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Cat Breed Recognition using Deep Learning and Xception Model to Improve the Accuracy

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ABSTRACT: Cats, a popular choice for pets, present challenges in their maintenance due to the unique characteristics of different cat breeds. This study aimed to identify cat breeds to assist in determining the appropriate breed for a particular cat. The research utilized transfer learning on the Pre-Trained Convolutional Neural Network Xception, which is inspired by the Inception CNN Model. The Xception model, a modified version of the Inception model using depthwise separable convolutions, was employed to enhance the accuracy of cat breed detection. The test results on the Oxford-IIIT Pet Dataset achieved an accuracy of 88.25%. Compared to the SSD Mobilenet_v1 FPN method with an accuracy of 81.74%, implementing the Xception method resulted in a 6.51% accuracy improvement.

KEYWORDS: Cat breed, Deep learning, Xception model

I. INTRODUCTION

Among the various types of pets available, cats are highly favored by humans [6]. However, keeping a pet cat is no simple task. According to Rahmiati and Pribadi [8], responsible preparation is crucial in raising animals, as it involves more than just providing a home for them; pet owners must also prioritize the welfare of their animals. A good understanding of pets is essential to ensure their well-being. In the case of cats, there is a wide range of knowledge to consider, including different cat breeds, their morphological characteristics, fur patterns, colors, and more. Each cat breed has its unique morphological features, which means that the care and upbringing required for each breed can vary significantly. Nevertheless, identifying different cat breeds can prove to be a challenging task. Therefore we need a system that can identify the type of cat race. Several researchers have conducted research on the detection of cat breeds, but the final results of these studies did not produce high accuracy. This is because there are several cat breeds that have minimal differences from one another, so it is very difficult to tell them apart [11]. The same thing was also conveyed by Mariani [4], that some cat breeds have many variations of patterns and colors, so they sometimes fail to be classified correctly. For example, based on information from Thornton [10], Ragdoll cats have 4 variations of fur patterns and 6 variations of colors. This makes it very difficult to extract unique traits from Ragdoll Cats.

The difference between this research and the research conducted by Mariani [5] are the CNN model and the dataset that will be used. which is Xception for the CNN Model and the dataset will be taken from the Kaggle website. There are also differences that exist from the research conducted by Pangestu and Bunyamin [7]. The first difference is in the dataset used, where the research conducted by Pangestu and Bunyamin [7] used a dataset of dogs and in this study will be using a dataset of images of cats. Another difference is that in this study, there is an additional preprocessing stage in the form of image grayscaling. The addition of this step was carried out because, based on information from research by Mariani [5] and research by Zhang et. al. [11], variations in color play a major role in reducing the accuracy of detecting cat breeds. According to Patricia Jacobberger [3], an article writer on the website of The Cat Fanciers' Association (CFA), pattern, color, and length of hair are not determinants of cat breeds. Therefore, by doing grayscaling, the system can focus more on the facial features and patterns of cats, which is expected to increase the accuracy of the system. In addition, research conducted by Pangestu and Bunyamin [7] tested the system by manually inputting images, this caused the images used for testing to be very limited and required a long time. In this study, the Confusion Matrix will be used in the testing phase.

The advantage of the proposed method, namely the Xception model, from other CNN models is that the Xception Model consists of separable depthwise convolutional layers and is also equipped with residual connections. This makes Model Xception very easy to define and modify. With 30 to 40 lines of code and a high-level library like Keras or Tensorflow-Slim, the Xception Model can already run well. With these advantages, the Cost of the Xception Model is

relatively cheaper than some other models that have high complexity, such as Inception V2 or V3 [1]. The contribution of this research is the use of the Convolutional Neural Network method with Pre-Trained Model Xception which will be used to increase accuracy, which is a problem in several previous studies, in identifying cat breeds.

