Faculty of Informatics and Computer Science

Module Title: Deep Learning

Semester: Two

Academic Year: 2024/2025

Phase2 Project's Report

Project Title: Image Classification using CIFAR-10

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Date of Submission: 02/05/2025

1. Introduction

This report concentrates on deep learning model practical implementation and design alongside analysis techniques. The main purpose consisted of studying various Deep Learning architectural models through TensorFlow with Keras execution on the CIFAR-10 image database. Three different neural network configurations were chosen: MobileNetV3-Small and EfficientNet-B0 served as well-known supervised Convolutional Neural Networks alongside an unsupervised Convolutional Autoencoder. The project included proper data preprocessing schemes for each model alongside transfer learning implementations and model training and hyperparameter tuning processes followed by relevant metric evaluation (Accuracy and Mean Squared Error) supported by learning curve analysis through TensorBoard and visualizations for predictions and internal feature elements. The project required solving issues with computational power as well as environmental setup problems and library compatibility problems during its execution phase.

2. Data Selection and Preprocessing

2.1. Dataset Choice

The research utilized the CIFAR-10 dataset for the investigation. This benchmark for computer vision consists of 60,000 color images in 32x32 pixel resolution while distributing them between ten object classes that include airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck. The dataset distribution divides its total 60,000 images into 50,000 training images and 10,000 testing images. This dataset matches our project requirements due to its ability to be processed by Keras while maintaining clear class definitions and being easy to handle in terms of size.

2.2. Data Loading and Initial Exploration

The standard tf.keras.datasets.cifar10.load_data() function enabled loading the dataset which provided numeric arrays containing image data along with their matching integer labels. The initial shape of the images verified their 32x32x3 dimensional format. Subsequent to loading the CAE model the label information was disregarded.

2.3. Preprocessing Strategy

2.3.1. Data type conversion from pixel data to float32 float happened at the beginning of training all models as a common step for numerical algorithm processing.

2.3.2. Preprocessing for CNN Models (MobileNetV3, EfficientNet-B0):

Resizing: The tf.image.resize function applied 224x224 pixel dimensions to all images.

Normalization: Both preprocess_input functions applied specifically to each model (mobilenet_v3_preprocess_input and efficientnet_b0_preprocess_input). The pre-processing functions normalize pixel values into the range [-1, 1] which matches the required scaling for models coming from ImageNet pre-training.

Label Encoding:

The labels ranging from 0 to 9 were transformed into one-hot vectors through the use of tf.keras.utils.to_categorical.

2.3.3. Preprocessing for Convolutional Autoencoder (CAE):

Resizing: Images remained at their initial resolution setting of 32x32 pixels.

Normalization: The array was transformed to the [0, 1] scale through the operation (astype('float32') / 255.0).

Label Encoding: The system treated labels as irrelevant data because it used images as its target output values.

2.4. Data Augmentation

To improve model generalization and reduce overfitting for the classification tasks, basic data augmentation consisting of RandomFlip("horizontal") and RandomRotation(0.1) was applied only to the training datasets for MobileNetV3 and EfficientNet-B0 during data pipeline creation .

2.5. Justification of Preprocessing Methods

The chosen preprocessing procedures followed standard deep learning approaches together with requirements from chosen models. The CNNs required input dimensions of 224x224 to function due to their initial training on the ImageNet database. The model-specific preprocess_input function plays an essential role in transfer learning since it enables input data distribution matching of original training data to effectively utilize pre-trained model features. The original 32x32 resolution of the CAE helps the model focus on data detail recovery because pixel value scaling to [0, 1] matches the sigmoid activation function in the last decoder layer output range. Standard practice for using CNNs in multi-class classification includes one-hot encoding combined with categorical crossentropy loss. The classifiers utilized data augmentation to enhance their training dataset through artificial manipulation of examples which included rotations and flips for the sake of reducing overfitting tendencies and boosting robustness levels.

3. Model Architectures and Implementation

tf.keras provided implementation support for three different models where tf.data.Dataset pipelines executed efficient training operations using shuffling and batching along with prefetching.

3.1. Model 1: MobileNetV3 (CNN Classifier)

3.1.1. Architecture Choice Justification: MobileNetV3 Small was chosen as the representative modern efficient CNN architecture because it exemplified both modern and efficient characteristics. The model delivers solid transfer learning performance at a computational cost lower than larger models thus making it appropriate for experimental use under standard resource limitations. According to the CW1 Research, we found that CNNs perform well in Image Classification tasks, especially in small datasets like CIFAR-10(Our Chosen Dataset). Additionally, the architecture’s design orientation centers on mobile applications efficiency while delivering concepts about designing efficient CNNs.

3.1.2. Implementation Details; The pre-trained MobileNetV3Small base was loaded through include_top=False and weights='imagenet parameters. At the output of the network a classification block was installed with GlobalAveragePooling2D for dimension reduction followed by Dropout (0.2) for regularization and a Dense (10, activation='softmax') output layer enabled CIFAR-10 classification.

3.1.3. Training Procedure: The project faced checkpoint loading issues with potential file system problems or incompatible saving format problems that led to switching to end-to-end fine-tuning for the reported final training procedure. The training process involved using the Adam optimizer with a learning rate set to 1e-5 and allowing the base model to train for 40 epochs while starting from index 100 with unfrozen layers (Will go in depth on this in the hyperparameter tuning section).

3.2. Model 2: EfficientNet-B0 (CNN Classifier)

3.2.1. Architecture Choice Justification: Like the first model, we choose it as It's CNN-based and it has an outstanding performance in Image Classification tasks with small datasets like ours. Model EfficientNet-B0 provides an optimal model selection because its compound scaling technique allows for high accuracy with efficient FLOPS and parameter usage. The B0 model represents the smallest MobileNetV3 version available because it provides the highest performance level.

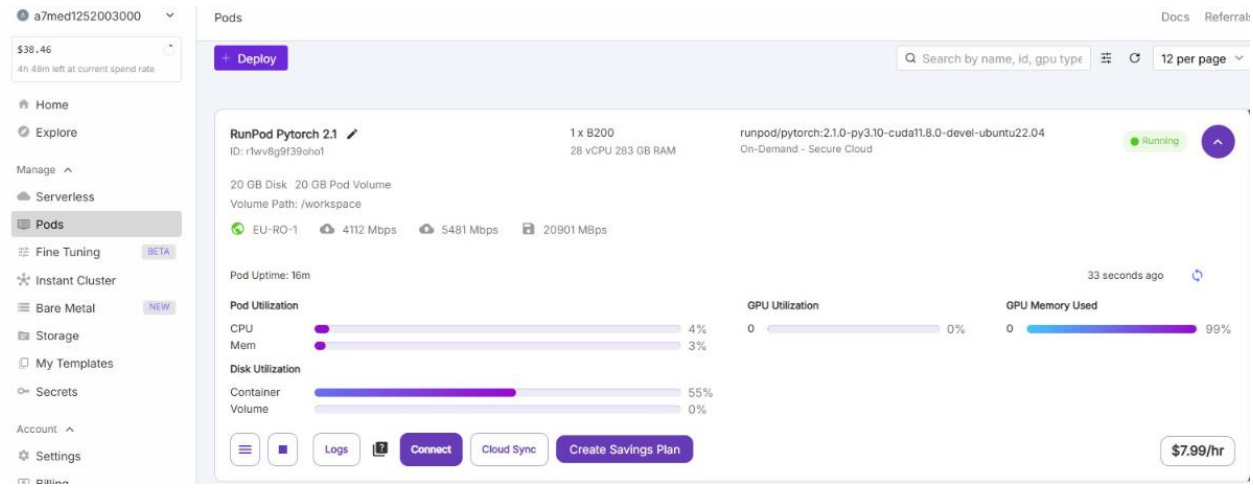
3.2.2. Implementation Details: The EfficientNetB0 base was loaded with parameters according to the following configuration include_top=False, weights='imagenet'). The same classification head sequence including (GAP, Dropout (0.2), Dense (10, 'softmax')) was added last.

