Wolf and Dog Breed Image Classification Using Deep Learning Techniques

MSc Research Project
Programme Name

Kumar Chaturvedi
Student ID: 18181970

School of Computing
National College of Ireland

Supervisor: Dr. Catherine Mulwa

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	KUMAR CHATURVEDI
Student ID:	18181970
Programme:	MSc. DATA ANALYTICS **Year:** 2019-2020
Module:	Research Project
Supervisor:	Dr. Catherine Mulwa
Submission Due Date:	17 August 2020
Project Title:	Wolf and Dog Breed Classification using Deep Learning Techniques
Word Count:	**5326** **Page Count** 25

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature: Kumar Chaturvedi

Date: 17/08/2020

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	□
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	□
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	□

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Wolf and Dog Breed Classification using Deep Learning Techniques

Kumar Chaturvedi
X18181970

Abstract

A huge money is involved in pet insurance and medical treatments of pets. Missing pet is a global issue also rescue teams face a lot of challenges while rescuing pets since sometimes they encounter wolfs also which looks same as dogs. For this purpose, new dataset has been created by combining Stanford dog dataset and wolf images from kaggle. Transfer learning technique has been used in this work by using pretrained convolutional networks like ResNet101, ResNet50, VGG16, VGG19, DenseNet201etc. These models can help in distinguishing between wolf and different dog breeds. For evaluating model's accuracy and model loss metrices has been used. ResNet101 performed better than all other transfer learning techniques and achieved 90.80% accuracy. Many state-of-the-art researches were considered and this work with new dataset of wolf and dog images performed well. One CNN model has also been created which also performed better and further accuracy can be improved by training with more images.

1 Introduction

False insurance claims and missing pet animals like dog is common problem all over the world. In Human life, pet like dog plays a significant role as they are considered as part of family and a best friend. But a lot of emotional turmoil happens if our family member goes missing or lost somewhere. Pet owners takes a lot of precautions like tags and GPS devices for their traceability. These steps do not help always in detecting and identifying pets as these tags and GPS are more likely to be lost or damaged and does not prove itself as effective measure. Veterinarians also face issues for providing adequate healthcare. Nowadays e-health is in practice by veterinarians for creating electronic medical records which is very helpful in providing adequate healthcare. Images of each and every pet are taken as record and are used for identification of every individual pet. Most of the times dogs are recovered in very pathetic condition in the remote areas and woods and to identify them from distance is very difficult from normal human vision. Captured images of animal can be used by biometric system for identification purpose. This animal biometric system also helps rescue team as most of the time they encounter wolfs also. So, it plays a major role by not picking up wolf considering it as a dog as due to not eating for days' wolf can be misjudged as dog since their appearance can be changed. Biometric applications using pictures can be proved cost effective and useful in long run for animal husbandry and medical departments as a lot of cost is associated with their insurance and healthcare. Some minimal research has already been done by some researchers using deep neural network. More analysis can be done in this field using convolutional Neural Network using transfer learning as it has been proved that deep learning and convolution neural network performs better in classifying images. Also, some machine learning models are implemented in this paper.

This research will help in classifying different dog breeds and wolf (Figure1) by facial recognition using deep learning models through Transfer Learning techniques like VGGNet and ResNet as these are state of the art neural networks.

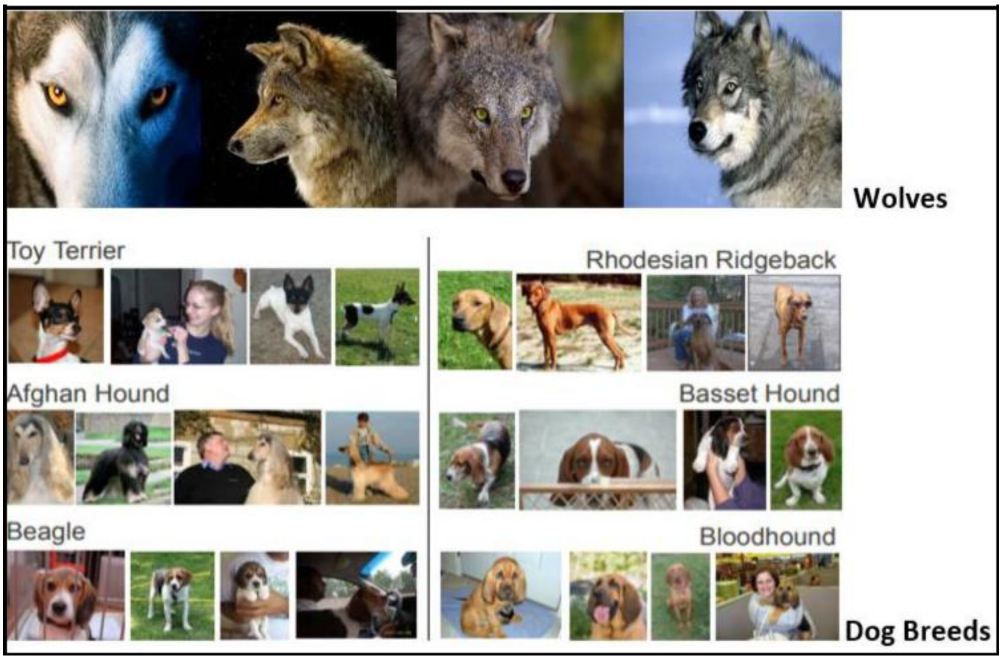

Figure 1: Wolf and different dog breed.

1.1 Research Question

RQ: *"To what extent can deep learning (CNN architecture) and transfer learning models (VGG16, VGG19, InceptionV3, DesNet201,ResNet101) help in distinguishing and classifying different dog breeds and wolf to improve security of rescue team who are involved in dog rescue?"* This research will help in classifying different dog breeds and wolf which will help in rescuing pets in woods as huge money is involved in their insurance and medical healthcare.

1.2 Research Objective and Contributions

Detecting wolf in woods using biometric system will help the rescue team a lot and provides security as encounters with wolf is not safe and happy always.

To solve the research question, the objectives (Table 1) were implemented. It includes identifying problem, defining research methodology and design, implementation, evaluation and research and for commercial purpose creating a web application.