II. RELATED WORK

Numerous studies have focused on cat breed recognition, employing diverse methodologies, with a primary emphasis on deep learning techniques. For instance, Wang et al. [13] utilized fine-tuned pre-trained models from Keras applications, such as ResNet-152 v2, Inception-ResNet v2, and Xception. They trained these models on image datasets sourced from ImageNet, enabling them to accurately predict 21 classes of dogs and cats. Their research demonstrated that the Xception model achieved the highest prediction accuracy, with a training accuracy of 99.49% in 14 hours. Cui et al. [14] classified dog breeds using a convolutional neural network and support vector machine. They used the Stanford Dog Dataset, combined with features from four CNN models filtered with principal component analysis (PCA) and the gray wolf optimization algorithm (GWO), which were then classified using support vector machine (SVM). The accuracy obtained was 95.24% out of 120 breeds and 99.34% when using 76 selected breeds. Karlita et al. [15] conducted research to recognize and classify cats using Convolutional Neural Networks (CNN). The dataset contained nine different cat breeds with 2,700 images. The experimental results achieved a maximum classification accuracy of 95% for cat breed images. In their research, Lo et al. [16] employed a deep Convolutional Neural Network (CNN) utilizing the Xception model to classify malware images. Their experiments involved two datasets, namely Maling and Microsoft Malware Dataset, and the results demonstrated that the Xception model achieved the highest training accuracy compared to all other methods, including the VGG16 model used for image-based malware classification. Furthermore, the Xception model also exhibited a faster processing time during the classification process. Trnovszky et al. [17] used Convolutional Neural Networks (CNN) for animal image classification in their paper. This method was compared with well-known image recognition methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Local Binary Pattern Histogram (LBPH), and Support Vector Machine (SVM). For the experiment, a wild animal dataset was created consisting of 500 different subjects (5 classes/100 images per class) and showed that the proposed method had higher performance for overall animal recognition and outperformed the other compared methods. Badre et al. [18] investigated gathering data on wild animals around forests, including cats, automatically using deep neural networks. The hope was that this automated method could reduce costs compared to manual gathering. Zhang [19] compared the performance of several deep learning algorithms, namely VGGNet, Inception-v3, and deep learning algorithms that had been optimized for cat breed recognition. From the experimental results, the accuracy of the optimized algorithm reached 84%, which was higher than the other models.

Dai et al. [20] proposed an improvement to the Mask R-CNN algorithm for cat recognition and segmentation, as the original Mask R-CNN algorithm had low accuracy. They added feature extraction to provide more comprehensive feature information and reduce training time. The experimental results showed that the segmentation detection accuracy using their method reached 87.54% for the dog and cat dataset from Kaggle. Liu et al. [21] developed an algorithm for classifying dog and cat images from the Kaggle dataset. They used two approaches. In the first approach, they employed a traditional pattern recognition model by extracting handcrafted features such as color and Dense-SIFT, representing images using the bag-of-words model, and then training a Support Vector Machine (SVM) classifier. They achieved the best accuracy of 94.00%. In their paper, Mahardi et al. [22] classified images of various breeds of dogs and cats (CDC) using two VGG models, VGG16 and VGG19, to create a classifier. The model produced by VGG16 had a training accuracy of 98.47%, validation accuracy of 98.56%, and testing accuracy of 83.68%. The model from VGG19 had a training accuracy of 98.59%, validation accuracy of 98.56%, and testing accuracy of 84.07%. Parkhi et al. [23] investigated the Oxford-IIIT-Pet animal dataset, which includes 37 dog and cat breeds, where the dataset's cat content was particularly different in shape, and the differences between breeds were very slight. The developed models were able to outperform the published results on the ASIRRA test. When applied to the discrimination test of 37 different pet animal breeds, the models achieved an average accuracy of around 59%, which was quite good given the difficulty of the problem.

Zhou et al. [24] developed a web application aimed at detecting feral cats in Australia, utilizing deep learning algorithms with data gathered from a network of remote sensing cameras. Identifying feral cats presents a significant challenge due to their striking similarity. To address this issue, the researchers trained four neural network models to differentiate among 75 classes, each containing 30 to 80 images. The selected model was Mask R-CNN, which made use of pre-trained ImageNet, along with the ResNet-50 network. By employing cat images captured in five different

forests across Victoria, they achieved an average accuracy of 89.4% in individual (distinct) cat identification, with the highest accuracy reaching 96.3%.

