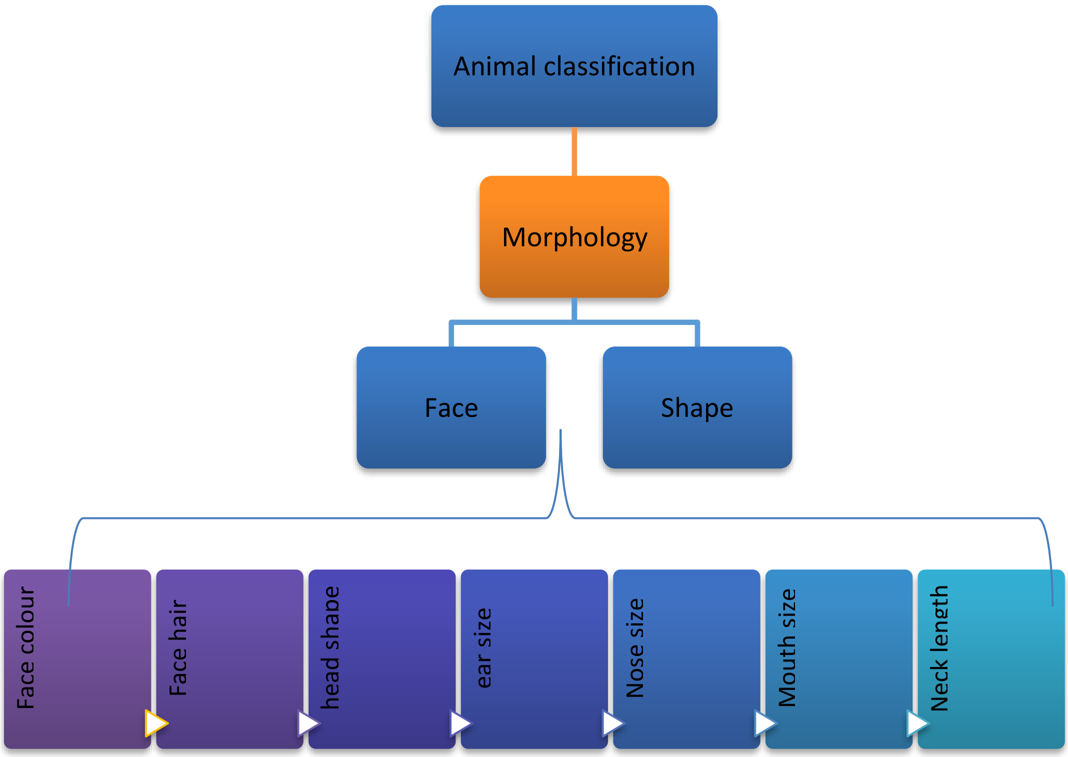


Figure 1: Animal proposed classification morphology features analysis

In this paper, the previous motivations for animal classification of different visual descriptors to categorize the animal ontology images are discussed. Researchers in (Ramanan, D., et al.., 2006) show animal recognition on an animal database using image retrieval of Gabor-like filters. It applies using four different classes with complex skin texture. Researchers in (Berg, T.L., & Forsyth, D.A.2006) present detecting textured animals utilizing the shape and texture data in video sequences. In an application for looking for pictures on the Internet. Researchers in (Penga, Z., Lia, Y., & Cai, Z., *et al.*, 2016) select the animal colours and texture for texturing object recognition in computer vision. Researchers in (Afkham, H., et al., 2008) use deep neural networks for the interpretation of the image classification of the dataset of LHI-Animal-Faces. It presents many features for boosting and dictionary learning in layers. Researchers in (Krizhevsky, A., et al., 2017) present a classification framework to classify animals into one of 13 different classes.