Table 1: **Objective list**

Objective no.	Description of objective	Used Metrices
obj.1	Critical analysis and Identifying gaps in related work of dog breed identification	
obj.2	Defining research methodology and design	
obj.3	Exploratory Data Analysis of wolf and dog breed dataset	
obj.4	Design Specification of wolf and dog breed model	
obj.5.1	Implementation, Evaluation and Results of CNN	Accuracy and Loss
obj.5.2	Implementation,Evaluation and Results of VGG16	Accuracy and Loss
obj.5.3	Implementation, Evaluation and Results of VGG19	Accuracy and Loss
obj.5.4	Implementation, Evaluation and Results of ResNet50	Accuracy and Loss
obj.5.5	Implementation, Evaluation and Results of ResNet101	Accuracy and Loss
obj.5.6	Implementation, Evaluation and Results of DenseNet201	Accuracy and Loss
obj.5.7	Implementation, Evaluation and Results of Inception-v3	Accuracy and Loss
obj.6	Web Application for identifying dog breed and wolf	

2 Critical Review of dog classification and Identified gaps

Image classification can be proved very useful for wildlife researchers, veterinarians and animal husbandry department. Computer Vision can play a significant role in identifying different breeds and animal species. The recent state of art technique for image classification is CNN method and it outperforms all other techniques. There are many recent developments in Transfer learning and deep learning techniques. Few techniques are discussed below using image classification for animal breed categorization.

2.1 Review of Literature on Dog Breed Classification using Transfer Learning Technique(s)

Capone et al. (2017) in their research analysed different (CNN) techniques for searching lost dogs from images captured under different conditions. Researchers have implemented VGG16 and inception V3 for classification to ascertain if image is containing dog or not. Two image datasets were picked viz. FlickrDog and DogsVsCats and it was found that VGG16 resulted better results than Inception-v3 with around 95% accuracy. Though researches faced poor light condition challenges, but accuracy of results obtained was better. If more images were incorporated in the research, then pointing dogs in the images can be done more easily. Also, other CNN models can also be analysed and compared as a future work. Li et al. (2016) used Clickture-Dog dataset for identifying different dog breeds. R-CNN was applied for faster data cleaning and filtering data noise for better dog identification. For checking test accuracy dense evaluation strategy was applied and it resulted in 89% top5 accuracy. In each image, detector was used and detected dataset was created after that cropped images were used in fine-tuned VGG model. As already best CNN models were used for recognition after detection performance dropped slightly. Szegedy et al. (2015) introduced deep CNN with improved resource utilization. Using Hebbian principles and multi scale processing depth and width was changed keeping cost of network same. In this research GoogLeNet architecture was used. With slight increase in computational requirements significant improvements were recorded which was not present in case of narrower architectures. Work suggested that non inception type architectures are too costly and results same accuracy. It was concluded that using Inception techniques we can check for more refined architectures. Also, as a future work sparser architecture can be analysed which can prove useful concept and better results can be achieved. Kumar et al. (2019) in their research paper mentioned work on distinguishing the breed of dog using ResNet101 architecture which extracts features using Transfer Learning. For training transfer learning was applied and involved softmax as Activation function. Authors pointed out that in future work noise can be filtered on training dataset through data masking. Training of model and performance can be enhanced if noise can be filtered and visibility can be increased. For extracting features more dimensional reduction techniques can be checked and with some alteration in configuration. Also, accuracy can be improved by changing different layer’s proportions.

Zalan Raduly et al. (2018) in their work introduced fine grained image recognition technique using two different CNN models. Software system having central server and mobile client was used for evaluation of model. Two mobile architecture were used namely Inception-ResNet-v2 deep architecture and NASNet-A. Stanford Dog Dataset was used for fine tuning the networks. Few good results were recorded even with less data and about 10% less accuracy was recorded for mobile architecture as compared to model Inception-ResNet-v2. Authors mentioned Generative Advarsarial Nets (GAN) can be used for further enhancements, increasing training data and using loss functions as center loss. Datasets for training can be increased and optimisation of servers for mobile applications can be done.

Lai et al. (2019) in their research identified the issues related with animal biometric identification especially for dogs. Varieties of soft biometrics were taken care and analysed like breed, gender and height and hard biometrics were mixed like face photographs. On different CNN models, transfer learning techniques were applied for achieving better accuracy. In absence of soft biometrics 78% accuracy was achieved but with soft biometric identification decision network resulted 84.9% accuracy. Fine-tuning can be taken as future improvements and optimized CNN architectures can be used with more features and advanced level fusion can be done. Sinnott et al. (2018) in his research paper presented an outline of his developed mobile application for dog breed identification using deep learning technique. Total 120 different dog breeds were introduced for dog breed identification. Different aspects for image performance were considered in the work and performance of model were dependent on the image's quality and quantity. To enhance the quality of image automated image adjustment method was used and same no. of images were present in all classes. Avoiding over fitting while implementing deep learning models was taken care in the work. Image filtering was done to ensure each and every image was eligible for model fitting. Significant clipping decreased inference of background. For storing information in a good way, lower learn rate was used while training the model. Authors suggested that for further improvement larger dataset can be used with larger memory GPU device for extra images. Unwanted and redundant parameters in the model can be removed and architecture can be changed. Labelling can be done more effectively in input data's bounding box.

2.2 Literature Review on Dog Breed Classification using Convolution Neural Network

Hammam et al. (2018) proposed a model using localizing technique for tracking purpose of pet animals in their research work. Authors found that Deep learning method with Fast R CNN proved to be more effective as compared to conventional CNN model. Different cat movements in different video sequences were used for testing model. As compared with GoogleNet and VGG, research model gave better results. As a future work, for real time conditions for pet animal identification, multi camera streaming could be included. For better accuracy other pets can also be used for increasing data size. Moreira et al. (2015) in their work compared four human face recognizers with two solutions based on CNN with datasets Snoopybook having 18 images (mongrel) and Flickr-dog having 42 images (pugs and huskies). Human face recognizers performed poorly attaining only 60.5% accuracy on the other hand CNN based solutions BARK achieved 81.1% accuracy and WOOF 89.4% accuracy. If more training samples and different CNN methods were applied for extracting more image's features accuracy can be improved.

Ouyang et al. (2019) performed an experiment where an algorithm containing dense scale invariant feature was transformed using Convolution neural network. This classic work helped in dog recognition with accuracy of 94% in public places. Using dense scale invariant feature transform algorithm, the experiment resulted in better results for image splitting and CNN for dog species identification. Still there are chances of better recognition though good accuracy was recorded by researchers. Also, feature model's generalization ability can be enhanced and improved. If light conditions are improved, results may improve as in poor light conditions desired results may not achieve. Li et al. (2017) in their work analysed CNN advantages and found in discriminating the different images, pixel pair method can be proved useful. Performance can be enhanced with hyperspectral image dataset classification if comparison is made against conventional deep learning-based methods. Central testing pixel and surrounding pixel were combined for performing testing. Also by majority voting strategy final label was captured. For small training samples, CNN-PFF can resulted in improving the performance of original Convolutional Network but computational cost gets increase.