III. METHODOLOGY

The cat breed detection system that will be developed consists of 7 processes. Since the target problem of this research is quite similar to the target problem of the Xception model, and transfer learning has proven to be effective when there is similarity between the problems [9],[12], the transfer learning method will also be used in this system. As shown in Figure 1, the processes include dataset input, pre-processing and the Xception model without the top layer and freezing other layers, creating the output/dense layer with the softmax activation function, data training, data testing on the trained model, and evaluating the results using the confusion matrix and classification report.

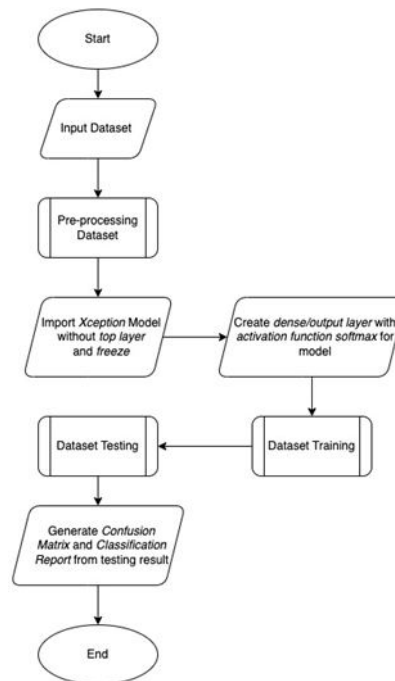


Fig. 1. Outline Process

The data pre-processing stage begins with receiving the input dataset. Next, the cat images in the dataset are resized. Image resizing involves changing the dimensions of the images to the required dimensions. In this case, the images from the dataset are resized to 299 x 299. After resizing, a segmentation process is applied to the images to separate the objects from the background. Once the segmentation process is complete, the images that have been separated from their background are converted to grayscale, resulting in a black and white color space.

After the data pre-processing stage, the pre-processed data is used to train the Xception deep learning model without its top layer (classification layer). The training in this research utilizes supervised learning, where the true class of the data is known [2]. An additional layer is added to the Xception model to replace the missing top layer. The added layer is determined based on the results of training performed on the pre-processed data. Once the model has been successfully trained using the cat breed image dataset, testing is performed on the trained model. The testing process utilizes a dataset obtained from www.kaggle.com, titled "Cat and Dogs Breeds Classification Oxford Dataset," which includes 14 types of cat breeds with approximately 200 images for each breed. The testing process generates four types of data: true positive, false positive, true negative and false negative. False positive data represents data that is incorrectly detected by the model as positive when it should be negative (a false match). True positive data represents data that is correctly detected as positive and is indeed positive (a true match). False negative data represents data that is incorrectly detected as negative when it is actually positive (a missed match). True negative data represents data that is correctly detected as

negative and is indeed negative (a correct rejection). Following the testing, the model is evaluated using a confusion matrix to determine accuracy, recall, and precision values [5].

