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DATA AUGMENTATION WITH GENERATIVE ADVERSARIAL NETWORKS FOR CNNS

CONTENT

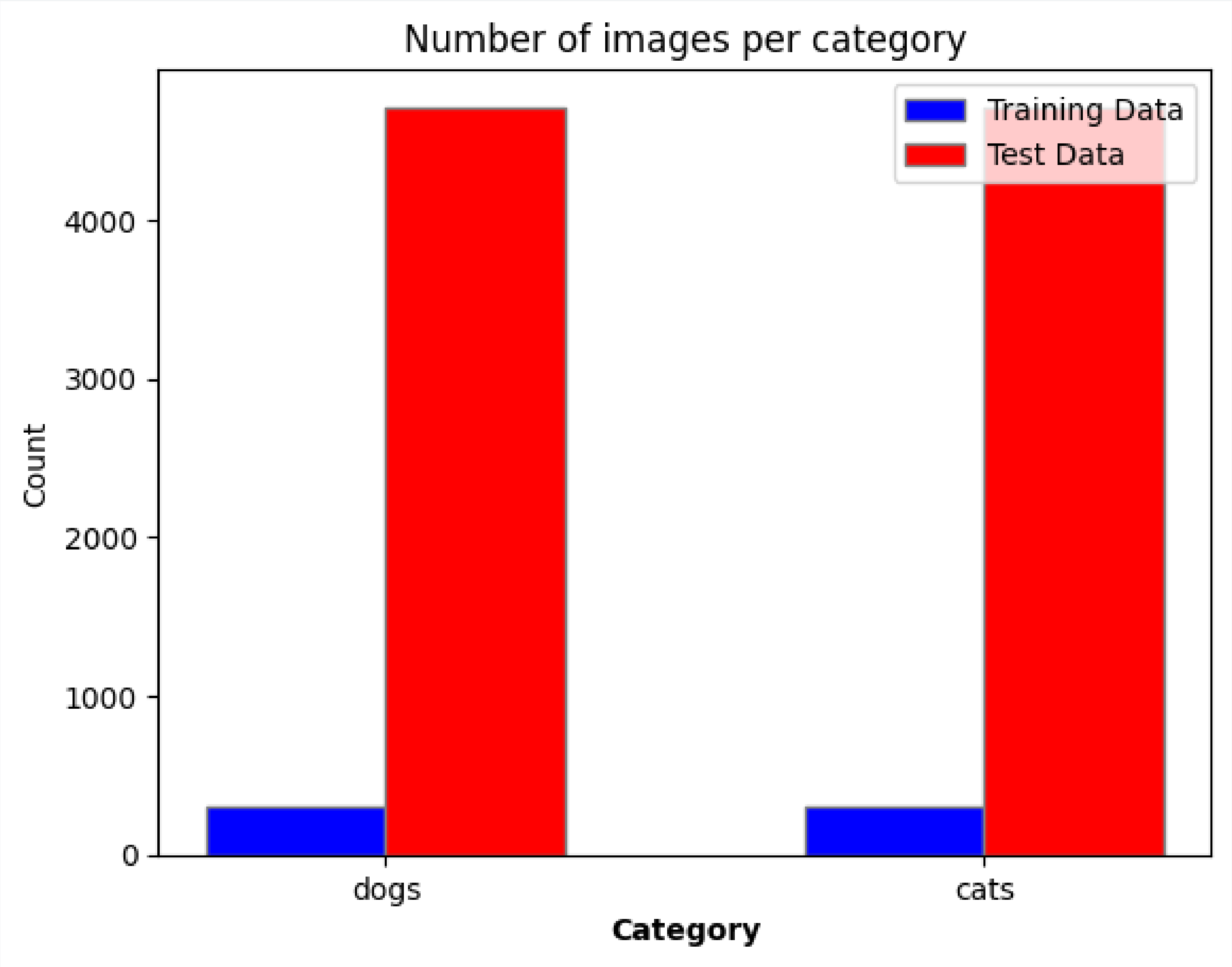
INTRODUCTION

As artificial intelligence evolves, generative diffusion models like OpenAI's DALL-E are gaining popularity for their ability to mimic human artistic abilities. This research delves into the potential of these models in addressing a critical challenge: limited datasets in machine learning. Our aim is to explore how generative diffusion models can augment training data, particularly in the context of improving the generalizability of convolutional neural network (CNN) models.

