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UTILIZING DEEP LEARNING AND DATA AUGMENTATION FOR EARLY DETECTION OF EYE DISEASES IN PETS

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ABSTRACT: This paper presents a deep learning algorithm for the diagnosis of eye diseases, which is taken from cats and dogs, using data augmentation. The database of eye images was collected from cell phone cameras, and with data augmentation techniques were used to increase the number of samples. The performance of the algorithms was evaluated on the original dataset of 146 diseased and 255 healthy images. The results showed that the VGG16 algorithm achieved a classification accuracy of 99.25% before data augmentation, which was significantly higher than the accuracy of existing methods. Furthermore, after the data augmentation again VGG16 model has significant performance metrics that are 99.9% than other algorithms. The proposed algorithm can be used to accurately diagnose various eye diseases, which can potentially improve the quality of care for patients.

Keywords: Classification, Eye disease, Deep Learning, Data augmentation.

1. INTRODUCTION

Deep learning is a type of artificial intelligence that involves the use of neural networks to learn from and make predictions about data. It is a subset of machine learning and is based on the idea of artificial neural networks, which are modeled after the neurons and synapses of the human brain. Deep learning algorithms are used in various areas, including computer vision, natural language processing, voice recognition, and robotics. Deep learning algorithms are designed to learn from large amounts of data, and can be used to identify patterns and make predictions. For example, deep learning algorithms can be used to identify objects in images, recognize spoken words, and even control robots.

Deep learning is also used to improve the accuracy and speed of other machine learning algorithms, such as those used in computer vision and natural language processing. Deep learning algorithms use layers of neurons to process data. Each layer of neurons is connected to the next layer and learns from the data that it receives. As the data passes through each layer, the neurons are adjusted so that the deeper layers learn more complex features of the data. This allows the algorithm to learn more complex patterns and make better predictions. Deep learning algorithms have been used in many applications, such as recognizing images, understanding natural language, and controlling robots. Deep learning algorithms are becoming increasingly powerful and are able to learn from large amounts of data quickly and accurately, making them an ideal tool for many applications.

Eye diseases, which are frequently seen in cats and dogs, are an alarming and early diagnosis is an extremely important issue. Animals can suffer from a variety of eye diseases, ranging from minor irritations to life-threatening conditions. The most common cause of eye diseases in animals is trauma. Injuries, such as scratches, bruises, or foreign objects in the eye, can lead to infection or other complications. In addition, there are numerous infectious diseases of the eye, such as conjunctivitis, that can be passed between animals. Allergies, genetic conditions, and exposure to toxins can also lead to eye problems.

When it comes to eye diseases in cats and dogs, there are a few potential issues that pet owners should be aware of to help keep their pets healthy. Cats are more prone to feline herpesvirus-1 (FHV-1) and feline calicivirus (FCV). FHV-1 is a viral infection that can cause severe inflammation and ulceration of the cornea. FCV is a highly contagious virus that causes inflammation of the conjunctiva and cornea, which can lead to ulceration. Both FHV-1 and FCV can cause blindness if left untreated. Dogs, on the other hand, can be affected by a variety of eye conditions, including glaucoma, dry eye, and cataracts. Glaucoma is a condition that occurs when fluid pressure in the eye increases and damages the optic nerve. Dry eye occurs when the tear glands do not produce enough tears to keep the eyes lubricated. Cataracts are caused by a buildup of proteins in the lens of the eye, which can lead to vision loss. Treatment for eye diseases in pets may include antibiotics, anti-inflammatory medications, or even surgery. It is important for pet owners to have their pets regularly examined by a veterinarian to check for any signs of eye disease. Early diagnosis and treatment are key to preventing vision loss or blindness [1].

The symptoms of eye diseases in animals vary depending on the condition, but some of the most common signs include redness, swelling, squinting, discharge, and excessive tearing. If your pet is exhibiting any of these symptoms, it is important to seek veterinary care as soon as possible, as some eye diseases can progress rapidly and cause permanent damage.