IV. EXPERIMENTAL RESULTS

Pre-processing Dataset

Testing will be carried out with several types of datasets, which are the Cat Breeds Dataset with a total of 67 classes and a total of 93,911 images, a custom dataset with a total of 56 classes and a total of 8,392 images, The Oxford-IIIT Pet Dataset with a total of 12 classes and a total of 2,398 images. In testing, the parameters used were 10 epochs (5 pretrain epochs and 5 fine-tuning epochs), batch size 8, activation function Softmax, learning rate 0.001 for pretrain, and learning rate 0.0001 for fine-tuning. The number of tests to be carried out is 11 tests. The 1st Test will be using Cat Breeds Dataset with 67 classes from kaggle.com, and before using it to train the model, it will be resized to 299x299 and grayscaled. The 2nd Test will be using The Oxford-IIIT Pet Dataset with 12 classes from kaggle.com, and it will also be resized to 299x299 and grayscaled. The 3rd Test will be using a custom dataset with 56 classes and its images will be resized to 299x299 and grayscaled. The 4th Test will also be using a custom dataset, but only with 12 classes and its images will be resized to 299x299 and grayscaled. The 5th Test will be using Cat Breed Dataset from kaggle.com but only using 12 classes from 67 classes and images in those 12 classes will be resized to 299x299 and grayscaled. The 6th Test will be using a custom dataset but only 12 classes of 56 classes that will be used and its images will be resized to 299x299 and instead using grayscale colorspace, in this test will be using RGB colorspace. The 7th Test will be using The Oxford-IIIT Pet Dataset with 12 classes and its images will be resized to 299x299 and will be using RGB colorspace. For the 8th Test and 9th Test, earlier custom dataset will be used with resizing step to 299x299, grayscale colorspace for 8th Test and RGB colorspace for 9th Test, and image segmentation process for both Test. For 10th Test and 11th Test, will be using The Oxford-IIIT Pet Dataset for the 10th and the earlier custom dataset for the 11th, RGB colorspace and image squaring will be implemented for both of tests.

Test 1

Initially, the first test was conducted using the Cat Breeds Dataset, which consists of 67 classes and a total of 93,911 images. The obtained accuracy for this test was 68.67% for training accuracy and 41.05% for testing/validation accuracy. The result of Test 1 can be seen in Figure 2.

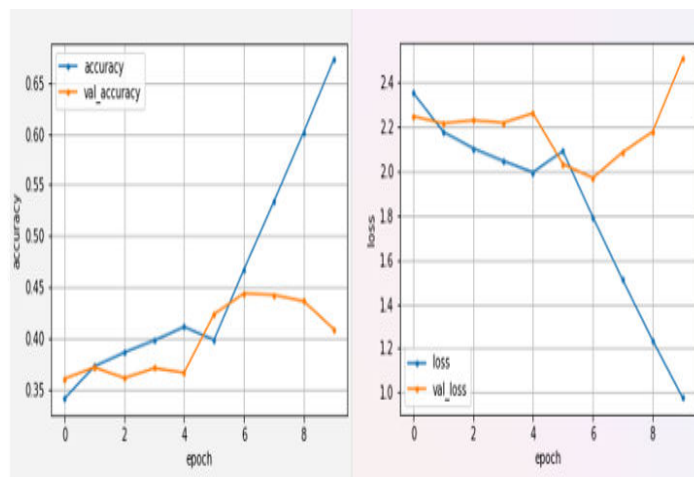


Fig. 2. Accuracy and Loss Values for Test 1

The low accuracy observed in Test 1 can be attributed to the disorganized nature of the dataset. Some classes had different names but were actually duplicates of other classes, and many images did not match their respective class.

Test 2

Following Test 1, Test 2 was performed using the Oxford-IIIT Pet Dataset, which includes 12 classes and a total of 2,398 images. This test aimed to examine the relationship between image quality and accuracy. Test 2 achieved an accuracy of 98.12% for training accuracy and 87.14% for testing accuracy. The result of Test 2 can be seen in Figure 3.

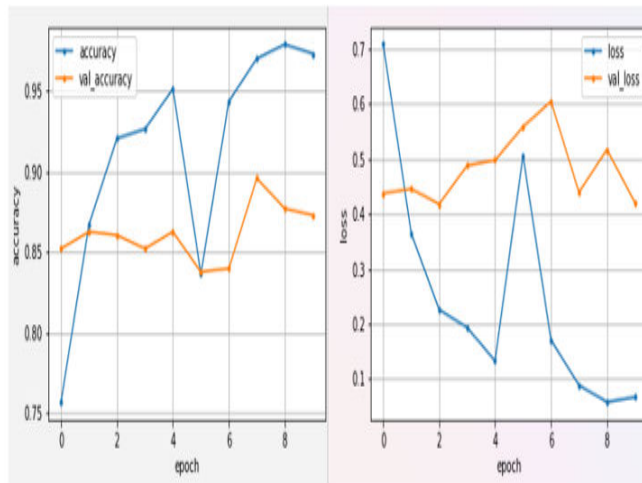


Fig 3. Accuracy and Loss Values for Test 2

Testing with the validated Oxford-IIIT Pet Dataset resulted in significantly improved training and testing accuracy compared to Test 1.

