So these are the Questions that the professor asked from our Project Presentation,
And our team answers for them

1The datasets don't seem to match for the regular CNN vs CNN with transfer learning. How come?

Confusion Matrices:

[94 4 [98 6

10 71 11 64]

Reason:

Mismatch in Datasets: The discrepancy between the datasets used for the regular CNN and the CNN with transfer learning arises from the use of the `Random.shuffle` function in loading the data. This function rearranges the order of the dataset each time it is loaded, leading to variations in the data order. Since we extract the test set from the larger training set, the differing order of the datasets each time we load them results in non-identical training and test sets across different runs. This variability is a factor in the different outcomes observed in the confusion matrices for the two models.

Did you stop the learning too early at 9 epochs? The test accuracy seems to have a positive trend.

Reason:

Epochs in Learning Process(tightplo: Regarding the learning process being stopped at 9 epochs, the decision to limit the number of epochs in the plots was not due to early termination of the training but was instead a choice made to ensure the plots were clear and fit well within the graph's display area. The learning continued beyond 9 epochs, and the trend in test accuracy was indeed positive, suggesting that the models were still improving.

plt.tight_layout()

bbox_inches='tight')

Did you try any explainable AI methods?

Reason:In our image classification project, we did not incorporate Explainable AI (XAI) methods primarily due to the inherent complexity of interpreting image data and the challenges posed by the multi-layered structure of deep learning models. Image data is high-dimensional and contains complex spatial relationships, making it difficult to pinpoint exactly what features the model is using to make predictions. Additionally, convolutional neural networks, which are extensively used in image classification, involve multiple layers of abstraction. These layers progressively extract and process features from basic textures and edges in earlier layers to more complex shapes and object parts in deeper layers. This layered complexity complicates the direct interpretation of how each layer influences the final decision, presenting a significant barrier to implementing straightforward XAI methods.

Moreover, the general applicability and scalability of existing XAI techniques also influenced our decision to forego their use in this project. Techniques that are effective for simpler, more transparent models or structured tabular data often do not translate well to the complexities of image classification models without significant adaptations. Methods such as LIME or SHAP, while useful, would require considerable modification to adequately address the unique spatial and feature dependencies present in image data. Additionally, the computational overhead associated with these XAI methods can be prohibitively high, particularly when dealing with the large models and extensive datasets typical in image classification tasks. This combination of required adaptations and high computational demands made the integration of XAI methods impractical within the scope and resources of our project.