MOTIVATION FOR DATA AUGMENTATION

As artificial intelligence improves, generative diffusion models like OpenAI's DALL-E are popular for mimicking human creativity. This study examines how these models can handle machine learning's dataset shortage. Deep learning struggles with limited training data. By artificially increasing datasets, data augmentation, especially GANs, can help. This is essential for training strong CNNs, especially when large and diverse datasets are scarce. Our research uses generative AI to reduce the effects of **limited original data**. To improve convolutional neural network (CNN) model generalizability, generative diffusion models can enhance training data.

DETAILS ON DATASET.



CATEGORY WISE DISTRIBUTION OF DATASET.

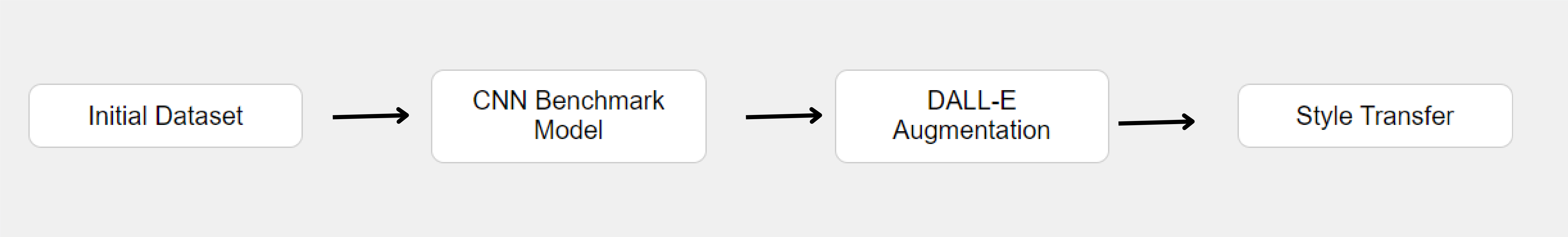
ORIGINAL DATASET SAMPLE IMAGES

DATA PREPARATION & AUGMENTATION

The initial dataset, comprising 610 images of cats and dogs, is meticulously prepared for the CNN model. Images are resized to 128x128 pixels and normalized. Data augmentation techniques, including shear, zoom, and horizontal flip, are applied for additional variations. We further augment the dataset using DALL-E, producing three distinct iterations of each image. Style transfer techniques are then employed to create a visually diverse dataset for training.

METHODOLOGY

Our methodology involves a two-step approach. First, we use a CNN to construct a benchmark model on an initial dataset. Then, we leverage generative diffusion models like DALL-E to produce augmented versions of each image. Additionally, we apply style transfer techniques to further diversify the dataset. This innovative approach aims to enhance the generalization ability of CNNs through the introduction of synthetic yet realistic training data.



MODEL IMPLEMENTATION & TRAINING

The baseline Convolutional Neural Network (CNN) serves as the foundation of our image classification model.

Key Components:

- **Architecture: Crafted with the Keras library.**
- **Layers: Utilizes convolutional layers, max pooling, dropout for overfitting mitigation, and dense layers for classification.**

Training Details:

- **Epochs: The model undergoes training for 50 epochs to optimize its learning.**

Data Augmentation:

- **ImageDataGenerator: Applies data augmentation techniques using Keras's ImageDataGenerator, enhancing the robustness of the model.**