Monteiro et al. (2017) carried out research for recognizing activity through deep convolutional network for people who are visually impaired. A video's dataset was taken for training purpose for training convolution neural network so that it can recognize activities which are taking place infront of camera aperture and helps visually challenged humans in providing suggestions. It used two CNN which were later merged. 75% accuracy was achieved with SVM and PP. Chen et al. (2018) presented PolSAR image classification using advanced deep convolution network for better classification performance with less images driven by Polarimetric Feature. Polarimetric synthetic aperture radar application is having advanced level of performance in image classification. Challenges were created due to few training samples for good generalization performance. Expert knowledge using interpretation of target scattering mechanism and polarimetric feature mining needs to be utilized for improving efficiency of deep CNN classification. Model performed 2.3 times faster as compared to Convolution network. Suggested model performed overall 4.86% more accurately than normal convolutional network. Having very limited samples still proposed model recorded better accuracy.

After making reviews on different researchers work, some important researches have been identified which can be shown in Table3. This work is extension of their work as wolf images has been merged with dog breed dataset and it will help in identifying wolf also along with different dog breeds.

Table 2: Comparing different methods for dog breed classification

Authors	Technique applied	Dataset(s)	Models applied	Results and Outcomes
Victor Capone et al. (2017)	Different CNN architectures	FlickrDog and DogsVsCats	VGG16 and Inception-v3	VGG16 performed better with 95% accuracy.
Chenghua Li et al.(2016)	CNN architecture	Clickture-Dog dataset	ensemble-CNN	89% accuracy
Kenneth Lai et al. (2019)	Transfer learning	Flick-Dog Dataset	Inception-v3 MobileNet VGG16 Xception	78.09 % Xception with Pugs and Husky combined
Rakesh Kumar et al. (2019)	Transfer learning	Stanford dog Dataset	ResNet101 ResNet50 InceptionResnetV2 InceptionV3	90.26% accuracy with ResNet101

3 Research Methodology

3.1 Wolf and Dog Methodology Approach

This work explains the deep learning techniques for identifying wolf and different dog breeds in the woods. Different Transfer learning techniques will be used on the images collected from Kaggle dataset. In this work modified CRISP-DM (CROSS INDUSTRY STANDARD PROCESS FOR DATA MINING) methodology is used as shown in Figure 2. This project will be discussing research work using Business Understanding, Data Understanding, Data Preparation and Modelling, Evaluation and Deployment sections. Since a lot of money is involved and invested in pet safety and insurance. Also pet rescuers also face many challenges while rescuing the pets this work will help in identifying the dogs in woods and also provides safety to rescue team from wolf. This work will benefit many people simply using web application if they are having image of animal for which they want to check if it's a wolf or dog and subsequently the dog breed. We have collected image data of dog breeds and wolf from KAGGLE.

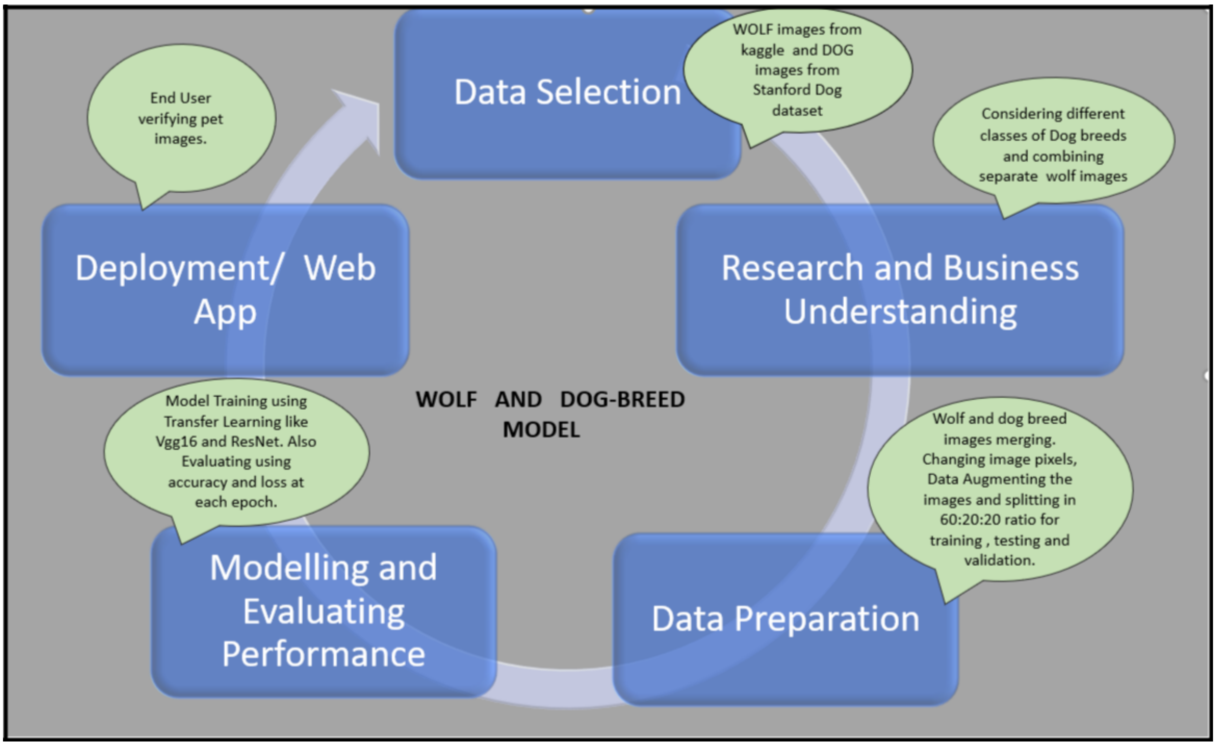

Figure 2: Methodology for Dog Breeds and Wolf Classification

3.1.1 Data Selection

Wolf and Dog breed dataset is taken from two different sources and merged. Wolf images has been taken from public repository of Kaggle and dog breeds data is taken from Stanford dogs dataset from ImageNet. Wolf dataset contains 1000 images and Stanford dogs dataset contains 20,580 images of 120 different dog breeds.

3.1.2 Business Understanding

Detection of pets in wild is challenging task for the pet's insurance company. There are encounters with wild animals like wolfs so biometric system will be a good option for security of rescue team. Biometric system can help in classifying different dog breeds and wolf. Since a lot of money is involved in the insurance and health care of pet animals like dogs so it is mandatory to research and make life easy for insurance and healthcare companies. For images Kaggle images for different dog breeds and wolf has been taken. There are different dog breeds and wolf images are merge with former dataset for getting desired dataset. In this work Transfer learning techniques i.e. VGG16 and Inception-v3.