Table.1: A Comparative Analysis of Classification

Ref	Methodology	Pros	Cons
(Ramanan, D., et al., 2005)	Fusion animal classifications	95% accuracy	Needs to apply multiple datasets
(Ramanan, D., et al.., 2006)	Deep learning animal recognition	Good accuracy	Requires improvement with videos
Berg, T.L., & Forsyth, D.A, (2006)	CNN of images and video sequences	High accuracy for many animals as zebra	requires constructing the spatial-tempos patio temporal to videos by individual animals
(Penga, Z., Lia, Y., & Cai, Z., *et al.*, 2016)	colours and texture for classifying objects recognition object	Improve accuracy of the any animal objects such as monkeys such s, spider monkeys, and rhesus monkeys	Requires multiple datasets
(Afkham, H., et al., 2008)	the animal colours and texture for classifying objects recognition	Improve accuracy of image recognition on several datasets 59.3% with regularized and 55.8% without regularized terms	Requires improves the accuracy
(Krizhevsky, A., et al., 2017)	classify animals from one to 13 different classes using the support vector r machine of machine learning interpretation	88%	Requires improving accuracy results
(Sharma, N., et al., 2018)	Classify animals image animal LSVRC image net	62.3% accuracy	Needs to improve the accuracy results

A) Deep Neural Networks methods

The deep neural network (DNN) is considered a neural network with diverse levels of complexity, at least two layers, and qualifies as a deep neural network as shown in Figure 2. Deep learning is considered a machine learning technique that uses human interpretation teaching. Convolutional Neural Network (CNN) is a useful machine learning technique from the learning trend of deep learning that is utilized in several computer vision tasks (Sharma, N., et al., 2018). This research uses two pre-trained convolutional neural networks, for example, a network stature extractor to extract discriminative representations for animal face images (Waheed, A., et al., 2020). That is a training group of training picture samples that is substantial. From this big training of group images, CNNs interpret the extracted discrimination properties. Feature extraction is a vital phase in a biometric system. The technique utilized for feature utilization significantly impacts the final decision for classifying the biometric object system. Many feature properties extractors that are utilized in the related works are designed in this paper's outlines. Clpaper'sal CNNs contain a stack of deep convolution layers that obey several fully communicated layers and utilize the SoftMax multi-category classifier with the cross-entropy loss function. In the first layer, we summarize the drawing of each convolutional layer of CNN. *Convolutional layer:* the objective of this layer is to discover the spatial correlation and invariant properties using diverse convolutional layers.

- Pooling filters.
- *Pooling layer:* interprets the high-frequency removal It also can extract feature maps of the deep convolutional layer down sample with extra layers of max (max-pooling) or average (avg-pooling) value of each patch in the property, fully mapped.
- *Fully connected layer:* every neuron in this layer is fully connected to all neurons of its double adjoining layers.

The following presents two convolutional neural network architectures that we use for the automated feature extraction of animal face images, known as the AlexNet and VGG-16.

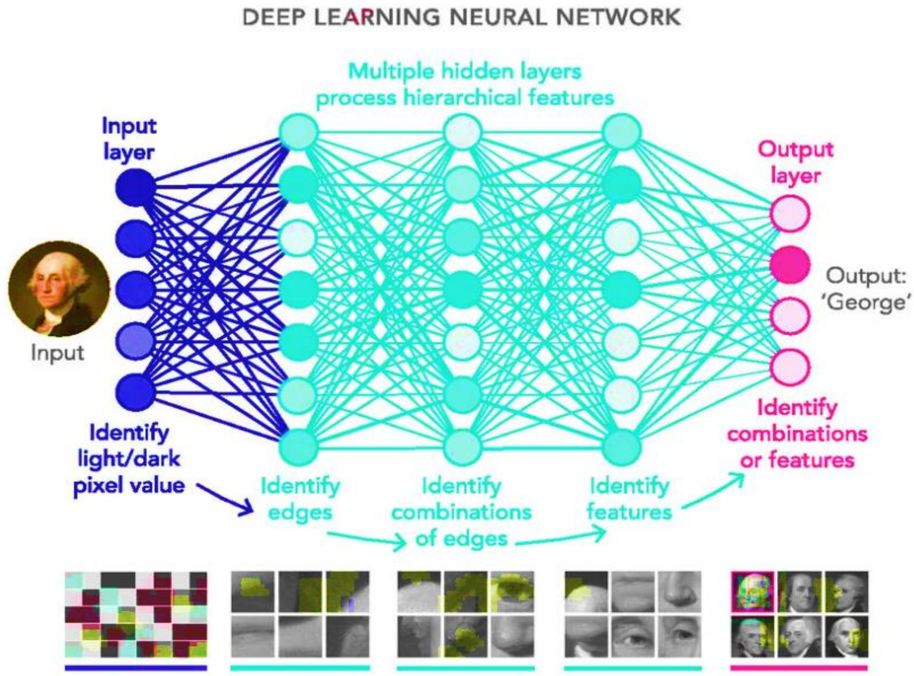


Figure 2: Deep neural networks.