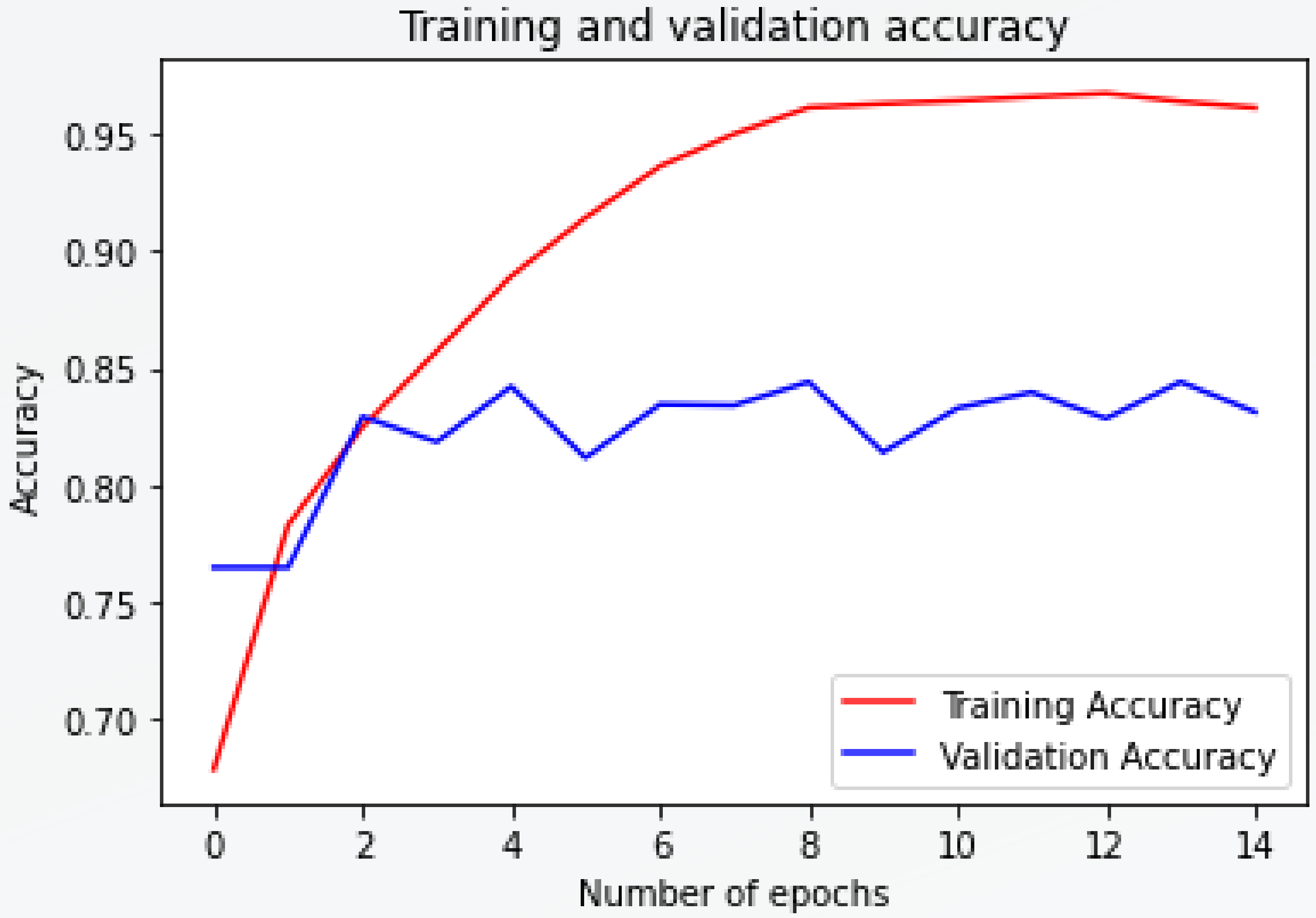
Optimization:

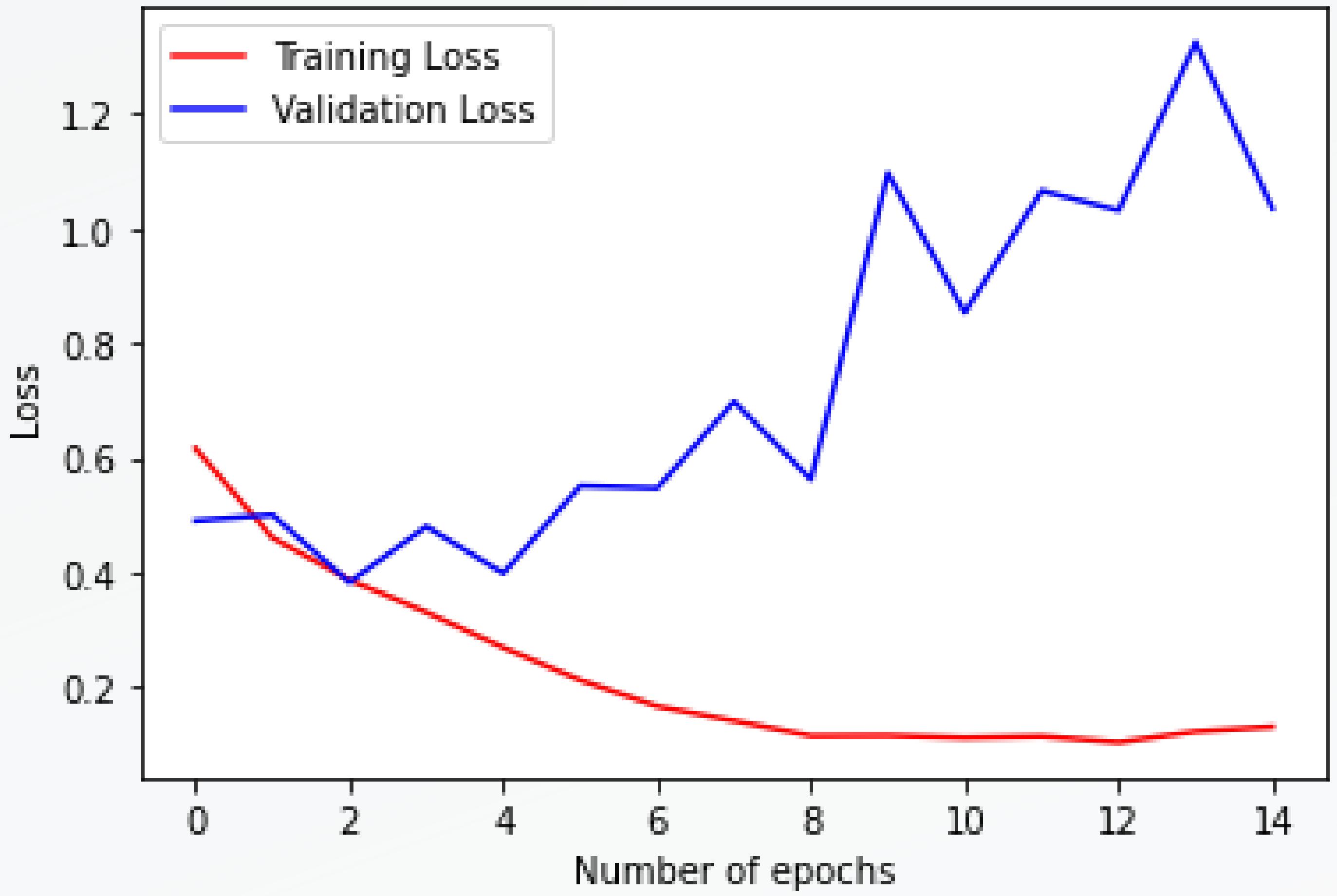
- **Adam Optimizer: The model is compiled with the Adam optimizer.**
- **Loss Function: Binary cross-entropy is employed as the loss function for effective optimization.**