3.2.3. Training Procedure: Standard two-stage fine-tuning was applied effectively for this procedure. A single stage of training was applied for 15 epochs to the head portion by freezing the base elements using Adam optimizer at learning rate 0.001. Experiments using hyperparameter tuning were performed during the fine-tuning stage where learning rate along with dropout rate and unfreeze point variations were tested for 10 epochs from the saved head checkpoint. The identified configuration proved to be the most effective.

3.3. Model 3: Convolutional Autoencoder (CAE)

3.3.1. Architecture Choice Justification: A CAE functioned as the third model selection because it served to fulfill the requirement of introducing an architectural framework different from the CNN classifiers. This method enables the study of unsupervised representation learning by reconstructing data. The implementation of a Swin Transformer model (a different architecture type) was prevented by library incompatibilities and resource issues within the available environments. SWIN stuck on colab's A100 which made me try different processor (B200- 180GB VRAM – 283GB RAM - 28 vCPU, 7.99USD/hr), but it also stuck due to disk issues, as the model was 50GB and the disk supports 40 GB only which led to the

choice of this alternative network design. Standard Keras layers enabled the CAE to provide an implementable and stable alternative.



3.3.2. Implementation Details: A symmetric architecture design combined encoder and decoder modules. The Conv2D layers with ReLU activation function and MaxPooling2D operation downsampled the input to create an 8x8 feature map using filter sizes that comprised 32, 64, 128 and 256. The decoder employed Conv2DTranspose layers (128/256, 64, 32 filters) that applied ReLU activation functions with strides of 2 to perform upscaling to the original 32x32 image dimensions. Its last layer consisted of a Conv2D layer with 3 filters and sigmoid activation. The number of filters in the deepest layer served as the bottleneck size parameter.

3.3.3. Training Procedure: The CAE started training from beginning to optimize the Mean Squared Error between original input images and reconstructed output images. Adam optimizer was used. A 30-epoch training session took place using default learning rate with 128 bottleneck filters as the starting point. The training period lasted 15 epochs for different values of LR and bottleneck filters. A training of 30 epochs applied the best discovered configuration (LR=0.001 with Bottleneck=256) for final assessment.

4. Hyperparameter Tuning Experiments

The investigation of performance variables relied on systematic experimental tests for the three models.

4.1. MobileNetV3 Training Evolution & Fine-tuning:

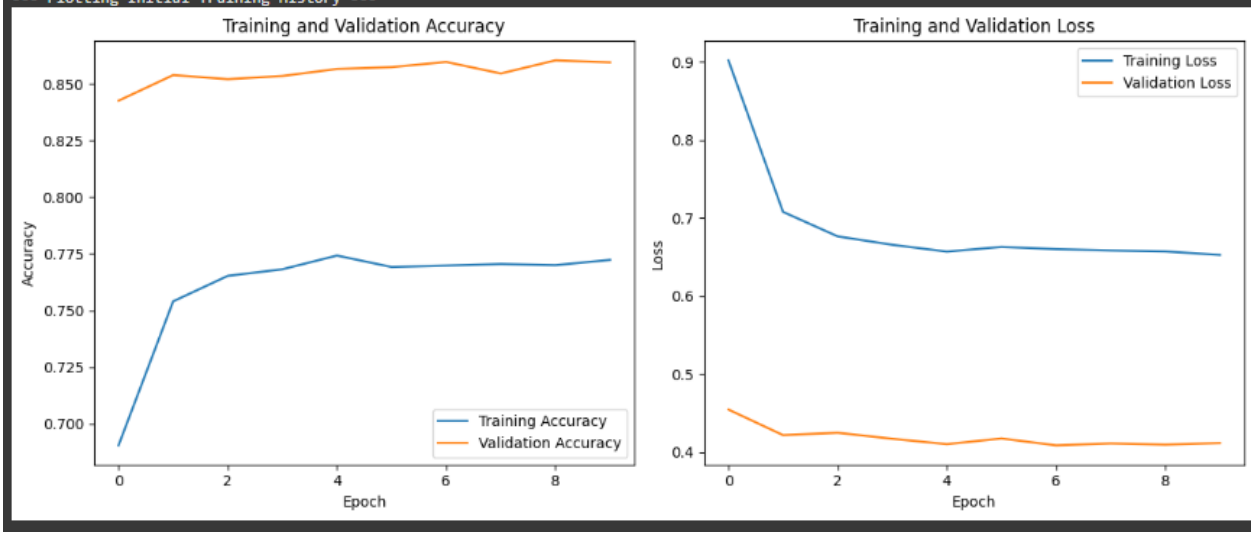
I initially started with INITIAL_EPOCHS = 10, LEARNING_RATE = 0.001 and the results were:

```
Epoch 10/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 927s 593ms/step - accuracy: 0.7712 - loss: 0.6510 - val_accuracy: 0.8594 - val_loss: 0.4119

--- Initial Training Finished ---

--- Evaluating Model After Initial Head Training ---
313/313 ━━━━━━━━━━━━━━━━━━━━ 104s 333ms/step - accuracy: 0.8565 - loss: 0.4181
Test Loss after head training: 0.4098
Test Accuracy after head training: 0.8603

--- Plotting Initial Training History ---
```