In this context, it has become necessary to develop a user-oriented system for the early diagnosis of diseases that affect the quality of life of our friendly friends, whom we consider as members of our family, and the early diagnosis of some diseases that may be the precursors of some serious diseases.

With the developing technology, mobile phone cameras can now take professional camera image quality shots up to 50 megapixels. At this point, this situation constitutes the main idea of the study. In other words, it is planned to classify the disease by using the deep learning algorithm of the photos taken with the mobile phone camera.

The main subject of this study is the use of diseased and healthy eye photos of cats and dogs, collected by mobile phone cameras from veterinary clinics, in deep learning algorithms. In the study, both an original dataset is used and the images collected with a mobile phone camera are used in deep learning.

In the original dataset, 146 photographs were taken for the diseased class and 255 photographs were taken for the healthy class. As it is known, deep learning algorithms work with a large number of data sets and produce meaningful results. In this context, some data augmentation methods were followed in this study.

What makes the study different is that first of all, different deep learning algorithms were tried without increasing the data and the results were recorded. Afterwards, using the TensorFlow data augmentation library, the number of diseased eye photos was replicated from 146 to 354 using data augmentation techniques and reached 500. The same data augmentation processes were also applied to healthy eye photographs, and 245 photographs were produced from 255 original photographs and the number reached 500 again. In summary, 500 photographs were obtained for each class using data duplication techniques.

As stated before, a comparison was made between deep learning algorithms applied without data augmentation techniques and the same algorithms applied using data augmentation techniques. At this point, the effect of data replication processes on deep learning algorithms has been observed. The deep learning algorithms used in this study are VGG16, InceptionV3, ResNet50, Xception, DenseNet121, and EfficientNetB0.

Shan and Li [2] proposed a two-layer stacked sparse autoencoder model for automatic detection of microaneurysm in images of the posterior part of the eye (fundus). In the proposed model, they used the unsupervised learning method to obtain high-level features from the pixel level. In a model, binary classification can be performed with logistic regression. However, in cases where the model needs more class labels, the softmax algorithm, which is the generalized version of logistic regression, can be used in supervised learning methods as well as in learning unsupervised features together with deep learning methods.

An Extreme Learning Machine-ELM based model consisting of four stages based on macro and micro feature extraction was proposed for Diabetic Retinopathy detection by Deepa et al. [3]. The performance of the proposed model is compared with the performance of ANN and KNN based classifier models.

Güldemir et al., in their study in 2021, OCT- Optical Coherence Tomography images used for Age Related Macular Degeneration (AMD) disease was detected using Xception, VGG16, InceptionV3 and ResNet50 deep neural network models trained with Convolutional Neural Network (CNN) architecture [4]. In another study, Tasmin et al., suggested the use of MobileNetV2, ResNet50 and Xception deep neural network models in the classification of normal, Drusen, AMD, Diabetic Macular Edema (DME) of the retina based on CNN architecture using OCT images [5].

As seen in the literature studies, images taken with professional devices were used in deep learning algorithms. And yet, with the user-oriented and developing technology, it has been determined that the photos taken using a mobile phone camera have not been used in deep learning architectures before. The different aspects of this study make an important contribution to the literature by using both eye diseases in cats and dogs and photographs taken with a mobile phone camera.

The article is organized as follows; In the second part, focuses on dataset studies on the subject. Section 3 focuses on deep learning methods applied for disease classification. Sections 4 and 5 include results and discussion. Section 6 contains the conclusion part.

2. METHODS

Different deep learning algorithms have been used in this study, emphasizing the importance of data augmentation techniques. There are 146 data belonging to the diseased class and 255 data belonging to the healthy class from the images originally taken with the mobile phone camera.

Samsung A50 mobile phone was used to obtain the original dataset. Eye photos taken with the permission of cat and dog owners are divided into two classes; diseased and healthy. This study is not subject to any ethics committee permission as it is only a photo shoot.