3.1.3 Data Understanding and Exploratory Data Analysis

Images taken from Stanford dog dataset contains 120 different dog breeds having 20580 images and wolf images which are taken from Kaggle contains 1000 images. These two datasets are combined and one single "wolf and dog breeds dataset" has been created. Stanford dog dataset is a part of ImageNet challenge and contains around 20580 images. The images in Stanford dog dataset contains different resolution images with a range of 4000*3000 to 400*300 and same in case with wolf dataset.

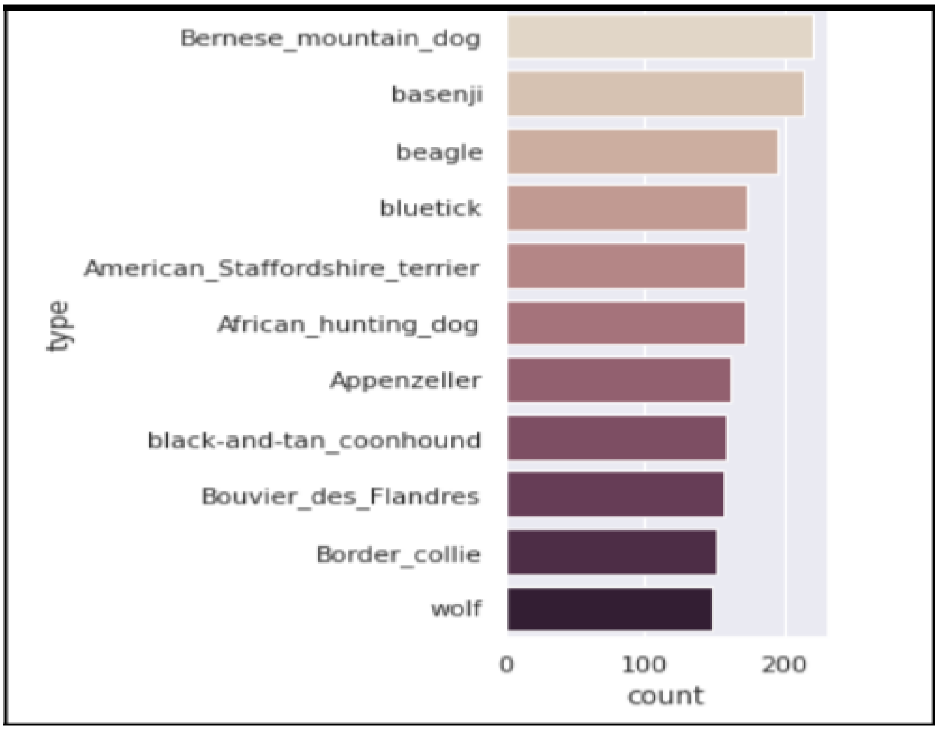

Figure 3: Counts of dog breeds and Wolf

Since dataset has become too big for training after merging 20580 dog images and 1000 wolf images and it has become impossible to train machine with limited resources. So finally, a subset has been created containing fewer dog breeds and wolf images. Figure 3 tells no. of images in each class of different dog breeds and wolf. 150 images are present in every class of dataset as an average. In Figure 4 different classes images has been shown.

Figure 4: Images in different classes of dataset

3.1.4 Data Preparation

Since images in each class is not high, Data Augmentation is used for creating different variations of available different sample images. Also, image size has been changed and fixed to 224*224 for VGG16, VGG19, ResNet models. For InceptionV3, Xception and InceptionResNetV2 images has been fixed to 299*299 pixels. Also, dataset has been splitted into training and validation in 80:20 ratio. Images are augmented through flipping, zooming and shifting. For data augmentation purpose in the work, ImageDataGenerator class has been used. It is used for real time augmentation for generating batches of tensor images. Also flow_from_directory method has been used for generating batches of augmented data by taking path of directory.

3.1.5 Modelling

Modelling is the process in which training of different convolutional models are done. This work is predicting pet is a wolf or not also if its a dog then which breed it falls under. Once training of models is done through different transfer learning techniques like VGG16, VGG19, inception-v3, ResNet101, InceptionResNetV2, Xception. evaluation happens which is described in detail in section5.

3.2 Implementation

This is the step when models are implemented by training the different models and then validation of models is done through validation data. A CNN has been created and accuracy has been recorded with matplotlib library. Since this is work is related with image classification with multiclass outputs, many pretrained convolutional networks has been used for analysing the performance of created image dataset for wolf and different dog breeds. Finally, all the models are tested based on metrices like Accuracy, precision and recall. This will be discussed more in section5.

3.3 Results and Deployment

The results are visualised and represented through different visualisations. This will be discussed more in section5.

4 Design Specification

Architecture design for projects are generally categorised into two types 2-Tier design or 3-Tier design. A 2-Tier architecture is being followed in this project as shown in Figure 5. In this project design everything is covered like tools, techniques, technologies and process flow which is used for overall implementation of the project. Data is collected from KAGGLE for both dog breed images and wolf images. The EDA has been done through python and its libraries. Once data is ready it will be splitted and send for model training using training dataset. After performing testing, validation is done for checking the model accuracy and loss.