This comprehensive approach ensures the model's adaptability and accuracy through rigorous training on augmented datasets, setting the stage for superior performance in image classification tasks.

SOLVING THE OVERFITTING PROBLEM

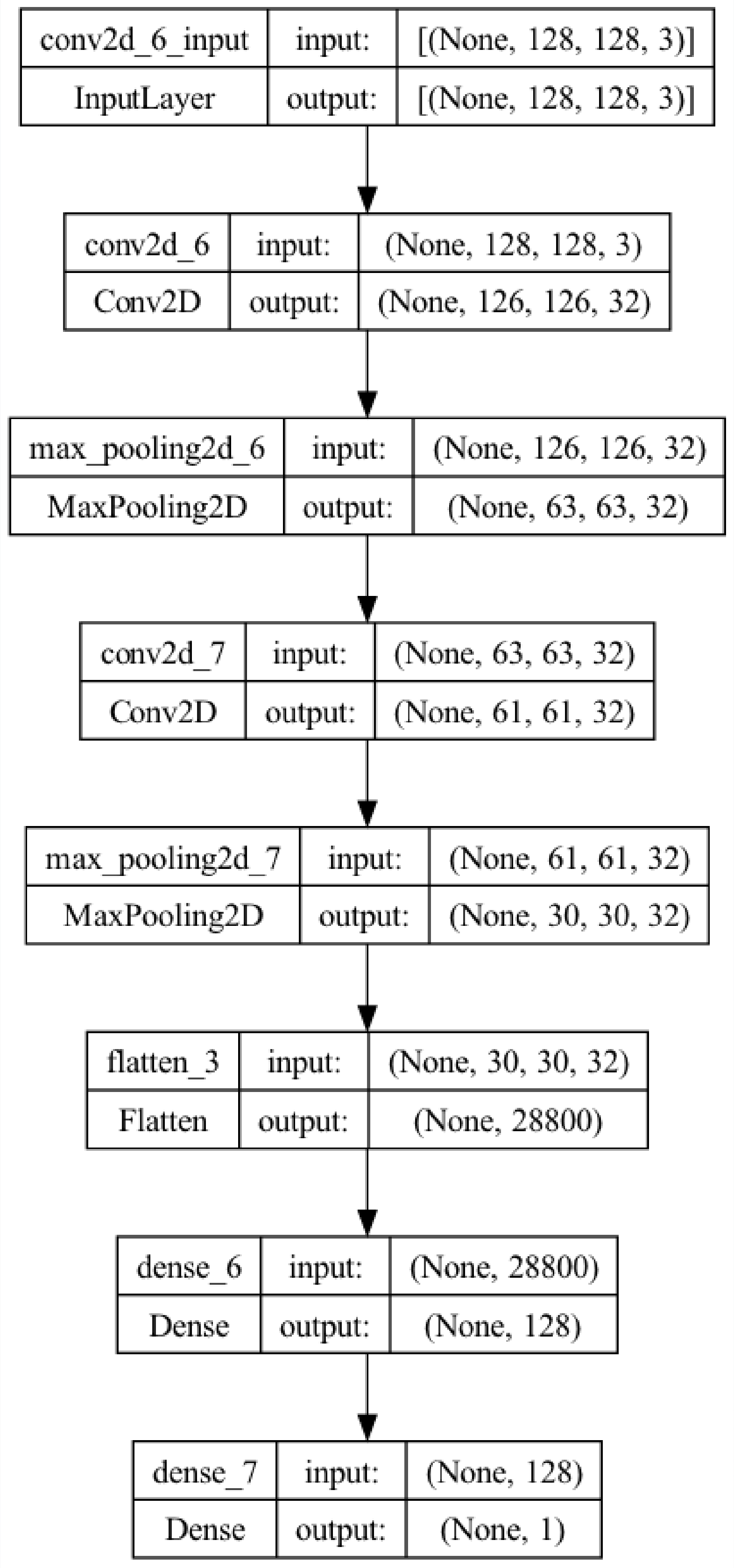
As we can see, the history of training and validation loss clearly shows that we have overfitting problem.One approach is augmenting the data, meaning tweaking our original data a little bit (for example rotating the picture, flipping it horizontally) to make more data which in turn might potentially solve our problem of overfitting