As stated in the introduction, the original dataset was first used in deep learning algorithms in the study. Afterwards, 354 pieces of data were augmented in the diseased class and 245 in the healthy class using data augmentation techniques, and these were used again in deep learning algorithms and the results were compared. Using the Tensorflow data augmentation library, the data augmented were 500 in the healthy class and 500 in the diseased class. The methods used from the Tensorflow data augmentation library are as follows; Flip left right, 90-degree rotation and Saturation techniques.

Flip left right operation which is augmentation technique, randomly flips an image from left to right, allowing for more diverse data to be used in a machine learning model. This is especially useful when training a model to recognize objects in images that may appear in different orientations. It is also useful when training a model to recognize objects in a scene that may appear from different points of view. By performing Flip Left Right data augmentation, the model will be better prepared to recognize objects in images regardless of the orientation of the image.

One of the most commonly used transformations is the 90-degree rotation. This transformation involves rotating an image by 90 degrees clockwise and counterclockwise. This transformation can be used to create new data points in the dataset without changing the object's original characteristics. Using the Tensorflow library, the 90-degree rotation data augmentation can be easily implemented. The library provides a function, which takes the image and rotates it by the specified angle. This function can be used to rotate the image by 90 degrees in either the clockwise or counterclockwise direction.

Saturation data augmentation is a type of data augmentation technique used to improve the accuracy of a deep learning model. It is a type of preprocessing technique used to increase the number of training samples by altering the saturation of the input images. Saturation data augmentation can be implemented using Tensorflow, a popular open-source library for deep learning. Saturation data augmentation can also be used to reduce overfitting in the model. By increasing the variation of the input images, the model is less likely to overfit on a single set of data. This helps the model to generalize better and to produce more accurate results. Saturation data augmentation is a powerful tool for improving the accuracy of deep learning models. It can be implemented using the Tensorflow library, which provides a number of preprocessing and augmentation functions that can be used to alter the saturation of input images.

2.1. VGG16 Algorithm

VGG16 is a convolutional neural network (CNN) architecture developed by the Visual Geometry Group (VGG) at Oxford University for the ImageNet Large Scale Visual Recognition Challenge in 2014 [6]. The network is 16 layers deep and consists of convolutional layers, pooling layers, and fully connected layers. It was one of the first CNNs to demonstrate good performance on the ImageNet dataset. VGG16 is a popular choice for transfer learning, which is the process of using a pre-trained model on a new dataset. VGG16 has been used in many applications, including image classification, object detection, and object recognition.

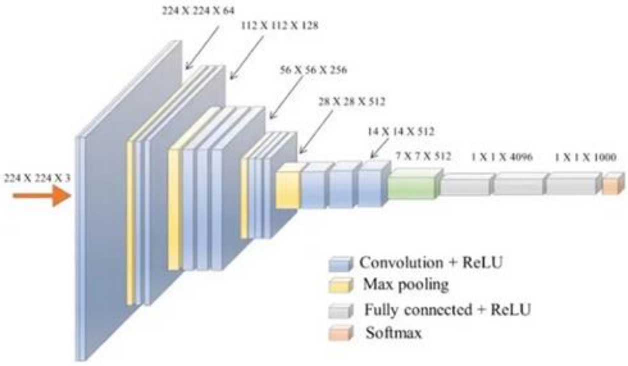

Figure 1. VGG16 Algorithm [7]

2.2. ResNet Algorithm

ResNet (Residual Network) is a type of deep learning neural network architecture designed to simplify the training of very deep networks. It was first introduced by Microsoft researchers in 2015 and has since become a widely used architecture for computer vision tasks such as image classification and object detection [8].

The key idea of ResNet is to introduce a "residual" connection between layers in a neural network. These residual connections are short-cuts that allow the network to learn more quickly and accurately. In addition, the residual connections help to reduce the vanishing gradient problem, which can occur when training very deep networks.