B-1 AlexNet

AlexNet (Hammam, A, et al., 2020), (Tang, W., et al., 2023) is a deep convolutional neural network (CNN) for categorizing the image classification that got the ImageNet large-scale apparent recognition problem (ILSVRC)-2012 competition and reached a winning top 5 test error rate of 15.3%, applied a comparison with 26.2% reached by the second-best entry (Eldem, H., et al., 2023). AlexNet is collected of five convolutional layers (C1 to C5) (Chen, H., et al., 2022) (Alom, M.,Z., 2018) kept track of double fully connected (FC6 and FC7) and a final SoftMax output layer (FC8). The essential structure of AlexNet is shown in Figure 3.

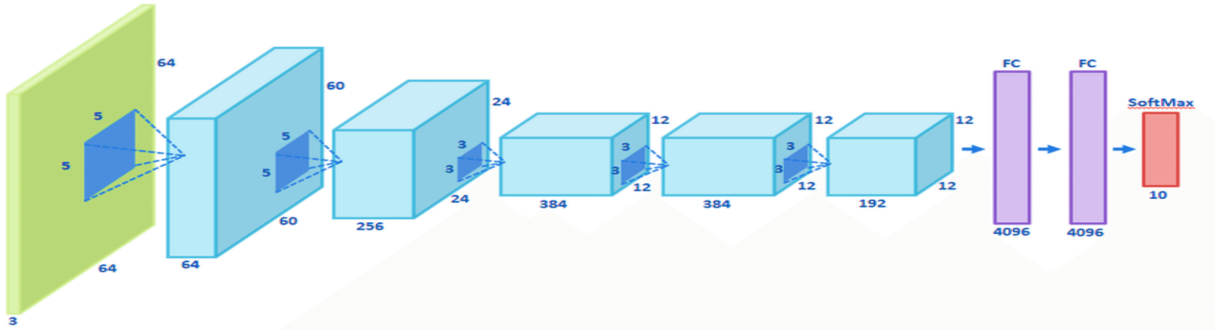


Figure 3: AlexNet architecture

B-2 VGG-16

VGG-16 (Eldin, D.M., et al., 2020) paradigm structure performs in ILSVRC 2014. The Oxford Visual Geometry Groups' model is deeper than the former CNN structure. VGG-16 consists of 5 batches of convolution processes, each batch contains of 3–5 adjacent convolution layers. Adjacent convolution batches are communicated through max-pooling layers. The volume of kernels in all convolutional layers is 3×3 convolutional layers in addition kernels' number within each batch is the same. Figure 4 shows Figure the VGG structure (Simonyan, K., & Zisserman A., 2015), (Kusumawati, D., et al., (2022). VGG-16 network paradigm structure has utilized several papers and it was the first one that outperformed human-level performance on ImageNet (Zakaria, N., & Hassim, Y., 2022), (Tammina, S., 2019), (Gayathri, P., et al., 2023).

