CONVOLUTION SUMMARY

OBJECTIVE

A new convolutional neural network designed specifically for computer vision applications is what our project aims to build from the ground up. We obtained the dataset we are utilizing from the "Dog-vs-Cats" dataset on Kaggle. It is difficult to create a good model because of the restricted amount of data available to us. One well-liked deep learning model that has proven to be quite successful in computer vision applications is convolutional neural networks, or convnets. Convolutional neural networks' primary advantage is their ability to detect and distinguish spatial patterns in images. That is why they excel at things like object identification, picture recognition, and segmentation.

PROBLEM

The goal of the binary classification job for the Cats-vs-Dogs dataset is to identify whether an image belongs to the dog or cat class.

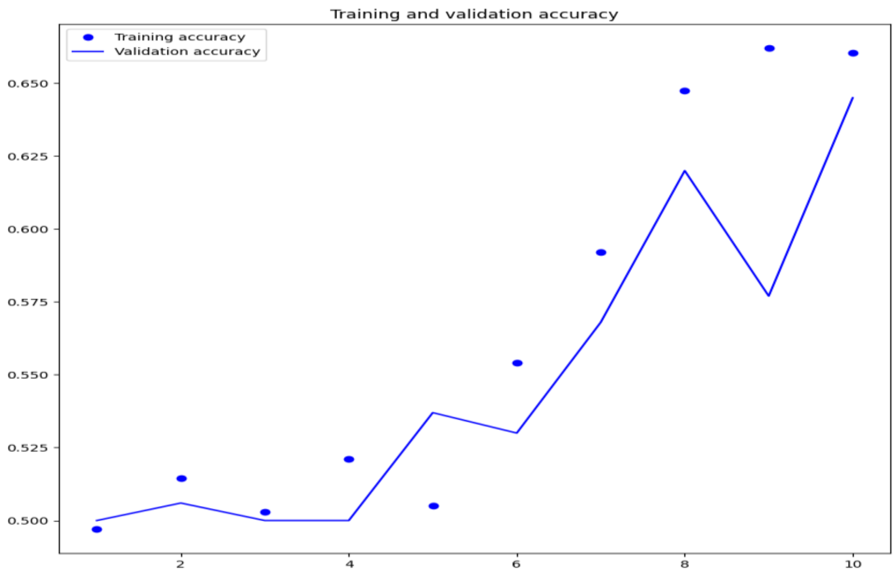
APPROACHES

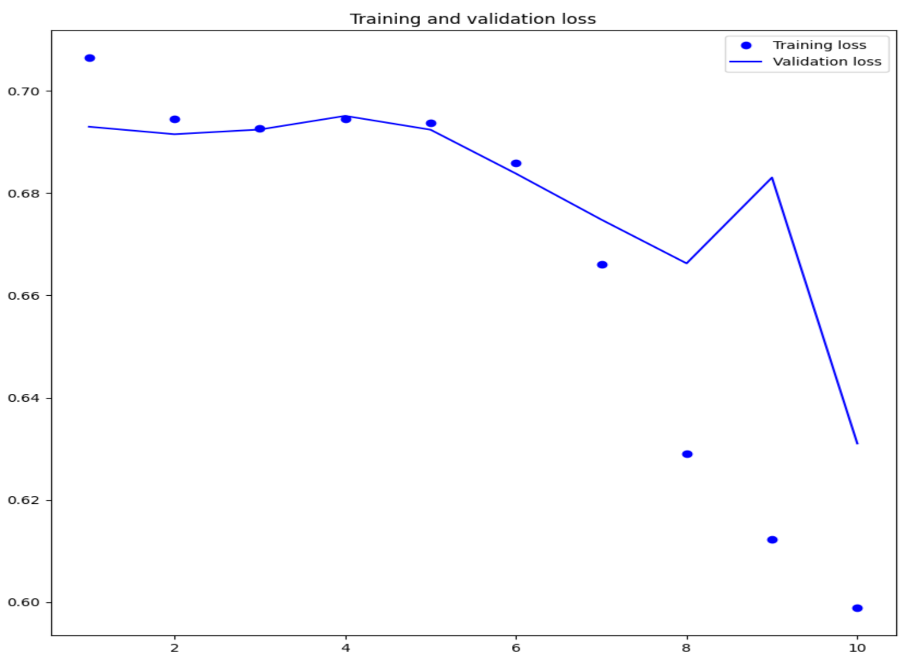
- Using a small dataset, I would train my model, refine it with state-of-the-art transfer learning methods, and test its performance with suitable assessment criteria.
- With minimal input, I aim to create an accurate and efficient convolutional neural network that can classify images from the "Dogs-vs-Cats" dataset.
- Demonstrating the potential of my model excites me, and I am driven to explore new frontiers in computer vision with limited data.
- My convolutional neural network will undoubtedly contribute significantly to the field of computer vision because it is focused on efficiency and creativity.