The basic building block of a ResNet is called a residual block. A residual block contains two convolutional layers, a batch normalization layer, and a ReLU activation layer. The output of the first convolutional layer is then added to the output of the second convolutional layer. This addition helps the network to learn more quickly and accurately by allowing gradients to flow more easily through the network.

The ResNet architecture can be used for a variety of computer vision tasks. It has been used to achieve state-of-the-art results in image classification and object detection tasks. In addition, it has been used for tasks such as semantic segmentation and image generation.

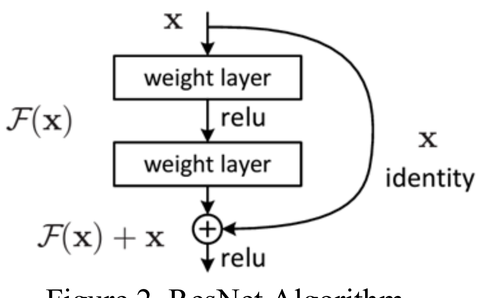

Figure 2. ResNet Algorithm

2.3. InceptionV3 Algorithm

InceptionV3 is a deep convolutional neural network (CNN) developed by Google and released in 2015 [9]. It is a class of deep learning architectures that are used for image recognition and object detection. InceptionV3 is the third incarnation of the Inception model, which is based on the concept of a “GoogleNet” and uses “inception blocks” to reduce the number of parameters in the network. It is one of the most accurate models for image classification and is the basis of many popular applications. InceptionV3 is trained using the ImageNet dataset and is able to identify over 1000 different objects. In addition to image classification, it can also be used for object detection, semantic segmentation, and image retrieval. The model is available for use in the TensorFlow library and can be used to develop new applications.

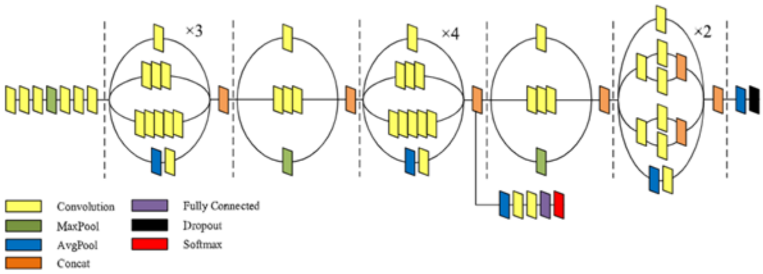

Figure 3. InceptionV3 Algorithm [10]

2.4. Xception Algorithm

Xception is a deep convolutional neural network architecture developed by François Chollet and published in the journal arXiv in 2016 [11]. It was developed as an improved version of the Inception architecture, which was widely used for image classification. Xception utilizes depthwise separable convolutions to reduce the number of parameters and computational cost, while still achieving high accuracy. Its primary benefit is that it requires fewer parameters and less computation than Inception, allowing it to train faster and more efficiently. Additionally, Xception is capable of training without requiring large amounts of memory. As a result, it has been widely used in many computer vision tasks, including object classification, segmentation, and object detection.

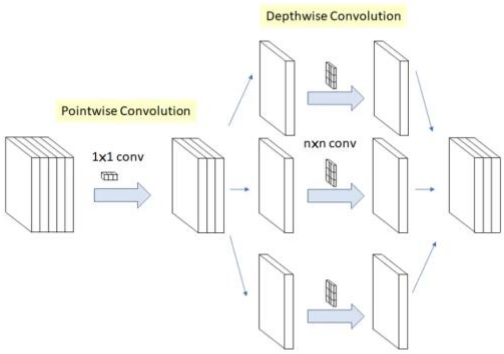

Figure 4. Xception Algorithm [11]

2.5. DenseNet121 Algorithm

DenseNet121 is a convolutional neural network architecture which is developed by Gao Huang, Zhuang Liu, Kilian Q. Weinberger, Laurens van der Maaten and Chen Change Loy [12]. DenseNet121 is a type of deep learning architecture that is used for image recognition tasks and is part of the DenseNet family of neural networks. The network is made up of 121 layers, with each layer connected to every other layer in a feed-forward fashion. The network is characterized by its dense connections between layers, which allow for a more efficient flow of information and better feature extraction. The network is trained on the ImageNet dataset, which is a large dataset of images of various objects. This allows the model to recognize objects in images and classify them accurately. The network is also used for transfer learning, which is a technique that allows the model to be used for other tasks such as object detection, semantic segmentation, and so on.