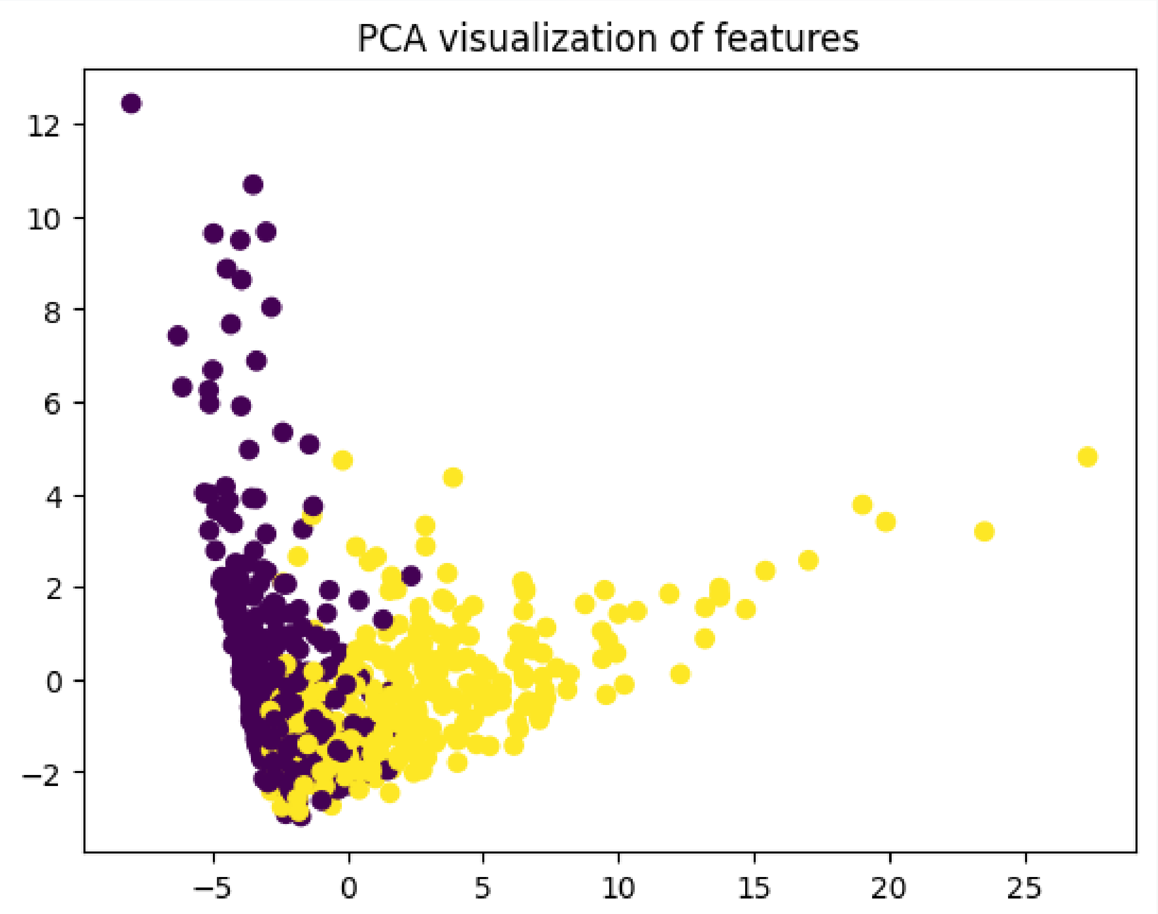
CNN MODEL ARCHITECTURE

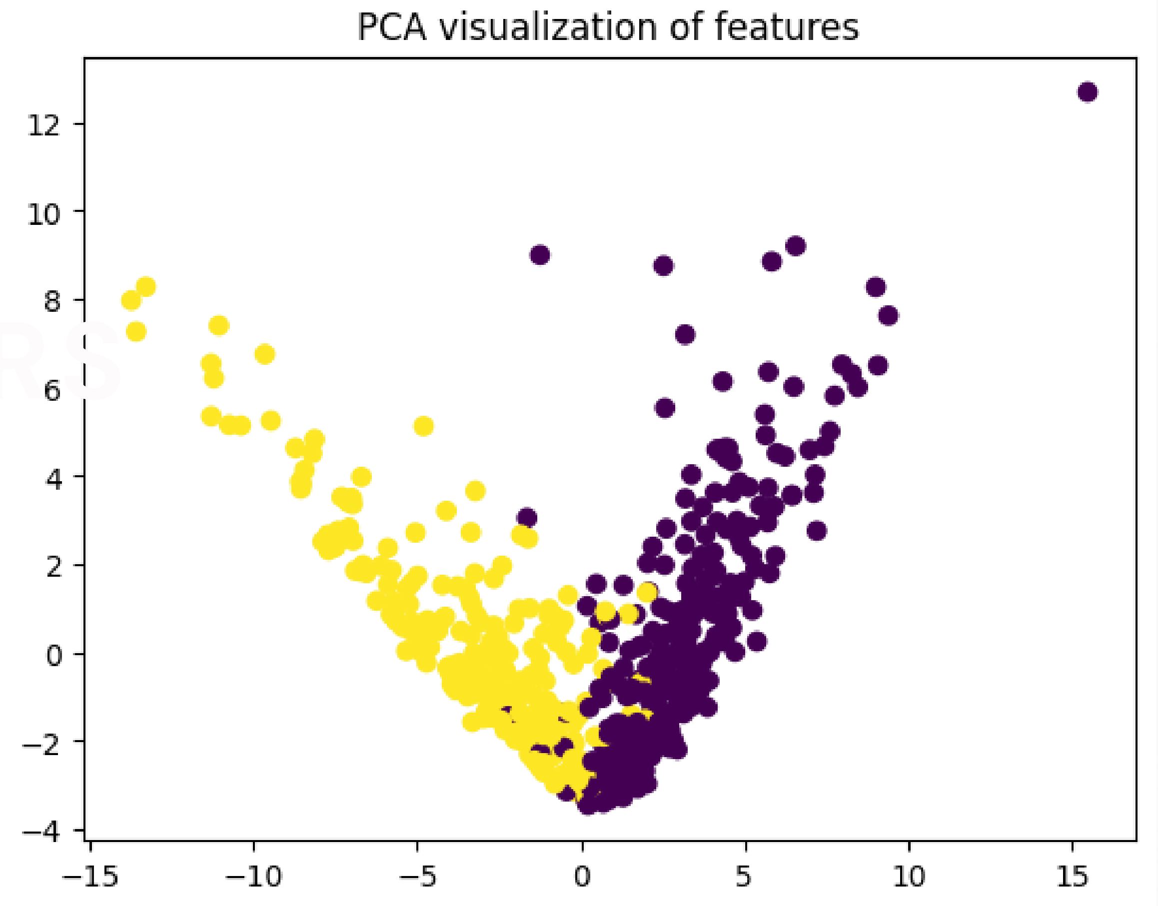
```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_8 (Conv2D)           (None, 126, 126, 32)      896

 max_pooling2d_8 (MaxPooling  (None, 63, 63, 32)       0
 2D)

 dropout (Dropout)           (None, 63, 63, 32)        0

 conv2d_9 (Conv2D)           (None, 61, 61, 64)        18496

 max_pooling2d_9 (MaxPooling  (None, 30, 30, 64)       0
 2D)

 dropout_1 (Dropout)         (None, 30, 30, 64)        0

 conv2d_10 (Conv2D)          (None, 28, 28, 128)       73856

 max_pooling2d_10 (MaxPoolin  (None, 14, 14, 128)      0
 g2D)

 dropout_2 (Dropout)         (None, 14, 14, 128)       0

...
Total params: 3,304,769
Trainable params: 3,304,769
Non-trainable params: 0
_________________________________________________________________
```



PCA VISUALIZATION & FEATURE ANALYSIS

Principal Component Analysis (PCA) visualizations offer deeper insights into the learned features of the CNNs. The Maximum Mean Discrepancy (MMD) technique reveals subtle differences in feature representations among the CNNs. PCA visualization (refer to Figure) provides a clear visual representation of these differences, emphasizing the impact of diverse augmentation methods on feature extraction.





