University of Jeddah
Collage of computer science & Artificial Intelligence

CCAI 433 Computer Vision

Final Report

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Introduction

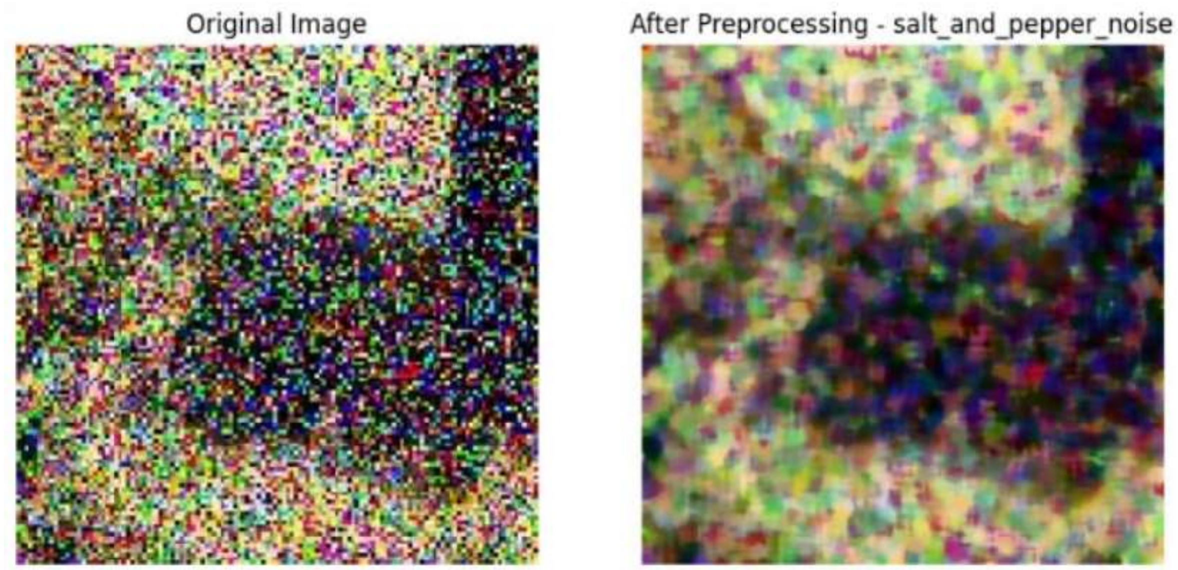
The objective of this project is to develop a classification model based on deep learning techniques to identify cats and dogs by processing images containing noise. This involves utilizing Convolutional Neural Networks (CNN) to handle and process images, aiming to achieve high classification accuracy despite the presence of distortions in the images. The dataset includes images with two types of distortions for training and testing: salt-and-pepper noise and motion blur. These types of noise represent a significant challenge, as they negatively affect the model's ability to recognize the correct patterns in images, leading to a decrease in classification accuracy. The goal is to restore the distorted images and enhance classification accuracy, demonstrating the robustness and effectiveness of deep learning methods in image restoration and classification tasks.

Types of Distortion and Their Processing

1. Salt and Pepper Noise:

- Description: Salt-and-pepper noise introduces random white and black pixels into the image, making it appear noisy.
- Processing: A **median filter** was applied to remove this noise. The median filter works by replacing each pixel value with the median value of the surrounding pixels, effectively reducing the random noise.