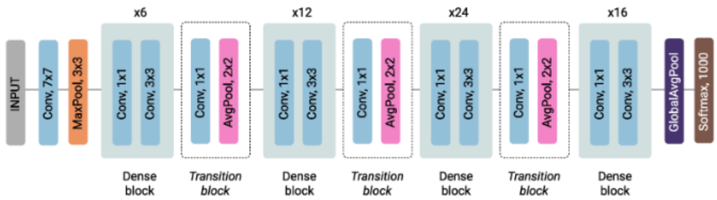

Figure 5. DenseNet121 Algorithm [13]

2.6. EfficientNetB0 Algorithm

EfficientNetB0 is a convolutional neural network (CNN) model developed by Google AI research team, which was introduced in 2019 [14]. The aim of the model is to improve the accuracy of the model while maintaining its efficiency. The model is based on a novel architecture called EfficientNet which incorporates three innovative techniques: compound scaling, depth-wise separable convolutions, and a global bottleneck.

Compound scaling adjusts the network width, depth, and resolution simultaneously, allowing the model to use fewer parameters while achieving higher accuracy. Depth-wise separable convolutions reduce the number of parameters without compromising accuracy, while the global bottleneck helps reduce the number of nodes in the network.

The model is trained on the popular ImageNet dataset and achieves a top-1 accuracy of 76.30% and a top-5 accuracy of 92.85%. It also performs well on other datasets like CIFAR-10, CIFAR-100, and SVHN. EfficientNetB0 is a great model for small-scale applications due to its efficient architecture and high accuracy. It also offers a good trade-off between accuracy and speed, making it suitable for real-time applications.

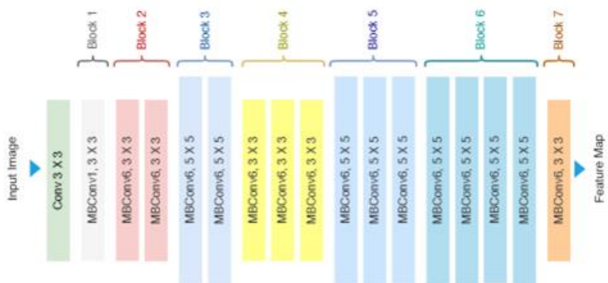

Figure 6. EfficientNetB0 Algorithm [15]

3. EXPERIMENTAL

The above-mentioned deep learning algorithms were first tested on the original dataset and the performance results were recorded. Afterward, the same deep learning algorithms were tried again on the dataset replicated with data augmentation techniques, and the results were recorded for comparison with the original dataset results. A confusion matrix was used to evaluate the results.

The confusion matrix is a matrix of true positive (True Positive-TP), true negative (True Negative-TN), false positive (False Positive-FP), and false negative (False Negative-FN) terms.

TP represents instances where the actual and estimated value is 1. TN refers to instances where the actual and estimated value is 0. The FP shows examples, where the true value is 0 and the estimated value, is 1. FN, on the other hand, indicates instances where the true value is 1 and the estimated value is 0. It is expressed by the performance metrics used in the evaluation of the performance of the eye disease diagnostic models created in the study and calculated according to the confusion matrix.

$$\text{Classification Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

$$\text{Sensitivity (Recall)} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{3}$$

$$\text{F1 Score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{4}$$

The performance of the proposed model for diagnosing eye disease and other models used in the study is measured by classification performance metrics such as accuracy, precision, recall, F1-score. Accuracy is a measure of how often the classifier guesses correctly. Precision refers to the proportion of samples belonging to the positive class and assigned to the positive class. The recall indicates how many of the values that should have been positively predicted were positively predicted. The F1-score provides a single score that simultaneously balances both recall and precision concerns by a single number.