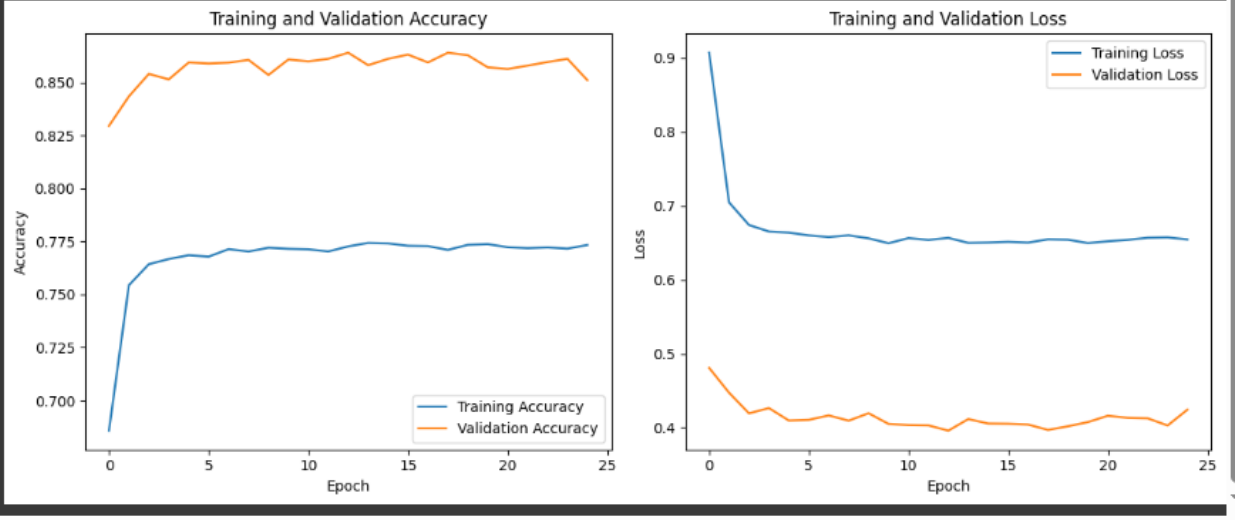
Observation: Underfitting (train acc < val acc, higher train loss). Good generalization (val/test acc ~0.86), but model not fully optimized.

Then, I raised the Epochs to 25 while keeping the learning rate value, the results were:

```
--- Initial Training Finished ---

--- Evaluating Model After Initial Head Training ---
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.8609 - loss: 0.4073
Test Loss after head training: 0.3960
Test Accuracy after head training: 0.8640

--- Plotting Initial Training History ---
```



Observation: increasing epochs slightly increased the test accuracy and reduced the test loss as well.

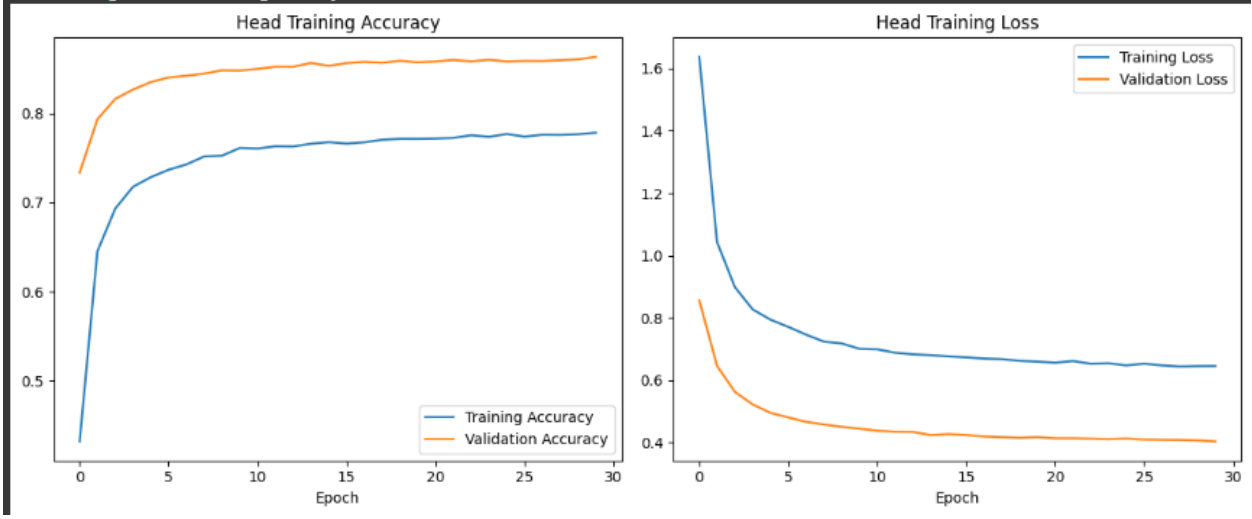
Subsequently, raised the epochs to 30, and decreased the learning rate to 1e-4, the results were:

```
Epoch 30: val_accuracy improved from 0.86030 to 0.86310, saving model to checkpoints/mobilenetv3_head/cp.weights.h5
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 46s 30ms/step - accuracy: 0.7794 - loss: 0.6457 - val_accuracy: 0.8631 - val_loss: 0.4026

--- Initial Head Training Finished ---
*** Best head weights should now be saved at: checkpoints/mobilenetv3_head/cp.weights.h5 ***

--- Evaluating Model After Initial Head Training ---
Loading best weights from checkpoints/mobilenetv3_head/cp.weights.h5 for evaluation...
Checkpoint index file not found after training. Cannot evaluate.

--- Plotting Initial Training History ---
```



It shows better results..

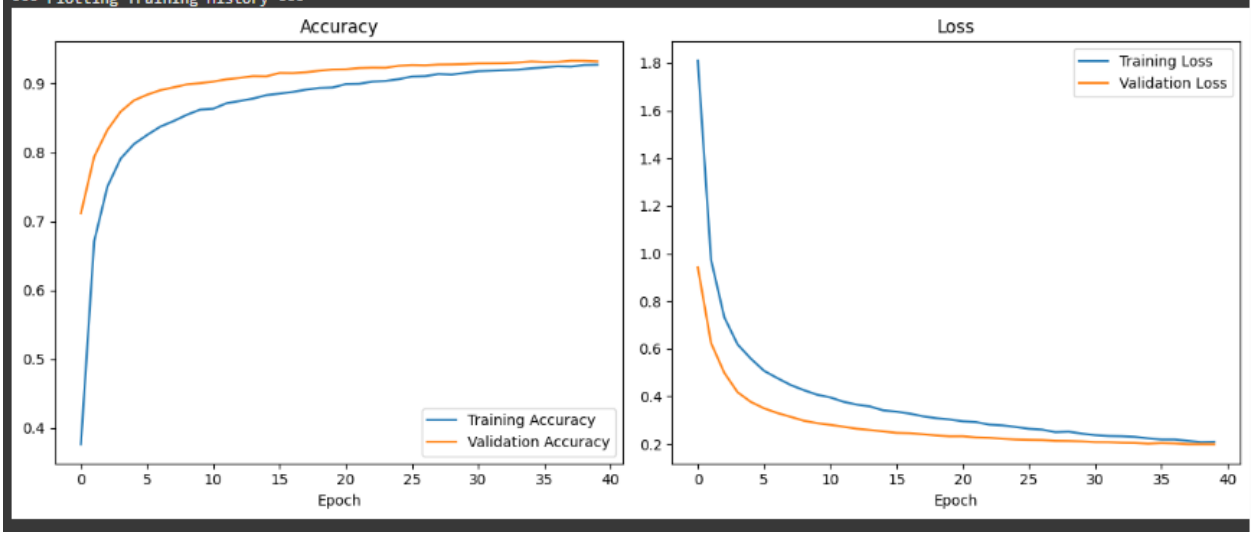
Finally, I increased the epochs to 40, and decreased the learning rate to 1e-5, the base model had layers from index 100 unfrozen from the start, and dropout of 0.2. The results were:

```
1561/1563 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - accuracy: 0.9269 - loss: 0.2090
Epoch 40: val_accuracy did not improve from 0.93300
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 47s 30ms/step - accuracy: 0.9269 - loss: 0.2090 - val_accuracy: 0.9321 - val_loss: 0.1987

End-to-End Training Finished

--- Evaluating Best Model From This Run ---
Loading best model from checkpoints/E2E_LR1e-05_DR0.2_FT100_20250501-133810/best_model.keras for evaluation...
Model loaded successfully.
313/313 ━━━━━━━━━━━━━━━━━━━━ 9s 15ms/step - accuracy: 0.9305 - loss: 0.2067
Test Loss: 0.1990
Test Accuracy: 0.9330

--- Plotting Training History ---
```