Test 3

Subsequently, Test 3 was conducted using a Custom Dataset, consisting of 56 classes and a total of 8,392 carefully selected images. These images were chosen to ensure clear depiction of the cat's face and accurate mapping of cat breeds to their respective classes, while removing classes with duplicate names. This optimization was performed to evaluate the model's performance using higher-quality datasets. The accuracy obtained using this Custom Dataset was 94.22% for training accuracy and 54.11% for testing accuracy. The result of Test 3 can be seen in Figure 4.

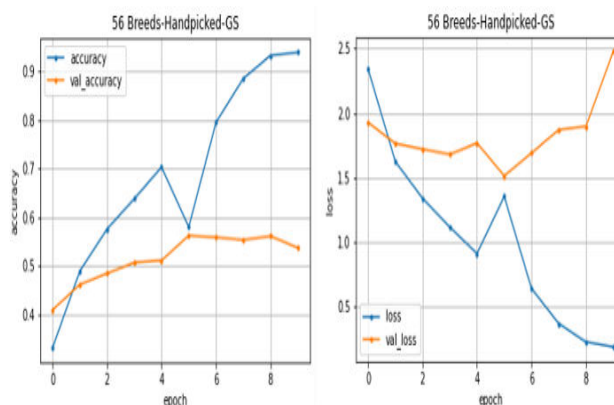


Fig. 4. Accuracy and Loss Values for Test 3

A significant improvement in training accuracy and testing/validation accuracy was observed due to the higher quality of the dataset used in Test 3. However, the issue of overfitting persisted, as the model still struggled to perform well on new and unseen data.

Test 4

To investigate the cause of overfitting in Test 3, Test 4 was conducted using the Custom Dataset but with only 12 classes. These 12 classes were selected to match those used in Test 2, including Abyssinian, Bengal, Birman, Bombay, British Shorthair, Egyptian Mau, Maine Coon, ersian, Ragdoll, Russian Blue, Siamese, and Sphynx. Test 4 achieved an accuracy of 98.02% for training accuracy and 92.68% for testing/validation accuracy. The result of Test 4 can be seen in Figure 5.

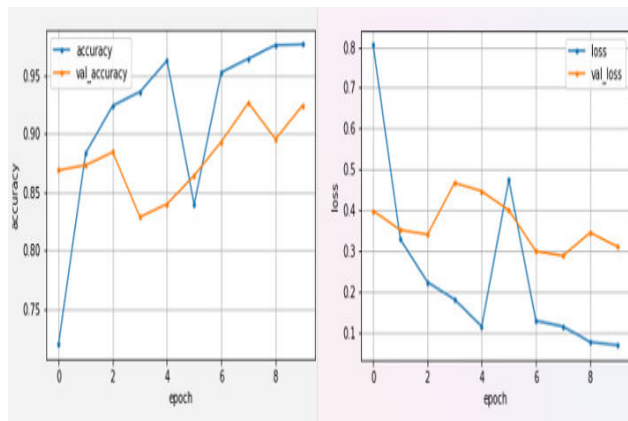


Fig 5. Accuracy and Loss Values for Test 4

In Test 4, the testing/validation accuracy showed a notable improvement compared to Test 3. This improvement can be attributed to selecting classes that have significant differences, thus reducing confusion during testing/validation. Apart from British Shorthair and Chartreux, which have minimal differences, several other classes also exhibited minimal dissimilarities. This was the primary cause of overfitting in Test 3. The classes used in Test 4 were carefully chosen to ensure distinct differences, resulting in reduced overfitting.

Test 5

To further support the results of Test 4, Test 5 was conducted using the Cat Breeds Dataset but with only 12 classes and a total of 18,576 images. The accuracy obtained in this test was 94.95% for training accuracy and 79.98% for testing/validation accuracy. The result of Test 5 can be seen in Figure 6.