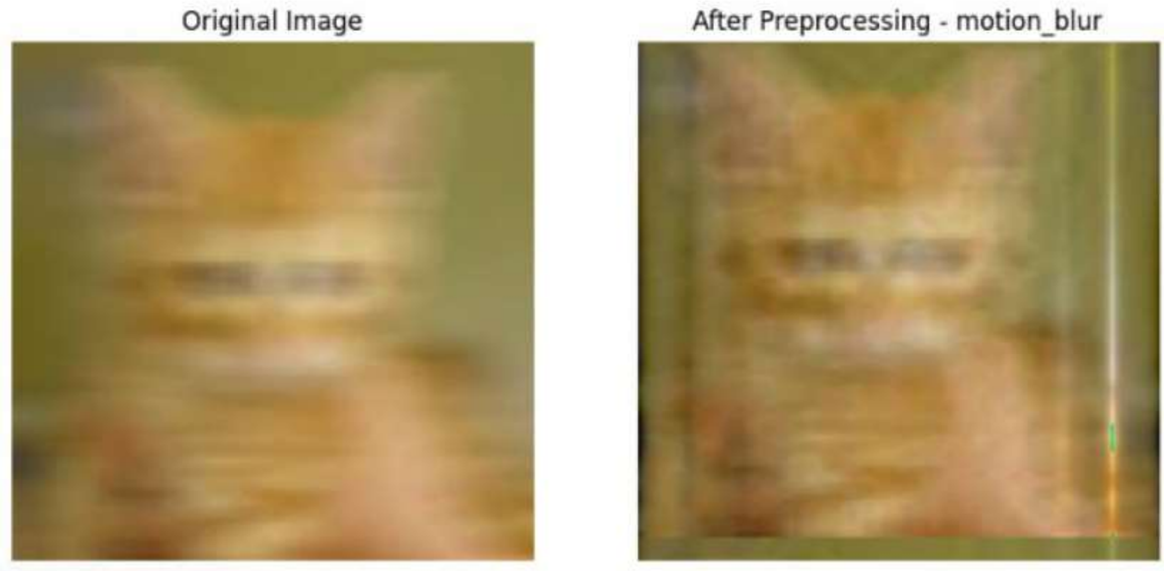
The image on the left shows the original image with salt-and-pepper noise, while the image on the right shows the result after applying the median filter to remove the noise.



2. Motion Blur:

- Description: Motion blur occurs when there is movement of the camera or the subject during the capture of the image, resulting in a smeared appearance.
- Processing: The **Wiener filter** algorithm was used to restore motion-blurred images. This algorithm estimates the original image by reducing the blurring effect.

The image on the left shows the original image with motion blur, while the image on the right shows the result after applying the Wiener filter to reduce the blurring effect.



Processing Stages:

1. Data Loading:

- Images were loaded from the training and test datasets.
- Images were categorized into four groups: cat images with salt-and-pepper noise, dog images with salt and pepper noise, cat images with motion blur, and dog images with motion blur.

2. Image Denoising:

- Applied median filter to images with salt and pepper noise.
- Applied Wiener filter algorithm to images with motion blur.

3. Data Preparation for Training:

- Combined denoised images with the original dataset.
- Split the data into training and testing sets.

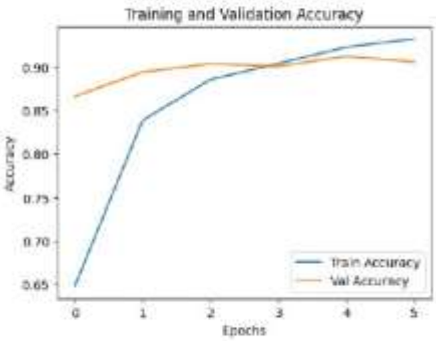
4. Model Training:

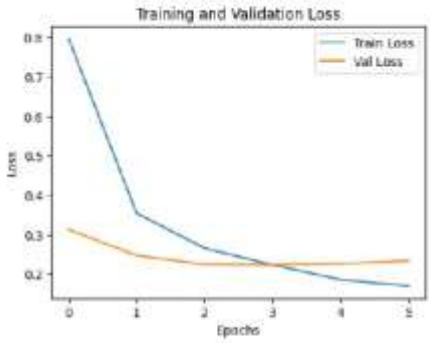
- An EfficientNetV2L classifier was trained on the prepared dataset. EfficientNetV2L is a state-of-the-art CNN architecture known for its efficiency and high performance in image classification tasks.
- Several convolutional layers, pooling layers, and dropout layers were used to improve the model's performance and prevent overfitting.
- The hyperparameters used in training include:
    1. Number of Epochs: 150
    2. Learning Rate: 0.0001
    3. Batch Size: 32
    4. Optimizer: AdamW optimizer, which is widely used for its adaptive learning rate capabilities.
    5. Dropout: 0.5