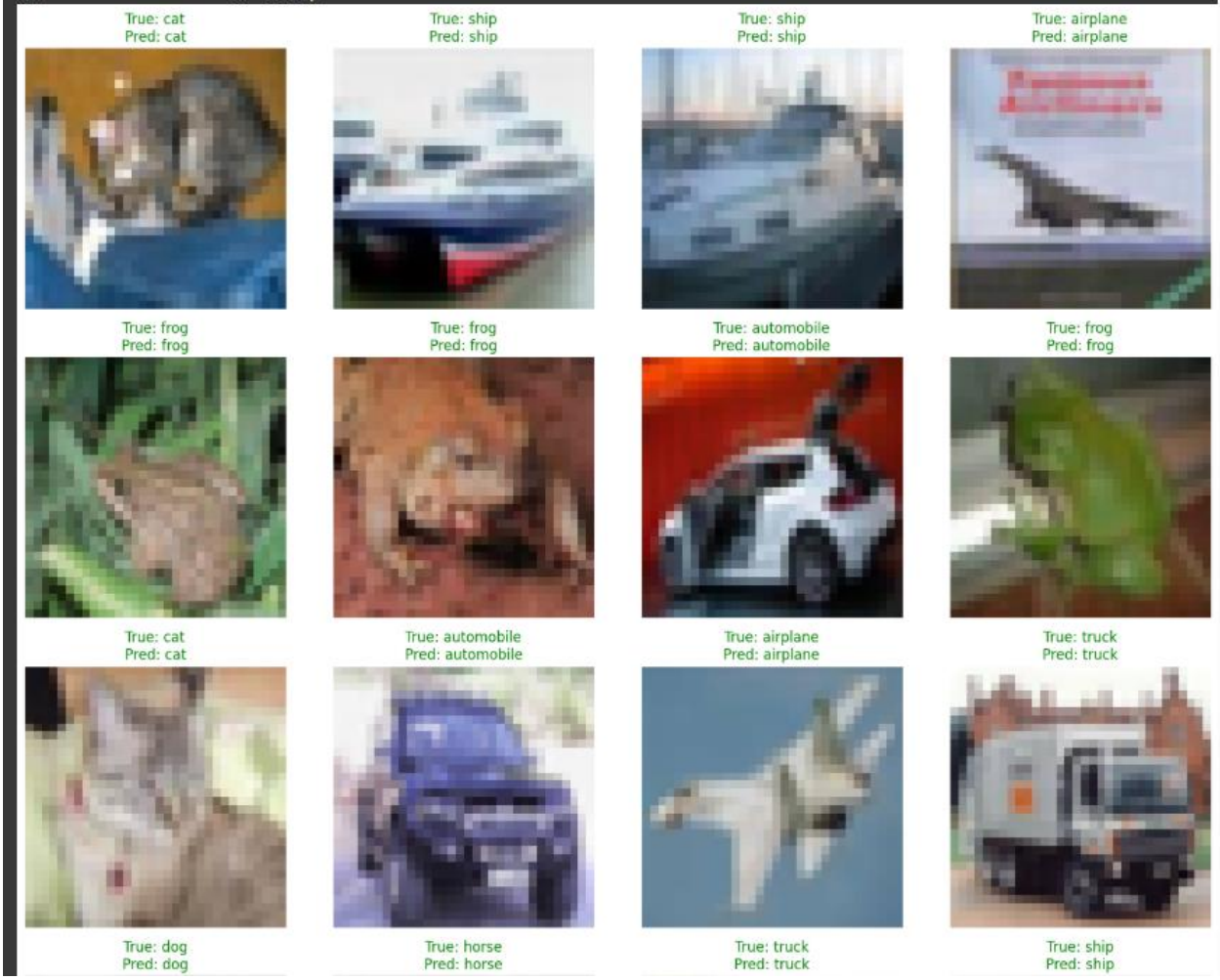


Observation: Unfreezing and dropout prevented overfitting, achieving excellent generalization. Everything has become better now.

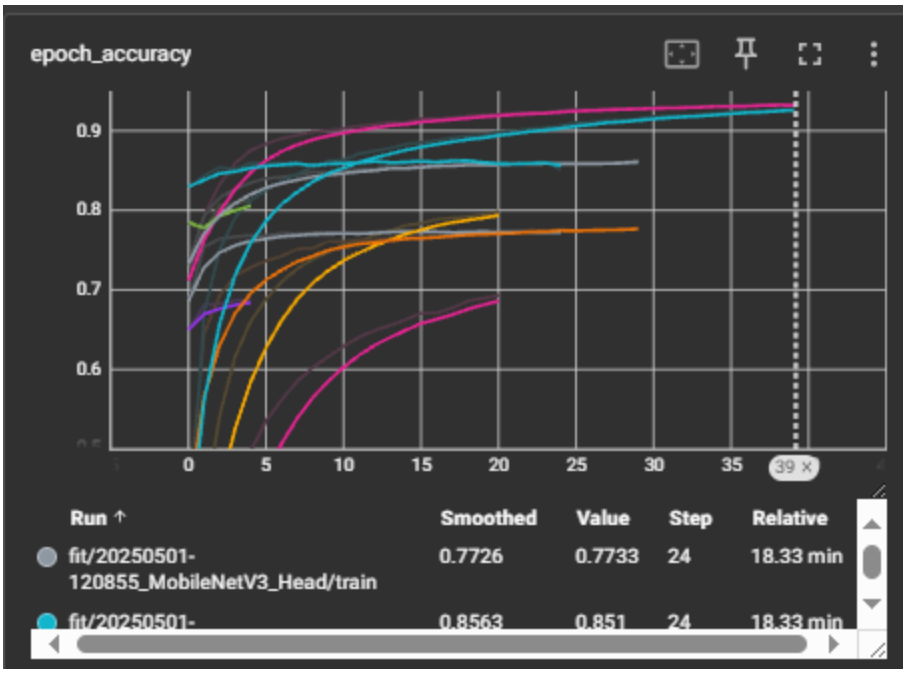
Inference for the last one (best model):

```
CIFAR-10 dataset loaded.
Test image dataset ready for prediction.
Loading saved model from: checkpoints/E2E_LR1e-05_DR0.2_FT100_20250501-133810/best_model.keras
Model loaded successfully.

--- Performing Inference ---
1/1 ━━━━━━━━━━━━━━━━━━━━ 4s 4s/step
```