4. RESULTS

The deep learning algorithms which are VGG16, InceptionV3, ResNet50, Xception, DenseNet121, and EfficientNetB0, are used in this study. Before data augmentation techniques, the original dataset is tested for those algorithms. Table 1 shows the result of the original dataset performance.

Table 1. Original Dataset Performance Evaluation

	AUC	**F1 (%)**	**Precision (%)**	**Recall (%)**	**Classification Accuracy (%)**	**Total Elapsed Time (second)**
VGG16	1.0	99.2	99.3	99.2	99.250	319.782
InceptionV3	0.789	79.3	85	81.5	81.530	881.014
ResNet50	0.517	23.6	17.1	39.9	39.884	678.843
Xception	0.768	75.7	82.3	78.6	79.598	564.006
DenseNet121	0.950	94.4	95.4	94.5	94.512	1076.078
EfficientNetB0	0.843	83.9	88.7	85.3	85.305	714.353

As seen in Table 1, when we look at the Classification Accuracy percentage in deep learning algorithms performed on the original dataset, the best-performing algorithm is VGG16. Considering the total elapsed time, the VGG16 algorithm again obtained the best accuracy rates in the least time (Figure 7). When we look at the data in the same table, the worst-performing algorithm was ResNet50. In terms of both classification accuracy and other values, this algorithm cannot correctly classify cat-dog eye pictures taken with a mobile phone camera.

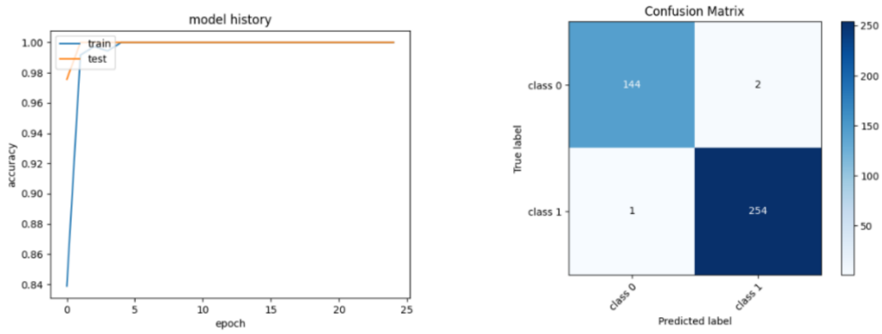

Figure 7. Model History and Confusion Matrix for VGG16 for Original Dataset

Table 2. After Augmented Dataset Performance Evaluation

	AUC	F1 (%)	Precision (%)	Recall (%)	Classification Accuracy (%)	Total Elapsed Time (second)
VGG16	1.0	99.9	99.9	99.9	99.9	747.194
InceptionV3	0.838	80.7	87.0	81.6	81.6	1414.395
ResNet50	0.510	33.5	25.3	50.0	50.0	1149.396
Xception	0.807	77.5	84.0	78.6	78.6	1030.830
DenseNet121	0.981	97.0	97.3	97.0	97.0	1670.396
EfficientNetB0	0.937	90.3	91.5	90.4	90.4	1163.967

When we look at Table 2, the performance values on the deep learning algorithms applied after the data augmentation processes show that the VGG16 algorithm has the highest value among all the performance criteria. But this value can be just as misleading. Compared to VGG16 architecture, DenseNet121 algorithm has the second-best classification accuracy compared to other algorithms because it is sensitive to over-fitting (Figure 8). But when the total elapsed time data is looked at, it unfortunately shows itself that it is one of the algorithms that process the most time. The ResNet50 algorithm also performed better after the data was replicated and the classification accuracy reached 50%.