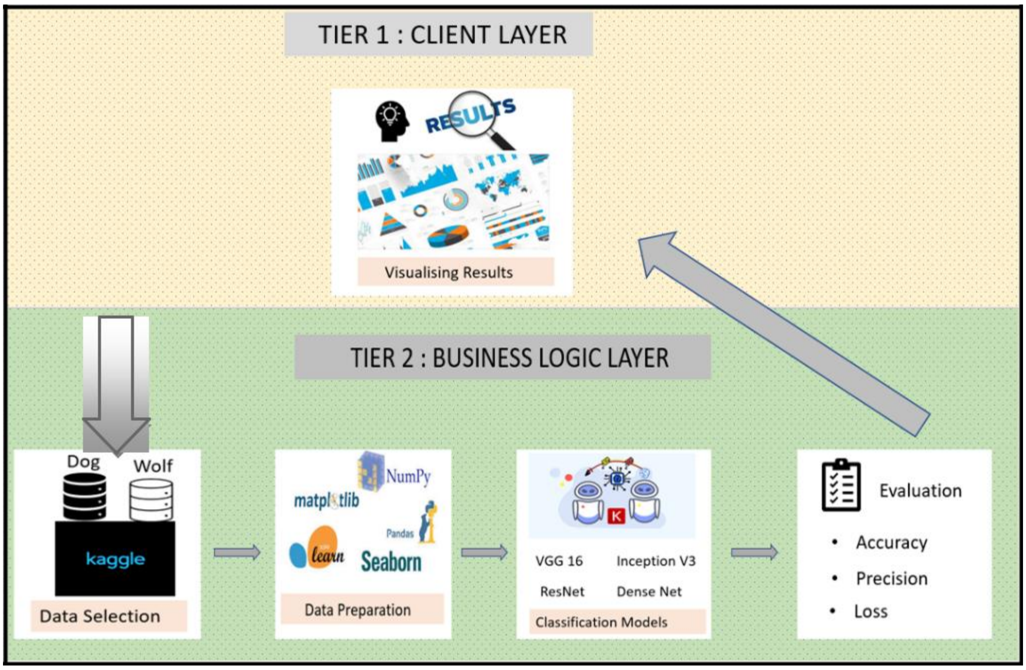

Figure 5: Two-Tier Architecture

5 Implementation, Evaluation and Results of Wolf and Dog Breed Classification Models

5.1 Introduction

In this section implementation, evaluation and results of different models used for identification of wolf and different dog breeds is discussed. Several transfer learning-based architectures are used in this work like VGG16, Inception-v3, ResNet50, DenseNet201, ResNet101, Xception and VGG19. A convolution neural network has also been created for this purpose and will be compared with transfer learning models or architectures. Since dataset contains multiple classes in output these model's accuracy in predicting correct class of the pet is calculated and analysed. 11 different classes of wolfs and dog breeds has been analysed only considering the system configuration limitations.

5.2 Hardware Configuration

Windows 10 processor of intel(R) Core(TM) i3-7020U 2.30GHz has been used . 64- bit operating system with 8GB RAM is installed in the system. For running code, python libraries are used in Google Colab. For storage and data repository Google Drive is used.

5.3 Implementation, Evaluation and Results of CNN

This project has created one CNN also which is multilayer perceptron's. CNN has been created using Sequential and used Maxpooling2D, Conv2D.CNN is an algorithm in which input image is assigned some weights to various portions of an image.

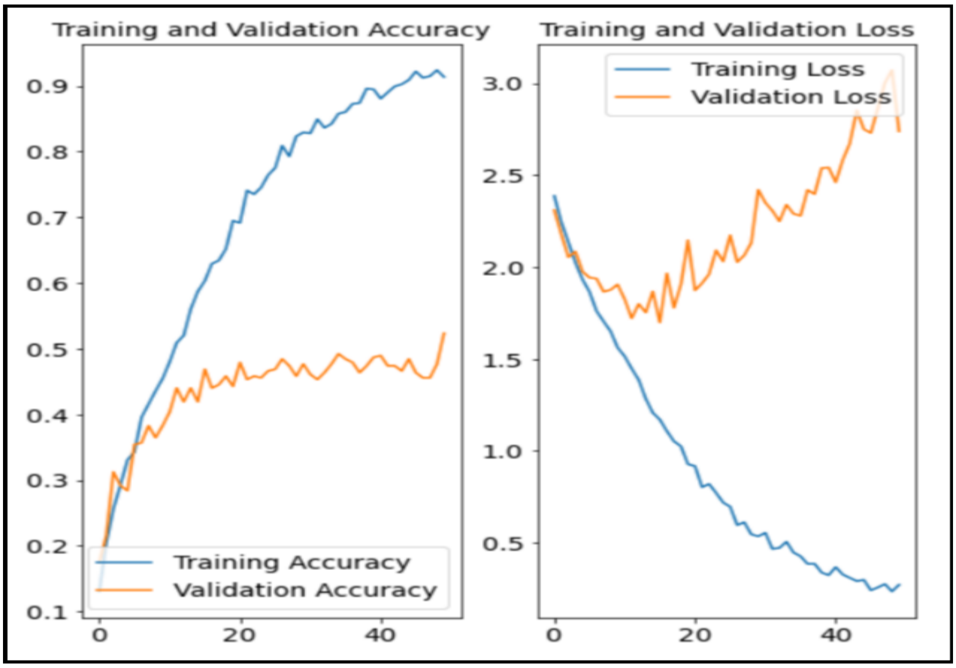

Figure 6: CNN's accuracy and loss at each epoch

After model fit is done training is completed and stored result in history is used for evaluating the model performance. Matplotlib library is used for calculating training and validation accuracy also training and validation loss has been calculated. Both accuracy and loss for training and validation at each epoch has been shown side by side in figure 6.

5.4 Implementation, Evaluation and Results of VGG16

VGG model is known for its simplicity, it uses 3*3 convolutional layers. Max pooling is used for reducing the volume. 4096 nodes are present in two convolutional layers which are connected finally with 'softmax' for final classification. Input image size is set to 224*224. All the layers are not trained so model.layers[0].trainable = False is set in the model while training.

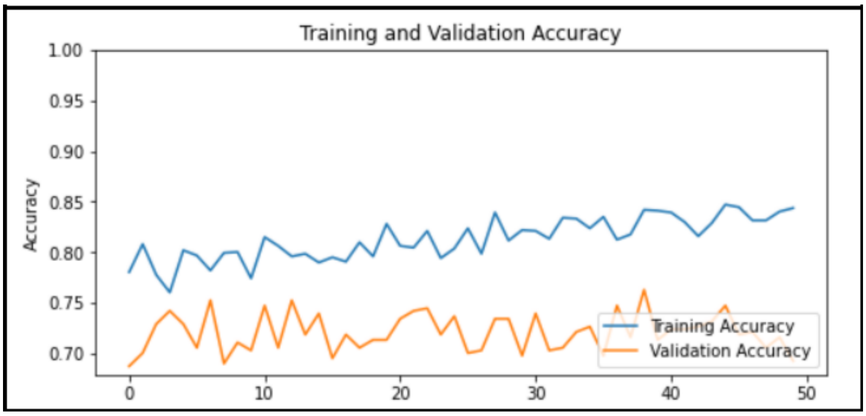

Figure 7: **Accuracy of VGG16 at each epoch**

After training is completed, accuracy has been calculated using Matplotlib library. VGG16 achieved 84.72% accuracy. 50 epochs were trained twice so total 100 epochs is used in training the model. Training and validation accuracy has been shown in figure 7.

Also using matplotlib library training and validation loss has been calculated and shown in figure 8.