TensorBoard Comparison



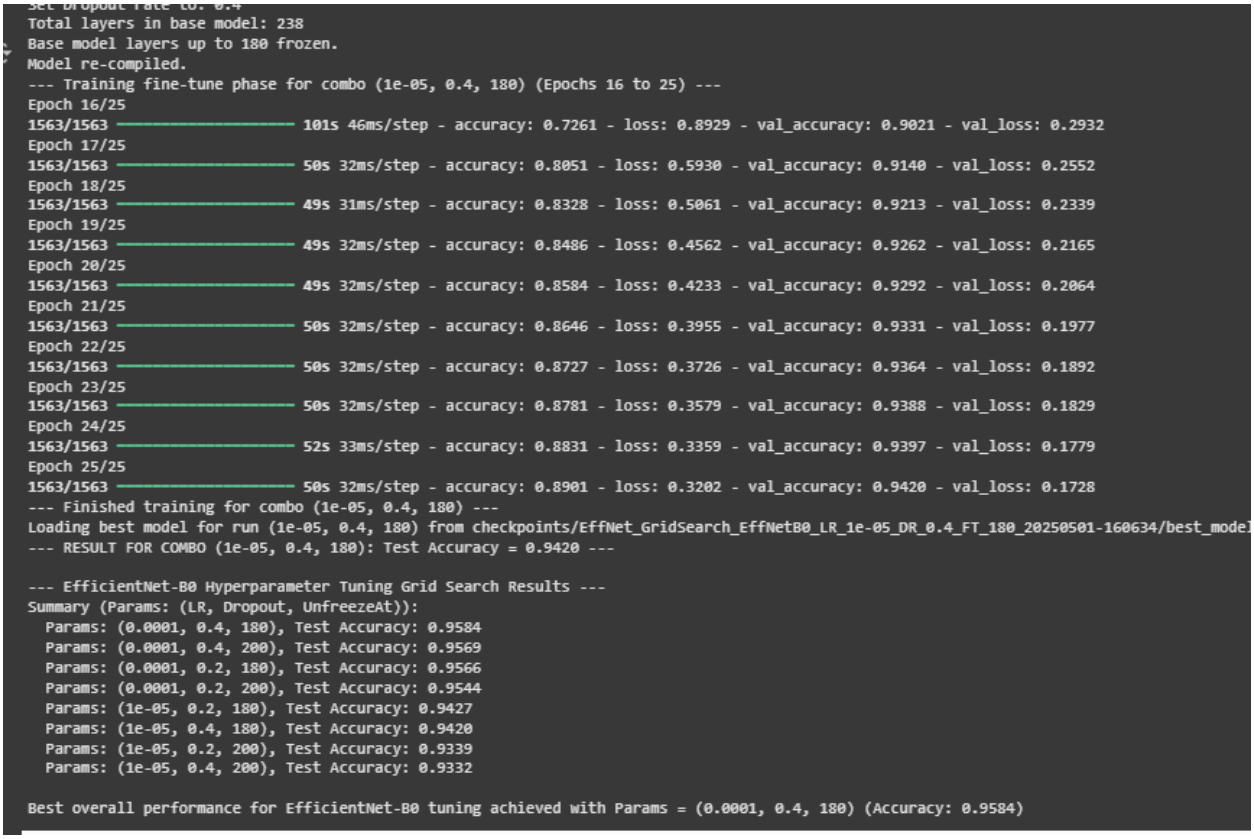
Key Insights: Stage 4 produced the optimal results by unfreezing and dropout to achieve 0.9305 accuracy and 0.2067 loss rate when compared to other stages. The model performance improved with a decrease in learning rate and increased training time though it needed regularization to prevent overfitting.

4.2 EfficientNet-B0

Parameters Tuned: Fine-tuning Learning Rate (LR), Head Dropout Rate (DR), Unfreeze Point (FT, layers before this index remain frozen).

Ranges Tested: LR= [1e-4, 1e-5], DR= [0.2, 0.4], FT= [200, 180], 10 epochs, 3 hyperparameters, 2 values for each, leading to 2^3 times which is 8 iterations within the same cell with 10 epochs resulting in 80 epochs overall to get the optimal values

Setup: 10 fine-tuning epochs per combination, starting from 15-epoch head checkpoint.

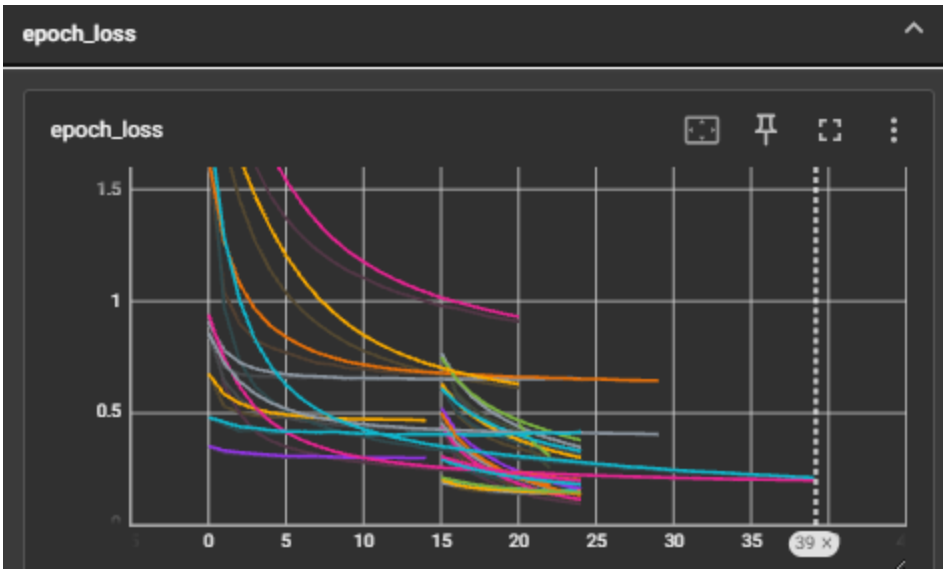


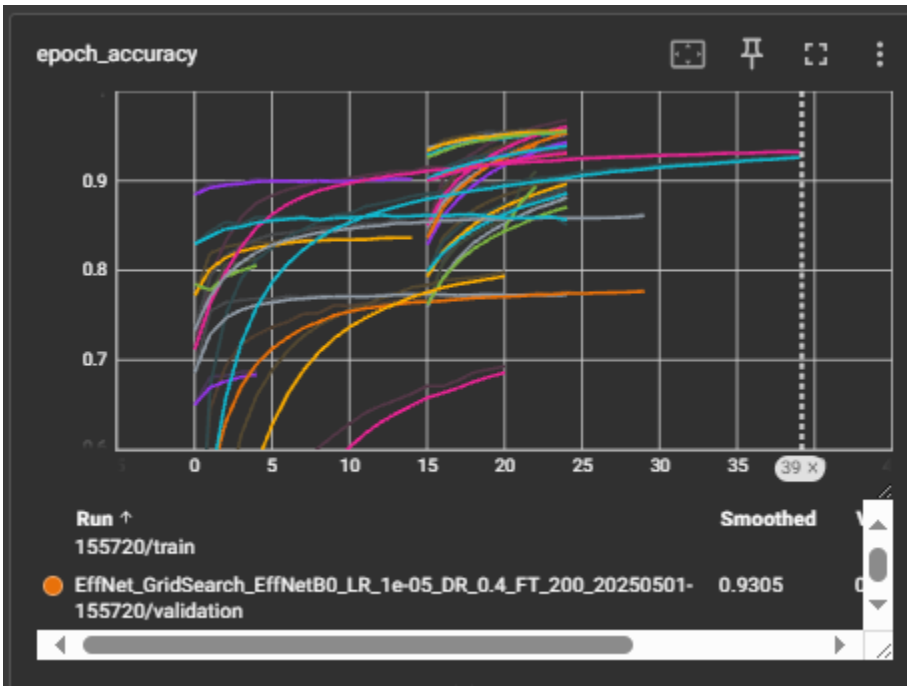
Detailed 8-time iteration in the notebook.