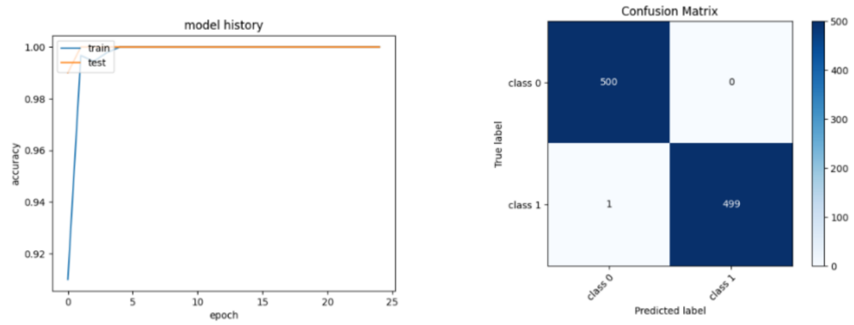

Figure 8. Model History and Confusion Matrix for VGG16 for Augmented Dataset

5. DISCUSSION

Data augmentation can be a powerful tool for improving machine learning models. By artificially increasing the size of the dataset, data augmentation can reduce the chance of the model memorizing the training data instead of learning from it. In addition, data augmentation can also help to reduce the variance of the model, as it enables the model to see more data and better generalize what it has learned. Furthermore, data augmentation can be used to increase the diversity of the dataset, thereby increasing the model's ability to learn robust features that are invariant to small variations in the data. Finally, data augmentation can help to reduce the amount of data preprocessing required, as the augmentation process can automatically create new data points with desirable properties. Data augmentation has been a useful tool for detecting eye diseases in the medical field. It has been used to improve the accuracy of computer-aided diagnosis systems, as well as to reduce the time and cost of manual data processing. By augmenting a dataset with additional data points, it is possible to increase the ability of the model to recognize patterns and be more accurate in its diagnoses.

Data augmentation can also help to reduce false positives, as increased data points can be used to provide more context and improve the accuracy of the results. Additionally, data augmentation can facilitate the training of models, reducing the need for large training datasets. Overall, data augmentation has been a beneficial tool for detecting eye diseases. It has the potential to reduce the cost of diagnosis and improve the accuracy of AI-based systems. It is important to note, however, that data augmentation should be used with caution, as it can also increase the risk of data bias. Therefore, it is important to ensure that any data augmentation techniques used are appropriate for the task at hand and do not introduce any bias into the system.

6. CONCLUSIONS

Special devices are used for the detection and diagnosis of eye diseases in academic studies. As the mobile phone camera features and image quality increase with the developing technology, it is now necessary to perform eye detection studies with mobile phone cameras as well. In this context, the images taken from cats and dogs with a mobile phone camera were divided into two as diseased and healthy. The original data set was first tested in deep learning algorithms, and then classification performance values were calculated over the same algorithms using data augmentation techniques. As can be seen in the performance result table, performance values increased after data augmentation.

Data augmentation can be a powerful tool for diagnosing and treating eye diseases. It enables doctors to analyze large amounts of data quickly and accurately, as well as to customize treatments for each individual patient. By leveraging the power of deep learning, data augmentation can help doctors to identify patterns in the data that can lead to earlier diagnosis and personalized treatment plans. In the long run, data augmentation will help to improve patient outcomes and reduce the costs associated with eye diseases. Data augmentation can increase the accuracy of diagnosis by providing more data points to be analyzed, and can also reduce the time and cost required for diagnosis. Furthermore, it can also be used to reduce the variability in data and improve the generalizability of models. With its ability to generate more data points, data augmentation can help to increase the accuracy of diagnosis and lead to better treatment outcomes. In conclusion, data augmentation is an essential tool for the detection and diagnosis of eye diseases, and its use should be encouraged.

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