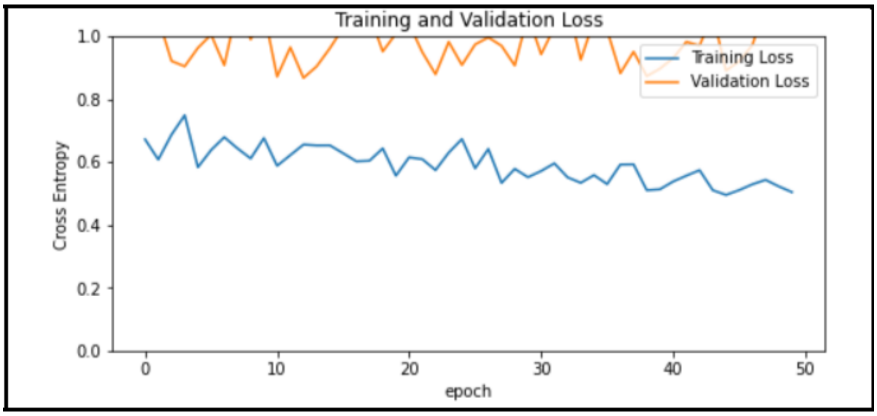

Figure 8: Loss of VGG16 at each epoch

5.5 Implementation, Evaluation and Results of ResNet101

ResNet101 is also one of the pretrained model which can classify many objects like animals. ResNet-101 contains 101 deep layers which helps to train the model in best possible way. It can learn many features from different kinds of images. Input size for image is 224*224. It uses global average pooling as compared to VGG models which uses fully connected nodes so size of model is small in ResNet.

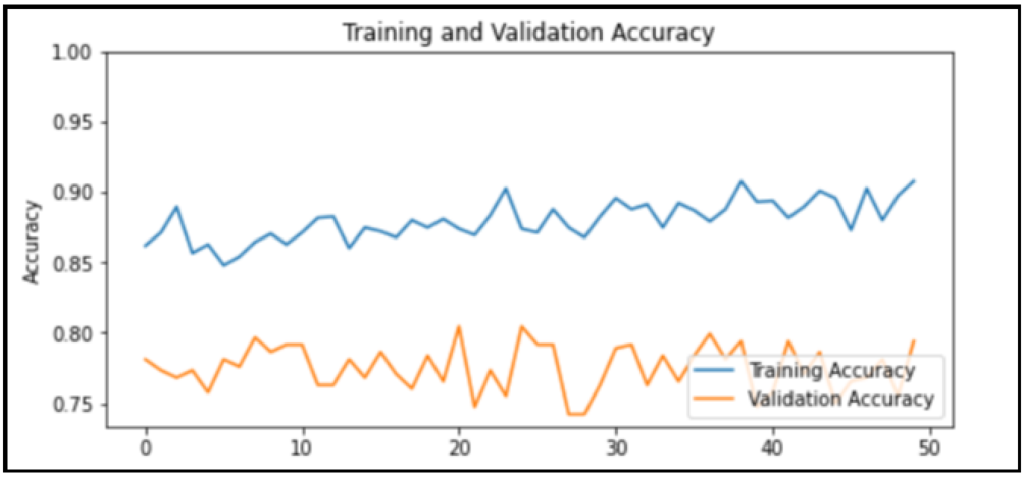

Figure 9: Accuracy of ResNet101 at each epoch

ResNet101 recorded good accuracy of 90.80% considering the new dataset with small training samples. Training and validation accuracy has been shown in figure 9.
Also training and validation loss has been calculated for knowing model's performance which is shown in figure 10.

Figure 10: Loss of ResNet101 at each epoch

5.6 Implementation, Evaluation and Results of VGG19

This is also a variant of VGG model in which 19 deep layers are present. Input images are fixed for 224*224 image size. It uses 3*3 convolutional layers on top of each other which makes it bigger network with more size. Even having bigger size VGG19 performs better and gave 84% accuracy. Total 100 epochs were used in training the model. Training and validation accuracy has been shown in figure 11.

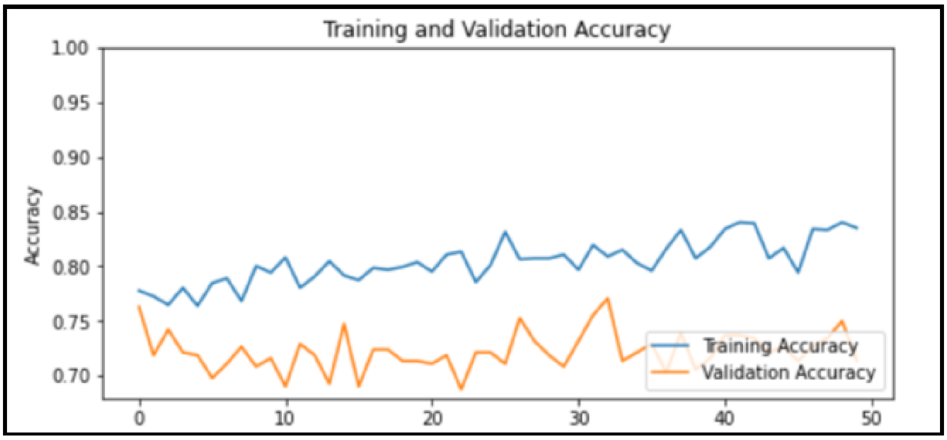

Figure 11: Accuracy of VGG19 at each epoch

Matplotlib is used for calculating training and validation loss which is shown in figure

Figure 12: Loss of VGG19 at each epoch

5.7 Implementation, Evaluation and Results of DenseNet201

DenseNet201 is a convolution network which accepts image input size of 224*224 and contains 201 deep layers. It can classify images in 1000 object categories. This is also one of the best performing model but for wolf and dog breed dataset it achieved only 65.80% accuracy and total 100 epochs is used for training the model as shown in figure 13. For training the model speedly model.layers[0].trainable = False is used while training the model.

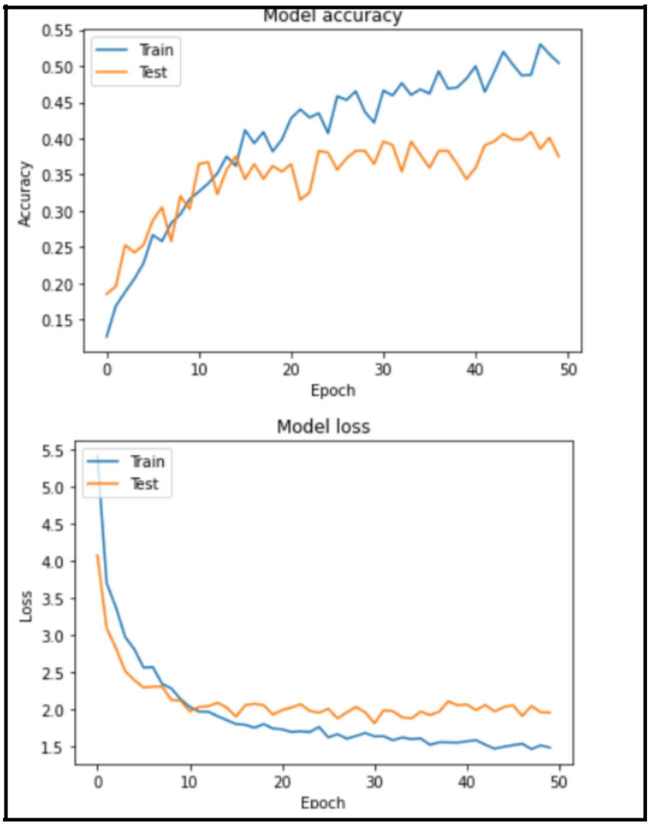

Figure 13: Accuracy and Loss of DenseNet201

5.8 Implementation, Evaluation and Results of Inception-v3

Inception-v3 or GoogLeNet contains 42 deep layers and is efficient than VGGNet models. Its computational cost is 2.5 higher than GoogLeNet. Input images are fixed for 299*299 image size while training the model. Model was trained for 50 epochs and 100 epochs, but maximum accuracy achieved after training the model was around 24%. This has been shown in figure14.