Analysis: The learning rate (1e-4) consistently outperformed (1e-5) within these 10 epochs. Unfreezing more layers (FT=180 vs FT=200) generally yielded slightly better or comparable results. A higher dropout rate (0.4) combined with LR=1e-4 and FT=180 gave the best performance.

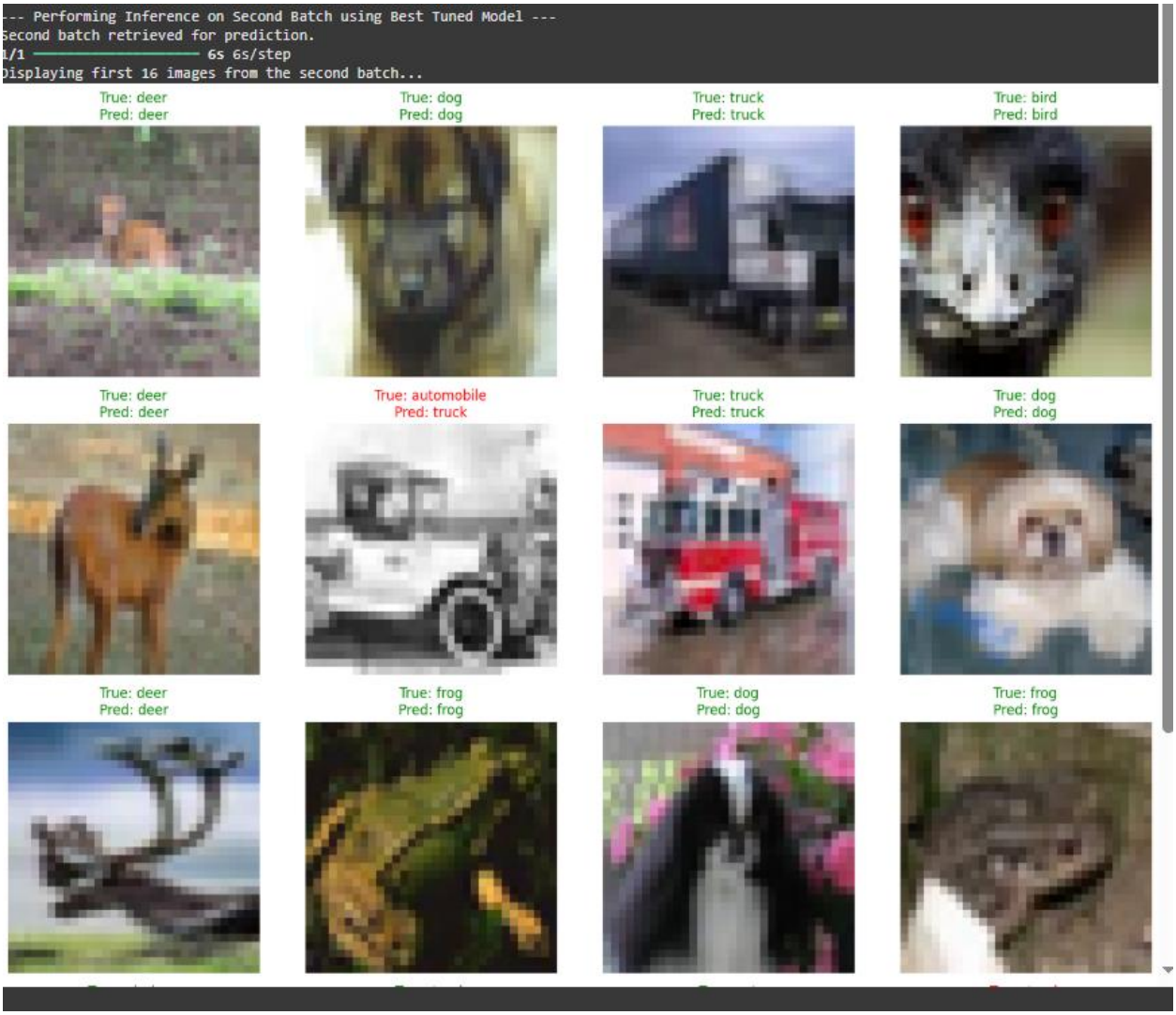
Best Configuration: LR=0.0001, Dropout=0.4, UnfreezeAt=180**.**

Results for the Two Models:





Inference for the best EfficientNet-B0

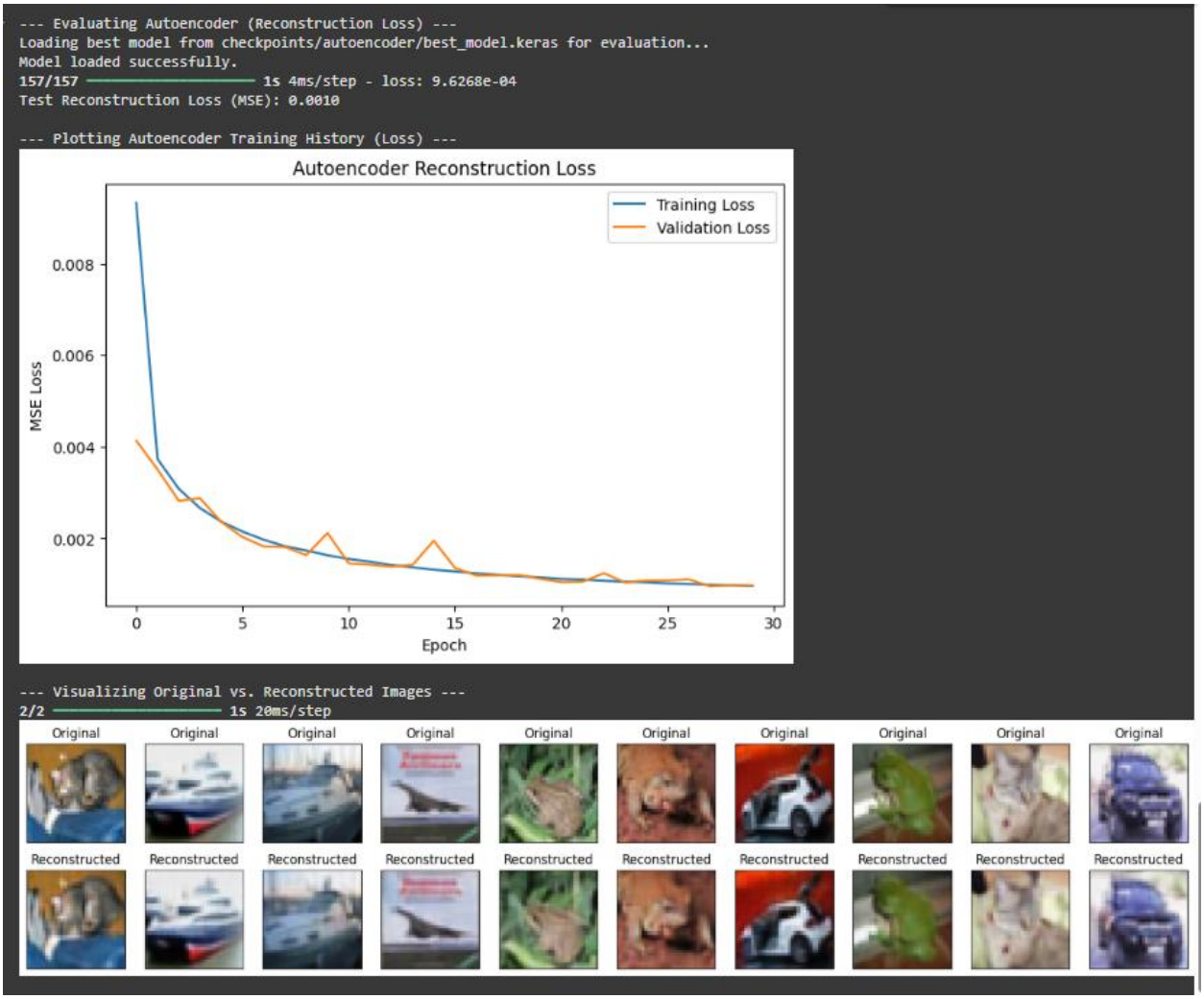


4.3. CAE

Parameters Tuned: Learning Rate, Bottleneck Filter Count (BF).

Ranges Tested: LR= [1e-3, 5e-4, 1e-4], BF= [64, 128, 256] .

Setup: 15 epochs per combination, 3^2 trained from scratch. Evaluation based on minimum Test MSE Loss.



Baseline Training: The base Convolutional Autoencoder (CAE) model started training with 128 filters inside the bottleneck layer and ran for 30 epochs by using the default Adam optimizer learning rate set to 0.001. The baseline achieved Test Reconstruction Loss (MSE) of roughly 0.0010 during its performance assessment.

Hyperparameter Tuning Experiments: To explore potential improvements, hyperparameter tuning experiments were conducted, varying the Learning Rate (LR = [1e-3, 5e-4, 1e-4]) and the Bottleneck Filter count (BF = [64, 128, 256]). To expedite the comparison across these 9 combinations, each configuration was trained for only **15 epochs**.

```
Epoch 13/15
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 0.0011 - val_loss: 0.0010
Epoch 14/15
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 0.0010 - val_loss: 0.0010
Epoch 15/15
782/782 ━━━━━━━━━━━━━━━━━━━━ 3s 4ms/step - loss: 0.0010 - val_loss: 0.0013
--- Finished training for combo (0.001, 256) ---
Loading best model for run (0.001, 256) from checkpoints/CAE_GridSearch_CAE_LR_0.001_BF_256_20250502-074327/best_model.keras
--- RESULT FOR COMBO (0.001, 256): Test Reconstruction Loss (MSE) = 0.001014 ---

--- Testing Combo: LR=0.0005, BottleneckFilters=64 ---
CAE model structure redefined.
Model compiled with LR=0.0005.
```

T**uning Results and Observation:** The results from these 15-epoch runs showed that the combination using LR=0.001 and BF=256 yielded the lowest MSE loss (**0.001014**) among the tested configurations. However, this result was slightly worse than the initial baseline model which had been trained for the full 30 epochs. This suggested that while the configuration with 256 bottleneck filters was promising, the shorter 15-epoch training duration during tuning likely limited its convergence.