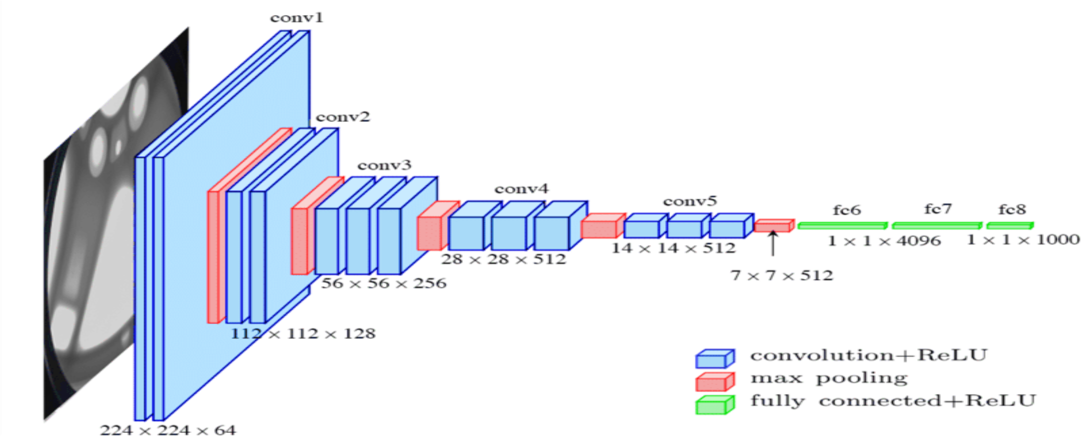


Figure 4 VGG16 architecture

3 Proposed Animal Classification Learning Model

The proposed animal classification solution presents an architecture diagram of the presented design for classification. The model will be shown. The proposed design flowchart is displayed in Figure 5. The figure passes through three phases. The primary phase is the pre-processing, whereas the image processing, preparation into matrixes, and preparation of feature extraction are prepared based on the classification method. Within the pre-processing stage, all input animal face images within the dataset were resized to input pixels to decrease the processing time within the training phase. Second phase, The second ossification phase with two pre-trained neural network models, AlexNet and VGG16. The feature extraction makes resizing images based on the type of neural network method while using AlexNet; the images convert to intconvert27, and VGG16 converts the images into 224 * 224. The third phase is the evaluation, measurement, and testing phase.

The primary portion for preparing purposes is shown with 70% of the initial information, whereas the moment portion was 30% for testing purposes. The preparation portion will be encouraged into the proposed demonstration for semantic demonstration and will be talked about in the next section. The testing stage is utilized for testing the exactness of the presented design over the test data.

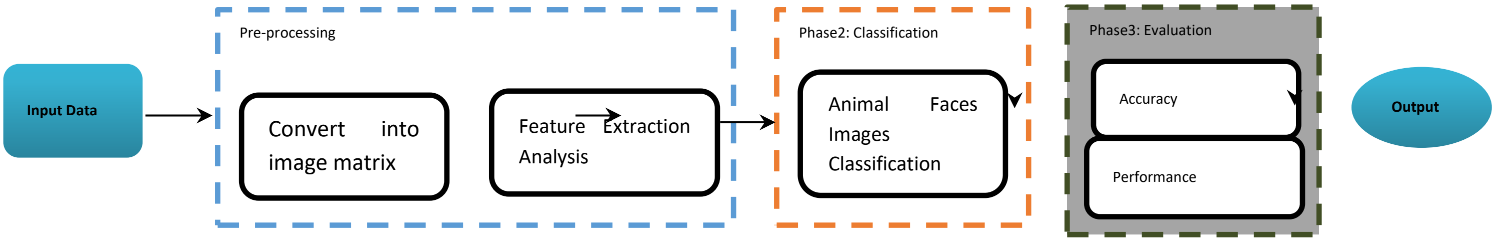


Figure 5: proposed animal classification learning model

4 Experimental Results

This section presents the animal dan dataset and a comparative result of deep neural classification methods using two pre-training models, AlexNet and VGG16. It shows the used benchmark dataset and experimental results.

4.1 Dataset

The Animal Faces dataset contains 3 classes of animal face heads with over 16,130 images (Larxel, 2020). Figure 6 illustrates a sample of animal face images in three categories. There is a high complexity of many types of animals in terms of facial hair, face painting, head shape, eye size, ear size, nose size, mouth shape, and neck length. Cats, dogs, and wildlife of wild animals have similar features, such as foxes, lions, cubs, lionesses, white tigers, golden tigers, and cheetahs.