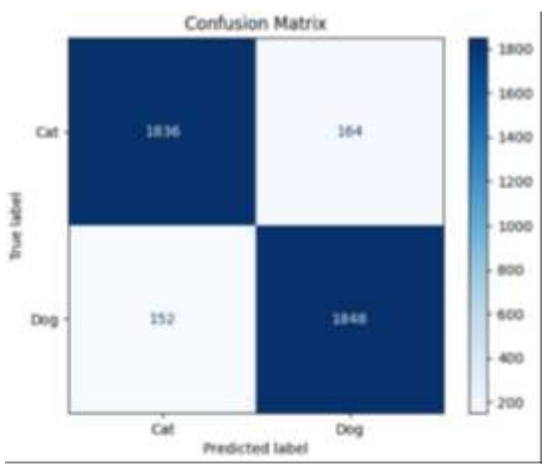
5. Model Evaluation:

We evaluate the model's performance based on training and validation accuracy, which indicates how well the model generalizes to unseen data, as well as a confusion matrix, which highlights the misclassifications. The validation accuracy of the best model achieved was 0.9210%.

The model's performance was further analyzed by plotting the accuracy and loss over the training epochs, providing insights into the model's learning progress. Below are the results, including the confusion matrix and the training and validation accuracy/loss curves:

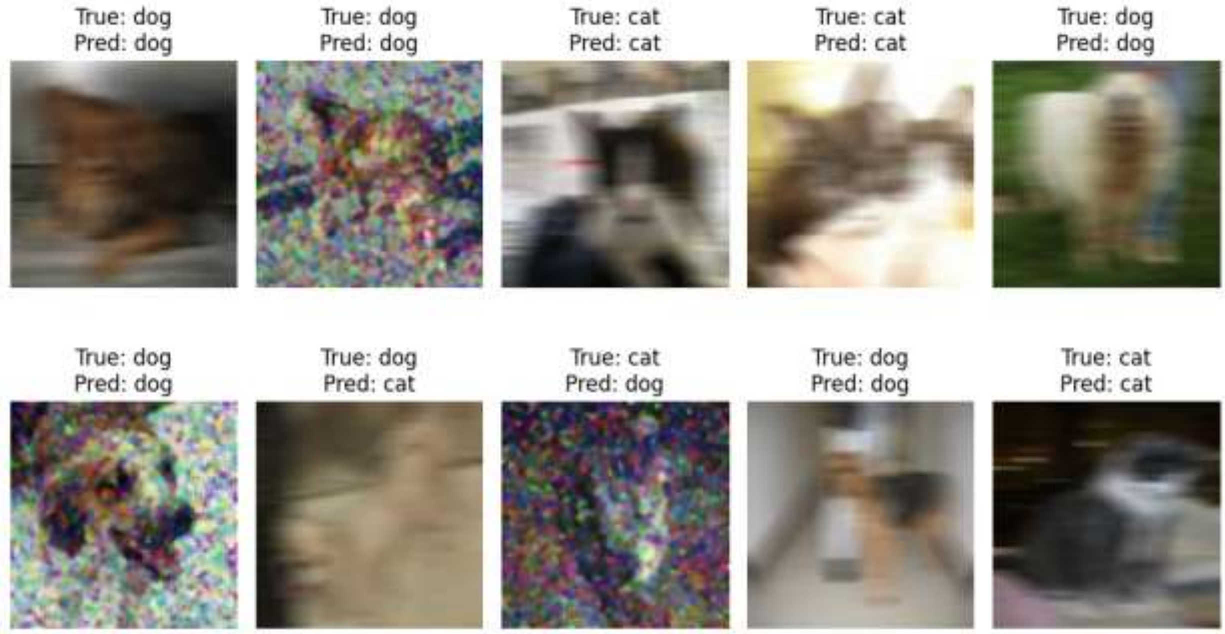






Model Evaluation through Visual Comparison:

A random set of images from the validation dataset was selected to display alongside their true and predicted labels. This visual comparison allows for an assessment of the model's performance by comparing its predictions with the ground truth. Through this process, we can observe how accurately the model classifies the images and identify any misclassifications or areas where the model may need improvement. This approach helps in analyzing the model's strengths and pinpointing areas for future refinement.



Conclusion:

This project presents a robust model for handling distorted images and improving classification accuracy using advanced image processing techniques and Convolutional Neural Networks. The results demonstrate the potential of deep learning methods in restoring images and enhancing their performance in classification tasks. The use of EfficientNetV2L, with its efficient architecture, further highlights the effectiveness of modern CNNs in achieving high accuracy and robustness in image classification.