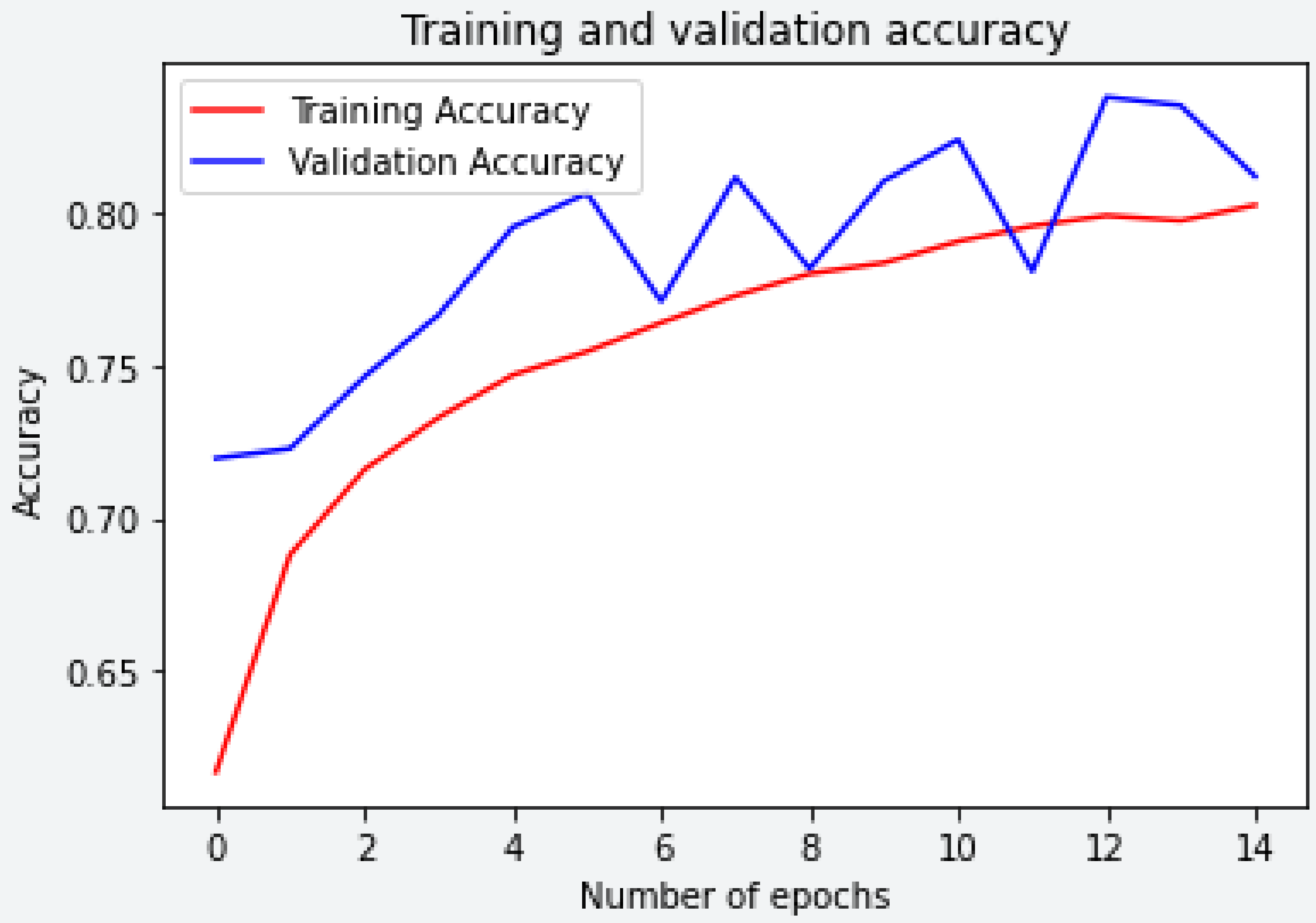
PERFORMANCE EVALUATION & RESULTS

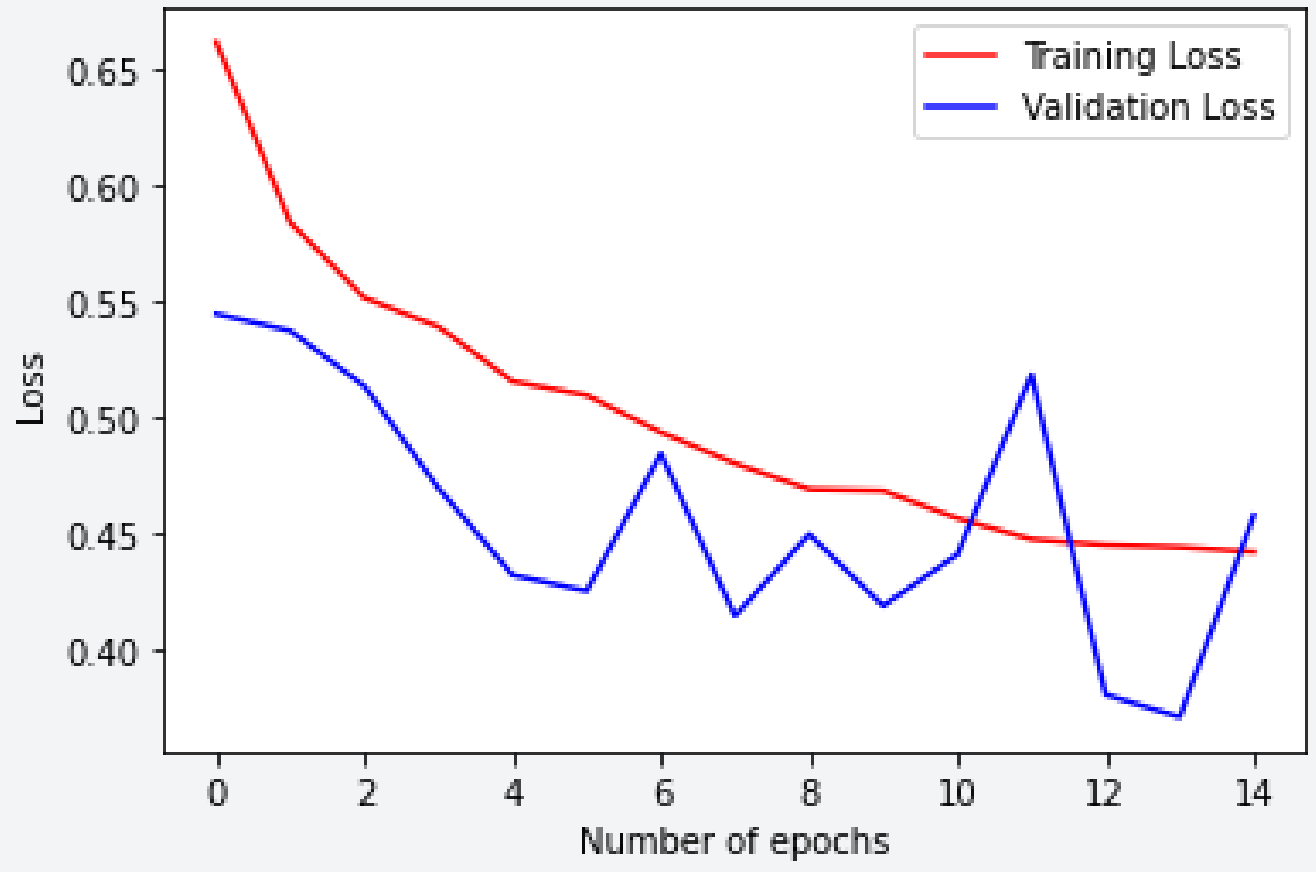
Performance evaluation is crucial in assessing the impact of data augmentation. The original CNN achieved a commendable accuracy of 87.7%. However, the second CNN, incorporating DALL-E generated images, showed a slight decrease in accuracy (84.2%). The third CNN, trained on a comprehensive dataset with style transfer augmentations, outperformed others with an accuracy of 91.86%. The table summarizes the performance metrics, highlighting the potential of generative AI in improving image classification.

TABLE 1. Performance Evaluation of CNN Models

CNN Model	Accuracy (%)	Overfitting Potential	MMD Score	PCA Visualization
Original Dataset	0.877	Low	-	-
DALL-E Augmented	0.842	High	0.00148	Different from Original
Style Transfer Augmented	0.9186	Low	0.00215	Similar to Original

As we can see, the validation and training loss move in a synchronized manner, which is a good indicator that our model is healthy





CONCLUSION

In conclusion, our project demonstrates the efficacy of integrating generative AI techniques into the data augmentation process, leading to notable performance improvements in CNNs for image classification tasks. The synergy between generative AI and CNNs presents a promising avenue for improving model robustness and generalizability, particularly in scenarios with limited original datasets.

THANK'S FOR WATCHING