Figure 6: Animal Faces sample

4.2 Animal facets

The classification estimations depend on the exactness and accuracy of precision (Choi, Y., et al., 2020),. Image classification can move forward the classification exactness in different measurements of information quality. These estimations of the exactness and precision of the combination appear in condition (2) and condition (3). Validity could be a characteristic of estimation in which a gadget truly measures what the investigator anticipates. anticipates, Faithful quality: 'A characteristic of estimation concerned with consistency.' Comfort The relationship between the time of collection, collation, and declaring to the coo-fruity of the data for choice-making shapes.

$$Rcall = \frac{TP}{TP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Precision Accuracy (a measure of bias) means the Precision (a measure of error) as resulted in Table 2.Table .2: precision accuracy metrics.

	Relevant	*Non-Relevant*
Retrieved	TP	FP
Not Retrieved	FN	TN

Measuring the performance of fusion,

$$F - measure = \frac{2\ Recall \cdot Precsision}{Recall+Precision} \quad (3)$$

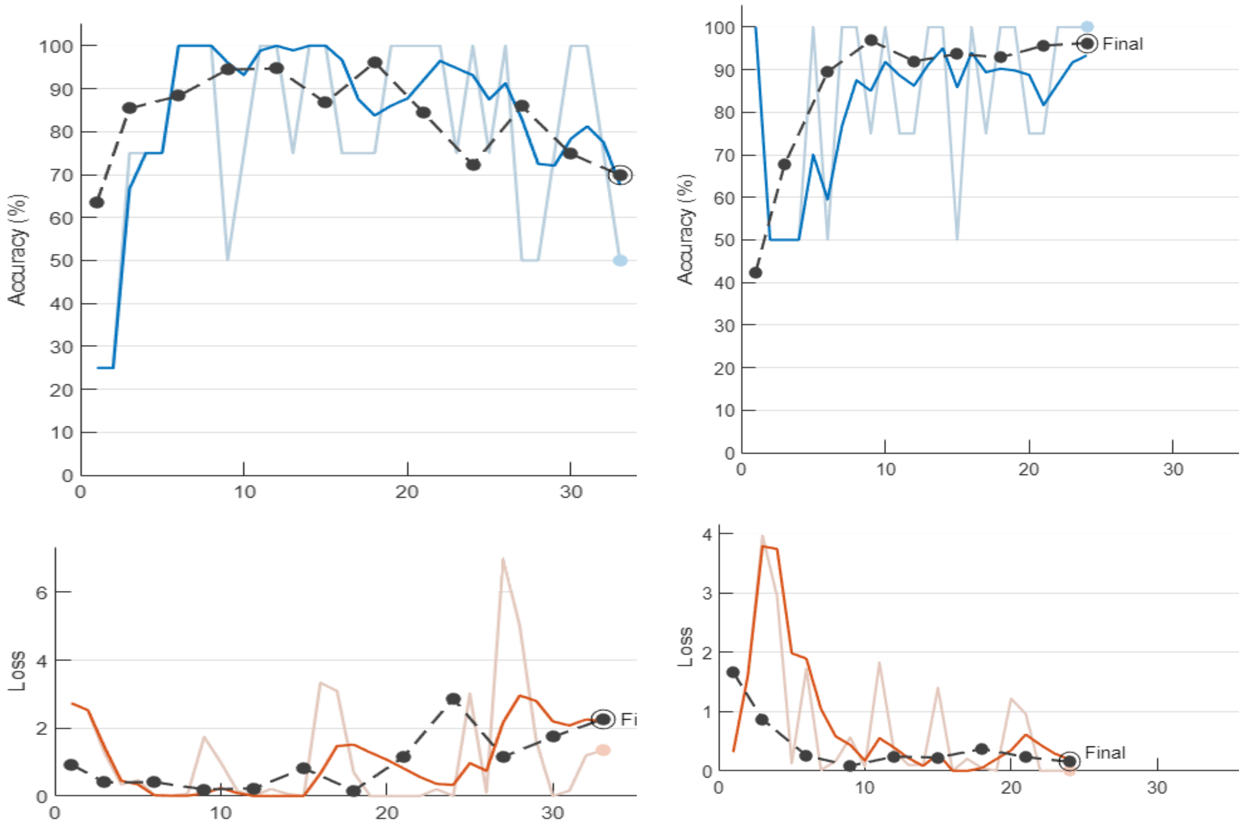
4.3 Results

The experiment is applied to the Kaggle dataset of animal faces. It includes 16,130 images with high resolution. The dataset is categorized into three categories: dogs and wildlife of wild animals with similar features, such as foxes, lions, cubs, and lionesses; white tigers; golden tigers; and cheetahs. The Face dataset is split into training and validation, and each training class has around 5000 images, approximately. Each image has a size of 512 x *512 pixels. The experimental classification accuracy results achieve 69, achieving AlexNet, although the VGG16 has more feature extraction and achieves 96.24%. The performance time using AlexNet with 227 x* 227 achieves 20 minutes and seconds; the VGG16 with 224 x 224 has 121 minutes with 20 seconds. The classification results show the accuracy classification results of VGG16 are better than the accuracy classification results of AlexNet on this animal face detection dataset.

The experiment uses the pre-trained methods that are designed based on a convolutional neural network (CNN) that can make automated feature extraction for AlexNet and architectures. The critical issue of using pre-trained models is shown in impressive training on a wide dataset previously to improve the accuracy results on 1000 classes. The convolutional neural network architectures of AlexNet and VGG-16 include millions of parameters. Interpretation learning presents several features via only a few hundred training images. Our proposed solution model applies to the Animal Faces dataset for 16,130 images to detect the animal objects from their faces and classify animals. The feature extraction utilizes the representational energy of pre-trained deep networks; 4096-dimensional properties are discovered via the activations of the FC7 layer. The cause that we chose the activation layer and FC7 layer to elicit features is that it is spent on a replacement for the suitable dataset.