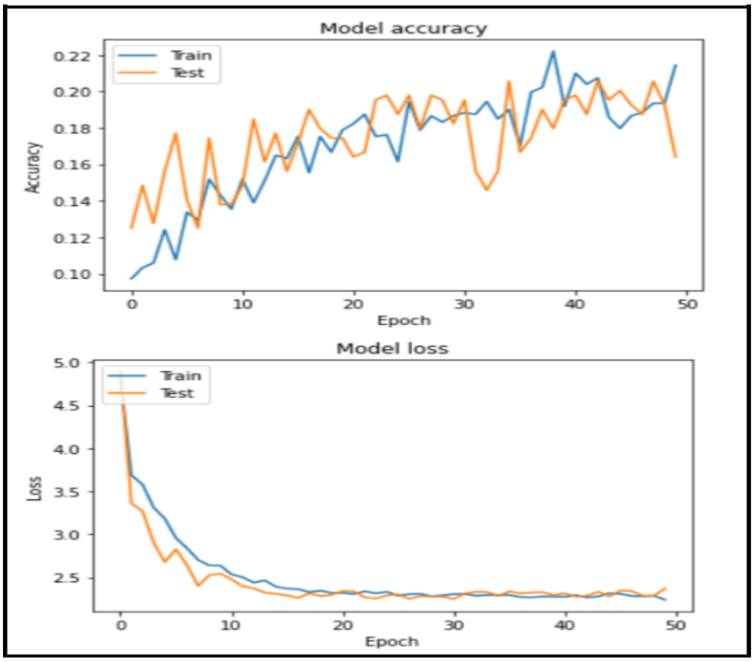

Figure 14: Accuracy and Loss of InceptionV3

5.9 Implementation, Evaluation and Results of InceptionResNetV2

InceptionResNetV2 is trained on Imagenet's million images. It can classify in 1000 categories with the help of 164 deep layers architecture. Images are fixed for 299*299 image size for training the model and model is run for 50 epochs and 100 epochs but it achieved only 15% accuracy. Accuracy and loss for inceptionResNetV2 is shown in figure15.

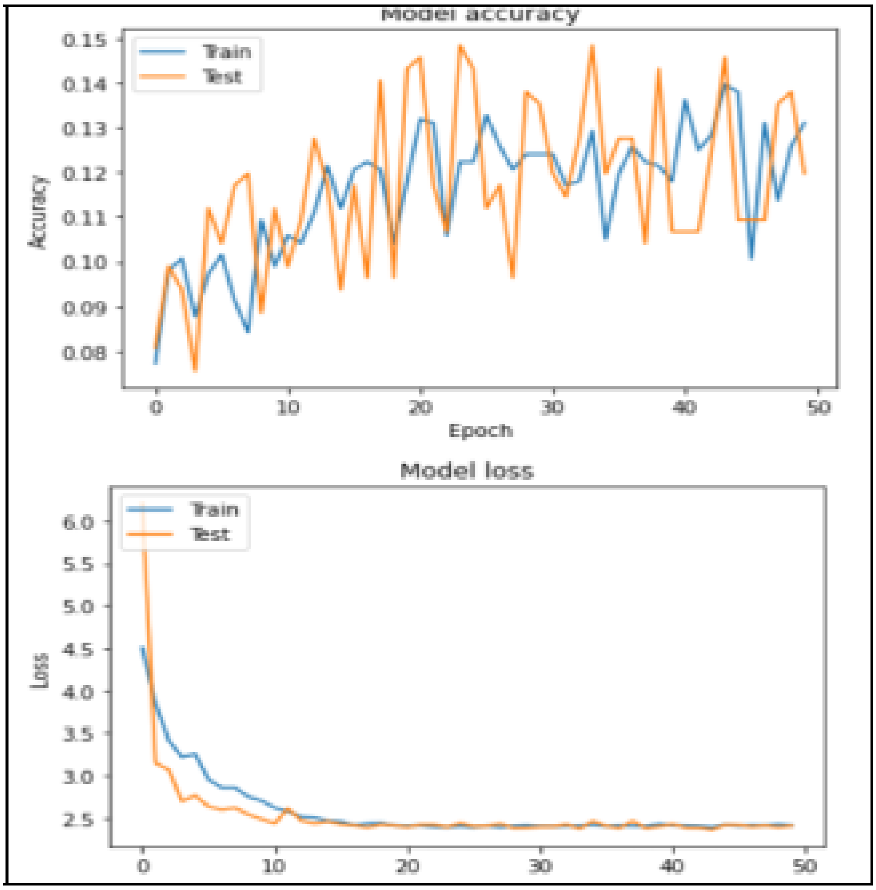

Figure 15: Accuracy and Loss of InceptionResNetV2

5.10 Conclusion

After all the models training is done it is clear that CNN model achieved highest classification accuracy of 92.48%. Few pretrained convolutional models performed good like ResNet101 with 90.80% accuracy and ResNet50 with 89.93% accuracy. VGG16 and VGG19 also performed good with 84.72% and 84% accuracy respectively considering less image data for training. Since image dataset created is new still models performed better.

Comparing with previous work of Rakesh Kumar et al. (2019) which achieved 90.26% with ResNet101 and Stanford dog dataset this work performed better and recorded 90.80% accuracy. All other works used different datasets and achieved different accuracies. This has been shown in Table 3.