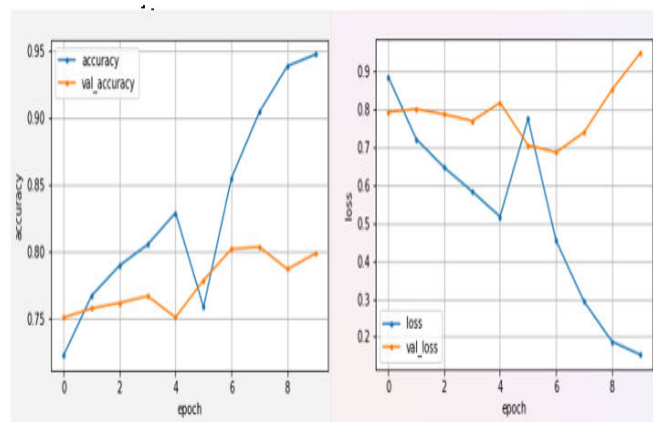


Fig 6. Accuracy and Loss Values for Test 5

Compared to Test 1, Test 5 exhibited a significant improvement in both training accuracy and testing/validation accuracy. Overfitting in the model was also mitigated.

Test 6

Following Test 5, Test 6 was performed as a variation test using the Custom Dataset with 12 classes, but without the preprocessing step of grayscale conversion. Instead, the data was trained and tested using the RGB color space. This test aimed to compare the performance of the model when trained and tested using RGB color space versus grayscale color space. Test 6 achieved an accuracy of 98.65% for training accuracy and 93.27% for testing accuracy. The result of Test 6 can be seen in Figure 7.

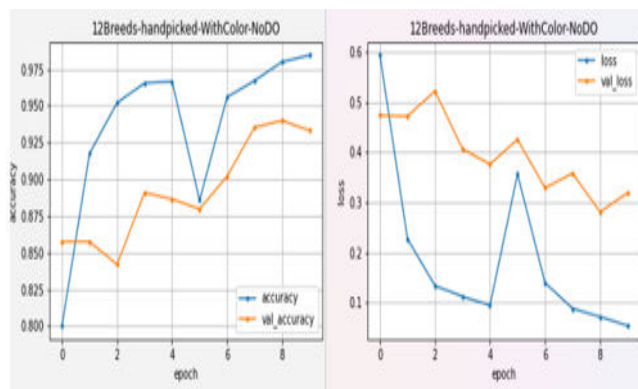


Fig 7. Accuracy and Loss Values for Test 6

The results of Test 6 showed higher training accuracy and testing/validation accuracy compared to Test 5, which used the same dataset but included the grayscale preprocessing step. This indicates that utilizing the RGB color space provides more information during the training process, resulting in improved accuracy compared to using grayscale color space.

Test 7

To further support the findings of Test 6, Test 7 was conducted using the Oxford-IIIT Pet Dataset with 12 classes. This test employed the RGB color space for both training and testing/validation processes. The accuracy obtained in Test 7 was 98.87% for training accuracy and 88.25% for testing/validation accuracy. The result of Test 7 can be seen in Figure 8.

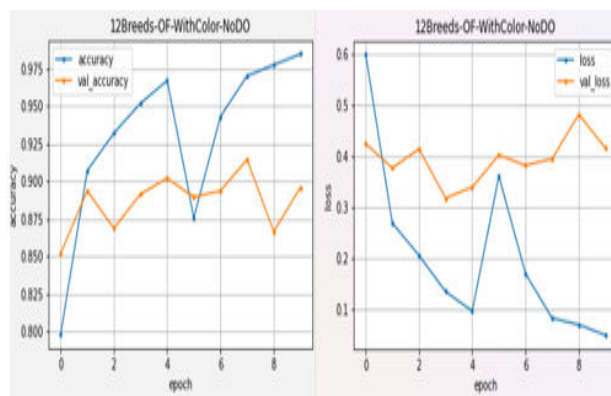


Fig 8. Accuracy and Loss Values for Test 7

Comparing the training accuracy and testing/validation accuracy of Test 7 with Test 2 (which achieved 98.12% for training accuracy and 87.14% for testing accuracy), it can be observed that using RGB color space during training and testing/validation led to higher accuracy compared to grayscale color space. RGB color space provides more information to the model, resulting in improved accuracy during training and testing/validation.