DATA PROCESSING

Verify the image files. Transcode the JPEG data into RGB pixel grids. These should be transformed into floating point tensors. Neural networks, as you may know, deal to function with small input values. Rescale the pixel values (between 0 and 255) to the [0, 1] range.

With a training sample of 1000 (validation = 500 and test = 500), we have examined the Cats & Dogs Data Set. Given that the training sample size of 1000 tends to be overfit, I have employed a 50% dropout strategy to address this problem. The graphs of sample 1000 without data augmentation is given below .Test Accuracy = 64.2%,Validation Accuracy=65.4%

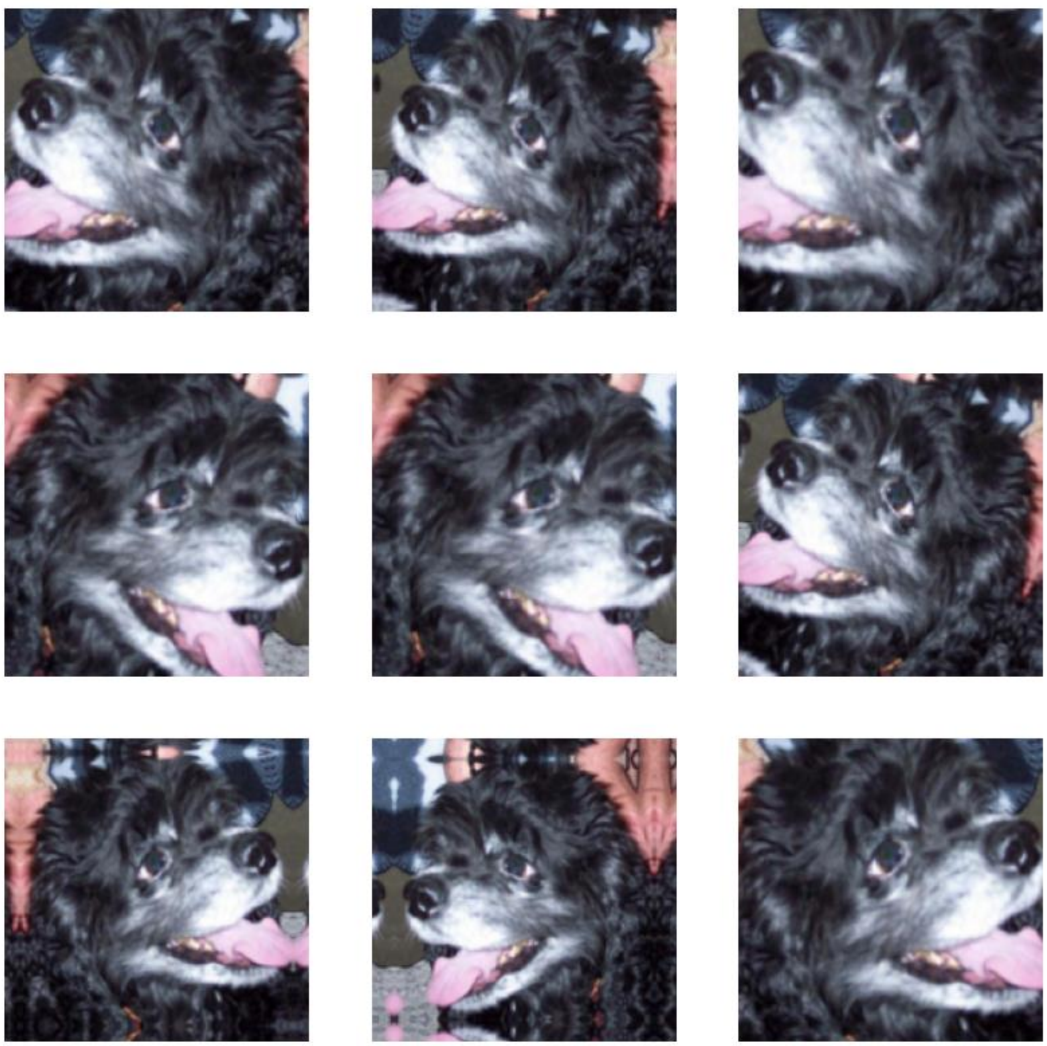




AUGMENTATION OF DATA

We propose using data augmentation methods to increase the accuracy of our model. We can achieve decent results with limited datasets by creating new data from the given training samples using random tweaks. As a result, the model will never see the same image twice during training, which promotes generalization.