Many targets of eliciting the features from animal faces, the input picture can be resized and fed to the CNN as a multidimensional array of pixel intensities. The input image size of the VGG-1 net converts the input animal face image into a 224 × 224 × 3 matrix since the input of animal face images uses the AlexNet architecture, which converts to a 227 × 227 × 3 matrix. Conclude The conclusion of the experimental results is shown in the figure. 7 presents, the classifier can be trained and utilized using the AlexNet properties, which performed near approximately 69.04% accuracy results, and the classifier trained using VGG-16 properties performed 96.24% accuracy, which is higher than the accuracy reached utilizing the several epochs' properties. AlexNet has several epochs, 5, with many iterations of 3 of 14110 and iterations per epoch of 2822. The validation frequency achieves 3 iterations, and the performance time has 20 misses and 7 seconds. VGG-16 includes the number of epochs, which is 5, has 24 iterations of [1311014110 iterations, and iterations per epoch are 2822. The validation frequency includes 3 iterations, and the performance time includes minutes and 20 seconds. The cause that VGG-16 outperforms AlexNet is that

VGG-16 architecture is higher in most results than their most, through 16 layers in total, 13 convolutional and three fully connected layers. VGG-16 utilizes small convolutional filters of 3 × 3 pixels; therefore, each filter is easier geometrical structures, but a comparative analysis can be highly complex reasoning, figure.7. Its raised depth. The output examples of classification are shown in Figure 7 and Figure 8.



a) AlexNet b) VGG16

Figure 7: A comparative analysis of accuracy results between Animal Faces classification AlexNet and VGG16

Figure 8: Animal classification accuracy results

5 Conclusion and Future Works

Animalization depends on the morphology of faces, which is vital in the investigation to back the robotized, shrewd framework to identify the creature sort classes. In this paper, we utilize a proposed neural network model using transfer learning strategies to prepare a show for classifying pictures. There's a high complexity of numerous sorts of creatures in facial hair, confront colour, head shape, eye estimate, ear measure, nose estimate, mouth shape, and neck length. Utilizing fake insights can robotize the location and classify the sorts of creatures to bolster ranchers, understudies, and vets' staff. It moreover can bolster the extraordinary needs as a daze to distinguish sorts of creatures without seeing them. Profound neural systems can bolster the creature question discovery and classify the categories with tall exactness. This inquiry presents an inquiry strategy for classifying creature faces with two pre-trained exchange learning strategies with AlexNet and VGG16. The exploration is connected to Kaggle. The dataset of Creature Faces incorporates 16,130 pictures with great determination; the dataset is categorized into three categories: puppies and the natural life of wild creatures.

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