Test 8

Test 8 was then conducted using the Custom Dataset with 12 classes but with an additional image segmentation preprocessing step. Image segmentation involves separating objects in an image from the background. This test aimed to evaluate the model's performance when trained on data free from background noise. Test 8 achieved an accuracy of 98.11% for training accuracy and 85.94% for testing accuracy. The result of Test 8 can be seen in Figure 9.

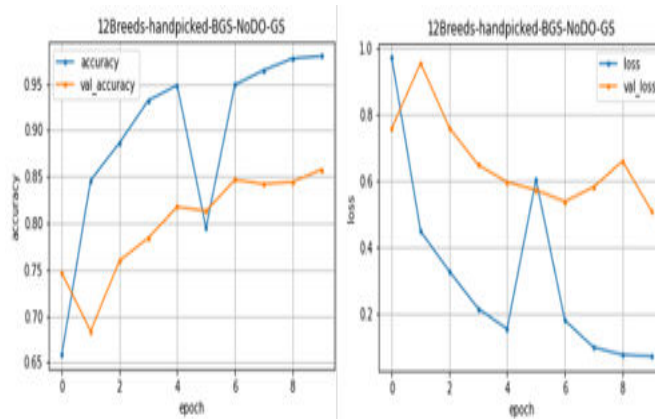


Fig 9. Accuracy and Loss Values for Test 8

Compared to Test 4, which used the same dataset and parameters but did not include image segmentation, the testing/validation accuracy in Test 8 was slightly lower (92.68% for Test 4 and 85.94% for Test 8). This discrepancy can be attributed to imperfect image segmentation in some cases, which affected the testing/validation accuracy.

Test 9

To further support the results of Test 8, Test 9 was conducted using the Custom Dataset with RGB color space preprocessing and image segmentation. The accuracy obtained in this test was 98.21% for training accuracy and 84.89% for testing accuracy. The result of Test 9 can be seen in Figure 10.

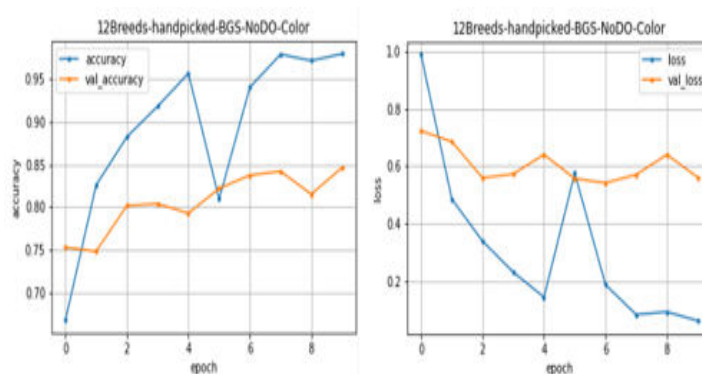


Fig 10. Accuracy and Loss Values for Test 9

Comparing the accuracy results of Test 9 with Test 6 (which used the same dataset and RGB color space but without image segmentation, achieving 98.65% for training accuracy and 93.27% for testing/validation accuracy), it can be observed that training and testing/validation without image segmentation yielded better performance. Among all the tests conducted, Test 6 achieved the highest accuracy, with training accuracy of 98.65% and testing/validation accuracy of 93.27%.

Test 10 and Test 11

After Test 9, Test 10 and Test 11 were carried out. In these final two experiments, the preprocessing steps included image squaring, resizing, and RGB color space conversion. Image squaring involves transforming rectangular image datasets into a square shape without distorting the image ratio. Test 10 and Test 11 aimed to evaluate the model's performance when using image squaring and compare it to tests that did not include this step. Test 10 used the Oxford-IIIT Pet Dataset with 12 classes and achieved an accuracy of 98.79% for training accuracy and 88.98% for testing accuracy. Comparing these results with Test 7, which used the same dataset and process but without image squaring, the accuracy values were 98.87% for training accuracy and 88.25% for testing/validation accuracy. The result of Test 10 can be seen in Figure 11 and the result of Test 11 can be seen in Figure 12.