Table 3: Comparison of work with state-of-the-art related work

Authors	Technique applied	Dataset(s)	Models applied	Results and Outcomes
Victor Capone et al. (2017)	Different CNN architectures	FlickrDog and DogsVsCats	VGG16 and Inception-v3	VGG16 performed better with 95% accuracy.
Chenghua Li et al.(2016)	CNN architecture	Clickture-Dog dataset	ensemble-CNN	89% accuracy
Kenneth Lai et al. (2019)	Transfer learning	Flick-Dog Dataset	Inception-v3 MobileNet VGG16 Xception	78.09 % Xception with Pugs and Husky combined
Rakesh Kumar et al. (2019)	Transfer learning	Stanford dog Dataset	ResNet101 ResNet50 InceptionResnetV2 InceptionV3	90.26% accuracy with ResNet101
Current work	CNN and different Transfer learning	new dataset (stanford dog + kaggle wolf images)	CNN ResNet101 ResNet50 VGG16 VGG19 DenseNet201 InceptionV3 InceptionResNetV2	CNN achieved 92.48 and ResNet101 achieved 90.80%

Objective 5 has been completed by implementing, evaluating and showing results. The research question (chapter1, section 1.1) has been solved.

6 Conclusion and Future Work

For detecting wolf and different dog breeds few pretrained convolutional networks has been used in the project like VGG16, VGG19, ResNet50, ResNet101, DenseNet201, InceptionV3 and InceptionResNetV2. One CNN has also been created for checking the accuracy of created network. Created CNN achieved 92.48% accuracy and it can achieve more if trained with more data images. ResNet101 and ResNet50 recorded 90.80% and 89.93% accuracy respectively which is decent with new image dataset created especially for wolf and dog breed identification. Also, VGG16 and VGG19 achieved 84.72% and 84% accuracy respectively. DenseNet201 recorded 65.80% but InceptionV3 and InceptionResNetV2 recorded relatively low accuracy. Basic idea for applying different transfer learning models is to learn about new dataset created. In future ensemble models can be applied which can boost the accuracy of wolf and dog breed dataset. Combining two best models can improve the efficiency of the model created. As a future work, this work can be commercialised so a web application can be created which can help many people like providing security to rescue teams and will also help pets to reunite with their real owners.

Since we had limited computing capacity and more GPU and TPU are required for more accurately classifying the wolf and dog breed with high accuracy. Firstly we tried to train models on 10000 images but google colab and Jupiter notebook didn’t support such no. of images then we tried to train our models on 5000 images then again repeated session out errors and regularly models were not processed properly. Finally, we took 10 classes of dog breeds and wolf images around 2000 in total images and started training our model. Also, due to combining wolf images with Imagenet dog breed image dataset, accuracy could not reach as expected. In future work, researchers can ensemble different models which can hopefully get better classification accuracy. Training dataset images per class can be increased for better accuracy. Since our image classification was multi class categorisation we need to make sure about pixels and other image qualities of training dataset. Since we are passing knowledge to new dataset i.e. wolf and Stanford dog breed (new dataset) and all transfer learning models were built in advance, we need to apply more datasets for training the models. Also, more robust powerful computers can be used in which NVIDIA graphics and more GPU's and TPU's are present. Objective 6 has not been achieved due to limited time which can be taken as future work.

References

A. Khosla, N. Jayadevaprakash, B. Yao, F.-F. Li (2011). Novel dataset for fine-grained image categorization: Stanford dogs, *IEEE Conference on Computer Vision and Pattern Recognition*

A. Krizhevsky, I. Sutskever and G. E. Hinton (2012). Imagenet classification with deep convolutional neural networks, *Advances in neural information processing systems*

A. A. Hammam, M. M. Soliman, A. E. Hassanein (2018). DeepPet: A Pet Animal Tracking System in Internet of Things using Deep Neural Networks, *2018 13th International Conference on Computer Engineering and Systems (ICCES)*

B. Yao, G. Bradski, and L. Fei-Fei (2012). A codebook-free and annotationfree approach for fine-grained image categorization, *IEEE Conference on Computer Vision and Pattern Recognition*

C. Li, Q. Song, Y. Wang, H. Song2, Qi Kang, Jian Cheng, H. Lu (2016). LEARNING TO RECOGNITION FROM BINGCLICKTURE DATA, *IEEE International Conference on Multimedia and Expo Workshops (ICMEW)*

C. Szegedy, W. Liu, Y. Jia, P. Sermanet, Scott Reed et al. (2015). GoingDeeperwithConvolutions , *Computer Vision Foundation*

J. Ouyang, H. He, Yi He, H. Tang (2019). Dog recognition in public places based on convolutional neural network-*International Journal of Distributed Sensor Networks*

J. Monteiro, J. P. Aires, R. Granada, R. C. Barros, and F. Meneguzzi (2017). Virtual Guide Dog: An Application to Support Visually-Impaired People through Deep Convolutional Neural Networks, *International Joint Conference on Neural Networks (IJCNN)*

J. H. Bappy and A. K. Roy-Chowdhury (2016). CNN based region proposals for efficient object detection, *IEEE International Conference*

K. Lai, X. Tu, S. Yanushkevich (2019). Dog Identification using Soft Biometrics and Neural Networks, *International Joint Conference on Neural Networks (IJCNN)*

O. M. Parkhi, A. Vedaldi, A. Zisserman, and C. Jawahar (2012). Cats and dogs, *IEEE Conference on Computer Vision and Pattern Recognition*

R. Kumar, M. Sharma, K. Dhawale, G. Singal (2019). Identification of Dog Breeds Using Deep Learning, *IEEE 9th International Conference on Advanced Computing (IACC)*

R. O. Sinnott, Fang Wu, Wenbin Chen (2018). A Mobile Application for Dog Breed Detection and Recognition Based on Deep Learning, *2018 IEEE/ACM 5th International Conference on Big Data Computing Applications and Technologies (BDCAT)*

Si-Wei Chen, Member, IEEE, and Chen-Song Tao (2018). PolSAR Image Classification Using PolarimetricFeature-Driven Deep Convolutional Neural Network, *IEEE GEOSCIENCE AND REMOTE SENSING LETTERS*

S. Kumar and S. K. Singh (2014). Biometric recognition for pet animal", *Journal of Software Engineering and Applications*

T. P. Moreira·, M. L. Perez, R. de Oliveira W. E. Valle (2015). *Multimedia Tools and Applications*

V. Capone, C. Figueiredo, E. Valle, F. Andaló (2017) CrowdPet: Deep learning applied to the detection of dogs in the wild, *XXV Congresso de Iniciação Científica da UNICAMP*

W. Li, Member, IEEE, G. Wu, Student Member, IEEE, F. Zhang, Member, IEEE, and Q. D. Senior Member, IEE (2017). Hyperspectral Image Classification Using Deep Pixel-Pair Features, *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*

X. Wang, V. Ly, S. Sorensen, C. Kambhamettu (2014). Dog breed classification via landmarks, *IEEE International Conference on Image Processing (ICIP)*

Y. Iwashita, A. Takamine, R. Kurazume, and M. S. Ryoo (2014). First-person animal activity recognition from egocentric videos, *International Conference on Pattern Recognition (ICPR)*