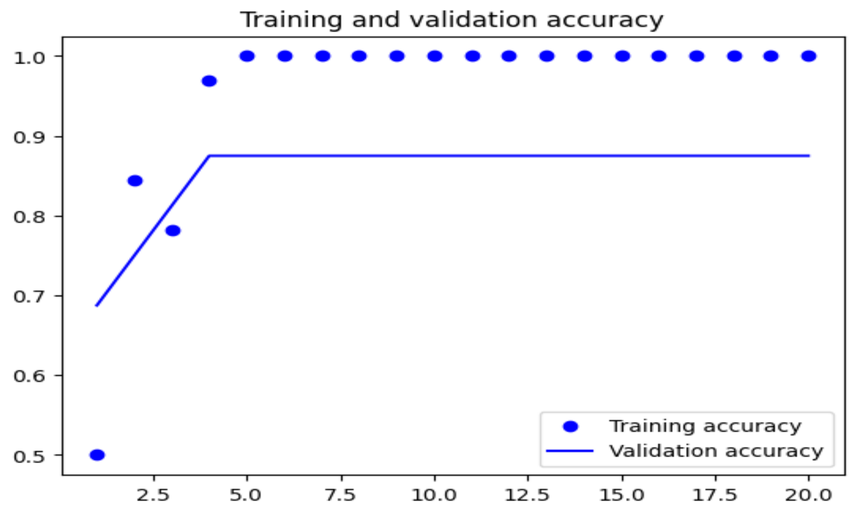
To achieve our specific goal, we wish to randomly apply effects like flipping, rotating, and zooming to the training set of photographs. By doing this, we might produce variations of the existing images, (as shown below) ,adding diversity to the dataset and enhancing our model's resilience.

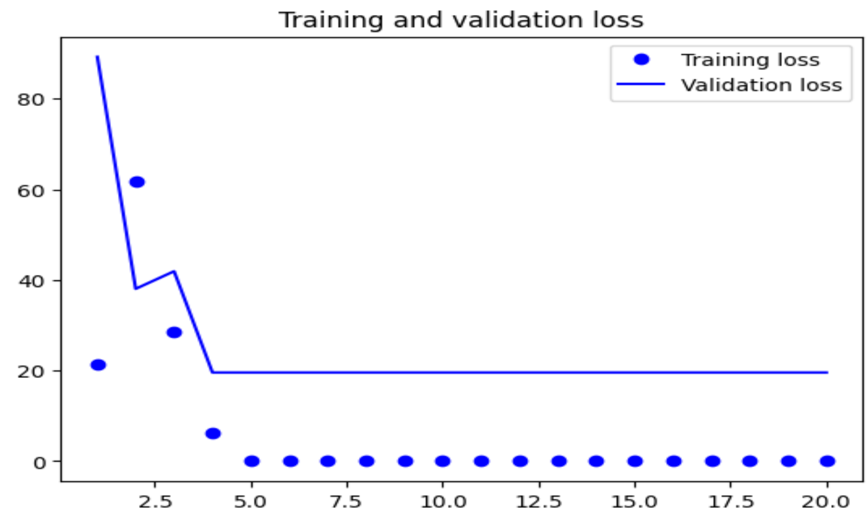


PRE-TRAINED MODEL:

Because the original dataset is broad and diverse, a pretrained network can be utilized as a generic model, having properties that apply to a wide range of computer vision applications. One of the most significant advantages of deep learning over other machine learning algorithms is its ability to transfer learned properties across tasks.
Consider a massive convolutional neural network trained on the ImageNet dataset, which has 1.4 million annotated images and 1,000 different classifications. This collection includes numerous animal classifications, including cat and dog breeds. This network's design, known as VGG16, is a simple and widely used convnet architecture for ImageNet.

Graph of pre-trained model with no data augmentation





Validation Accuracy = 87.5%
Train Accuracy =100%,which indicates this is the best model when compared to all the other models we performed .

RESULTS

MODEL	TRAIN ACCURACY	VALIDATION ACCURACY	DATA AUGMENTATION
Sample 1000	66%	64.5%	NO
Sample 1500	79.9%	75.6%	YES
Sample 2000	80%	75.6%	YES
Pre-trained model	100%	87.5%	NO
Pre-trained model	97.3%	97%	YES
Fine-tune model	98.4%	97.7%	YES

CONCLUSION:

The results show that no model was able to outperform the others, regardless of whether it was regularly trained with or without data augmentation. Growing the training set or changing the size of the validation set are further ways to improve the model's accuracy. As can be seen by comparing the two sets of data, data augmentation did not improve the accuracy of the pre-trained model or the validation accuracy. Pre-trained models frequently perform better than scratch models when dealing with little amounts of training data.