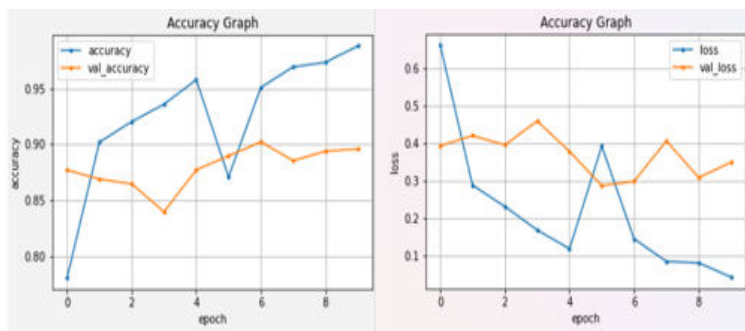


Fig 11. Accuracy and Loss Values for Test 10

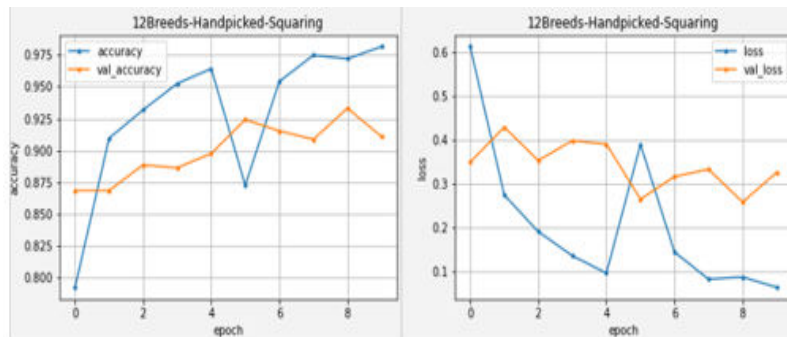


Fig 12. Accuracy and Loss Values for Test 11

Test 10 demonstrated that the use of image squaring had only a slight impact on accuracy compared to the direct resizing step on the image. To further validate the results of Test 10, Test 11 was conducted using the same preprocessing steps but with a different dataset. Test 11 achieved an accuracy of 98.09% for training accuracy and 91.25% for testing/validation accuracy. Comparing these results with Test 6, which used the same preprocessing steps but a different dataset, the training accuracy was 98.65% and the testing/validation accuracy was 93.27%. The accuracy values between the two experiments exhibited minimal differences.

V. CONCLUSION

After conducting the tests, the first research problem addressed in this study has been answered in Test 7. The Oxford-IIIT Pet Dataset was utilized, and an accuracy of 88.25% was achieved. This accuracy surpasses the results of Zhang et al.'s study, which utilized the SSD Mobilenet_v1 FPN average method and achieved an accuracy of 81.74%. By employing the Xception method, an additional 6.51% accuracy was attained.

In Test 1, the Cat Breeds Dataset, which is a low-quality raw dataset, was used, and an accuracy of 41.05% was obtained. This low accuracy was caused by the dataset itself, which data was raw and unfiltered. Test 6, which used

much better dataset, resulted an accuracy of 93.27%. This test highlights the impact of using RGB colorspace, a high-quality dataset, and significant differences between dataset classes, which collectively contribute to improved accuracy. Additionally, Test 6 outperformed Test 4, which used the same dataset and parameters but employed grayscale colorspace. This comparison demonstrates that grayscale colorspace during training is inferior in terms of accuracy compared to RGB colorspace. In conclusion, the findings suggest that utilizing the Xception method, RGB colorspace, and high-quality datasets with distinct class differences can significantly enhance accuracy in image classification tasks. Moreover, the results emphasize the importance of selecting appropriate colorspace during training, with RGB colorspace proving to be superior to grayscale colorspace in achieving higher model accuracy.

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