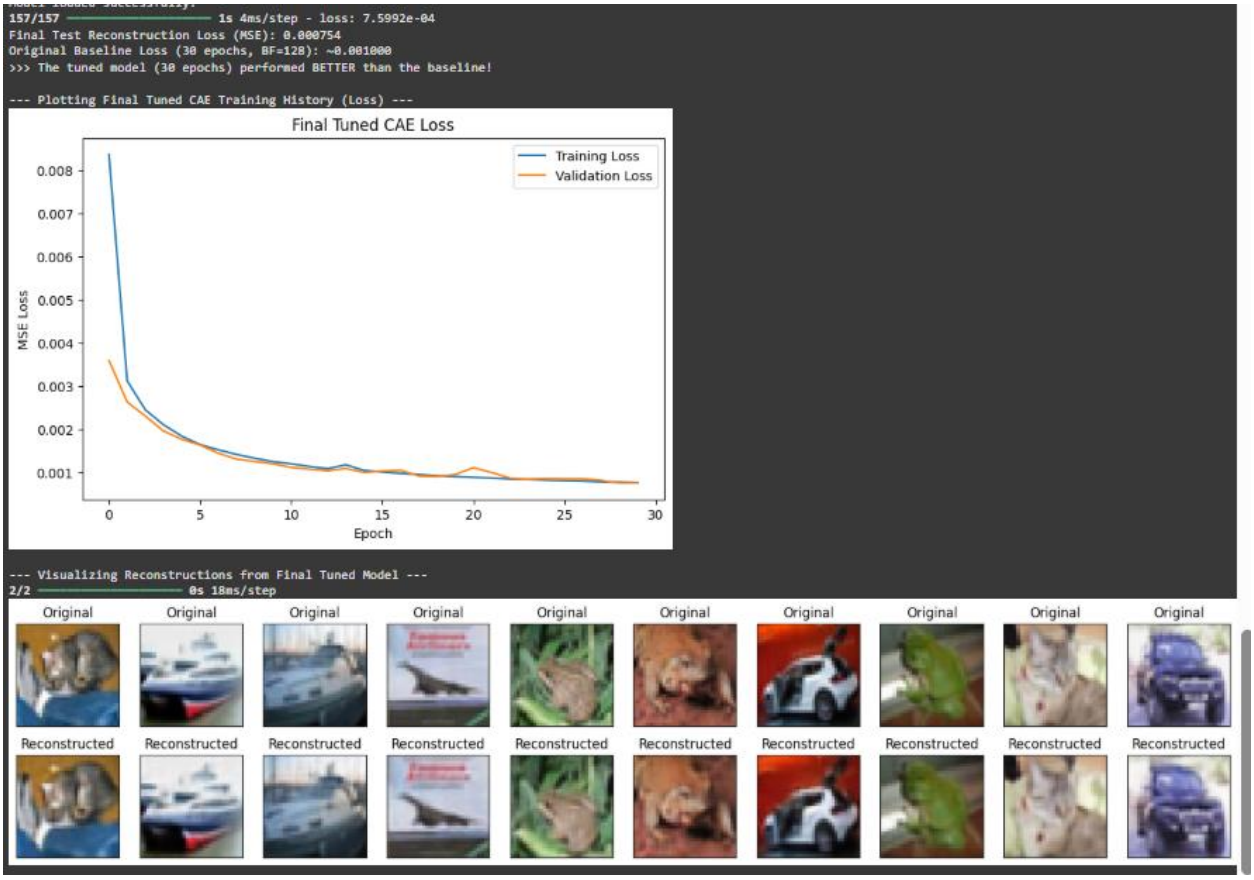
```
Epoch 21: val_loss did not improve from 0.00090
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 8.9124e-04 - val_loss: 0.0011
Epoch 22/30
781/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 8.8883e-04
Epoch 22: val_loss did not improve from 0.00090
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 8.8878e-04 - val_loss: 9.9570e-04
Epoch 23/30
770/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 8.5193e-04
Epoch 23: val_loss improved from 0.00090 to 0.00087, saving model to checkpoints/CAE_BestRun_LR0.001_BF256_20250502-075450/best_model.keras
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 8.5186e-04 - val_loss: 8.6648e-04
Epoch 24/30
770/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 8.4245e-04
Epoch 24: val_loss improved from 0.00087 to 0.00084, saving model to checkpoints/CAE_BestRun_LR0.001_BF256_20250502-075450/best_model.keras
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 8.4242e-04 - val_loss: 8.4477e-04
Epoch 25/30
770/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 8.1731e-04
Epoch 25: val_loss did not improve from 0.00084
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 8.1731e-04 - val_loss: 8.5721e-04
Epoch 26/30
778/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 8.0712e-04
Epoch 26: val_loss did not improve from 0.00084
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 4ms/step - loss: 8.0711e-04 - val_loss: 8.5218e-04
Epoch 27/30
772/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 7.9917e-04
Epoch 27: val_loss did not improve from 0.00084
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 7.9915e-04 - val_loss: 8.4974e-04
Epoch 28/30
781/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 7.8023e-04
Epoch 28: val_loss improved from 0.00084 to 0.00082, saving model to checkpoints/CAE_BestRun_LR0.001_BF256_20250502-075450/best_model.keras
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 7.8024e-04 - val_loss: 8.1552e-04
Epoch 29/30
777/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 7.7262e-04
Epoch 29: val_loss improved from 0.00082 to 0.00075, saving model to checkpoints/CAE_BestRun_LR0.001_BF256_20250502-075450/best_model.keras
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 7.7262e-04 - val_loss: 7.5360e-04
Epoch 30/30
776/782 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 7.5902e-04
Epoch 30: val_loss did not improve from 0.00075
782/782 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 7.5904e-04 - val_loss: 7.5500e-04

--- Final CAE Training Finished ---
*** Best tuned CAE model (30 epochs) should now be saved at: checkpoints/CAE_BestRun_LR0.001_BF256_20250502-075450/best_model.keras ***

--- Evaluating Final Tuned Autoencoder (30 Epochs) ---
Loading best model from checkpoints/CAE_BestRun_LR0.001_BF256_20250502-075450/best_model.keras for evaluation...
Model loaded successfully.
157/157 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - loss: 7.5992e-04
Final Test Reconstruction Loss (MSE): 0.000754
Original Baseline Loss (30 epochs, BF=128): ~0.001000
>>> The tuned model (30 epochs) performed BETTER than the baseline!

--- Plotting Final Tuned CAE Training History (Loss) ---
```

Final Tuned CAE Loss



Final Training of Best Configuration: Based on the tuning results indicating the potential of the LR=0.001, BF=256 configuration, this specific setup was **re-trained for the full 30 epochs** to match the baseline training duration and assess its complete potential. This final, longer training run achieved a significantly lower final Test MSE loss of **0.000754**, successfully outperforming the original 30-epoch baseline. This confirmed the benefit of the larger bottleneck (256 filters) identified during tuning, once adequate training time was provided.

6. Discussion and Comparison

A testing of three different deep learning algorithms including MobileNetV3-Small and EfficientNet-B0 and the Convolutional Autoencoder was successfully implemented on CIFAR-10.

6.1. Model Performance Comparison

After applying hyperparameter optimization to the EfficientNet-B0 CNN classifier it reached 95.84% test accuracy which proved best among both models evaluated. MobileNetV3-Small achieved 93.30% test accuracy after completing end-to-end fine-tuning because of initial checkpoint problems. The design strategy behind EfficientNet-B0 that enhances performance allows higher accuracy while exceeding the

parameter count of MobileNetV3Small. Accurate calculation of CAE performance through accuracy metrics is difficult since it operates independently for unsupervised image reconstruction tasks. The optimal configuration of this model demonstrated an exceptionally low-Test Reconstruction Loss (MSE) of 0.000754 during the final stage which proved the high image reconstruction fidelity both in quantitative and qualitative terms.

6.2. Impact of Hyperparameter Tuning

The experiments confirming hyperparameter settings yielded essential findings. A grid search confirmed that EfficientNet-B0 achieved its highest classification accuracy with a learning rate set to 1e-4 while using 0.4 dropout together with layer unfreezing starting from index 180 within the 10-epoch experiment duration. Rate learning and regularization demand careful adjustments because they affect the response of fine-tuning methods. The multidimensional optimization process found the combination of default Adam learning rate 0.001 and 256 filter bottleneck to deliver highest CAE model performance during 15 epochs. A 30-epoch training session of the discovered optimal configuration produced better performance than both the baseline model and the shorter optimization period proving that proper training duration is vital for high-capacity models discovered through tuning.

6.3. Model Generalization Analysis

The three finalized models achieved satisfactory generalization abilities when tested. The best tuned EfficientNet-B0 demonstrated steady training because validation accuracy accurately followed the training progress throughout the process. Throughout training the end-to-end MobileNetV3 consistently achieved higher validation accuracy compared to training accuracy due to the strong regularization effects of dropout combined with a very low fine-tuned learning rate which prevented overfitting effectively. Generalization of models during training can be attributed to data augmentation techniques utilized during CNN training. Testing data's MSE measurements validated the CAE's generalization ability due to its validation loss curve matching training loss during the last 30 epochs and achieving a low test MSE. This was verified through both quantitative and qualitative evaluation. Implicit class segmentation in the t-SNE visualization indicates that the CAE successfully obtained generalized features.

(Screenshots for the models’ metrices/graphs have been shown earlier)

6.4. Challenges and Limitations

Several challenges were encountered. The Swin Transformer implementation process encountered multiple library incompatibilities alongside resource constraints within RunPod and Colab platforms which made training unsuccessful so the researchers chose to use the CAE model instead. The saving approach for model checkpoints required modification because it failed to save .index files when saving

weights using the .h5 extension so we adapted the method to store complete models using the .keras format. Proper setup of cloud environments like RunPod for CUDA work needs special attention because correct library compatibility requires particular care. Despite its usefulness the performed model hyperparameter tuning included only a restricted selection of parameter values and epoch counts because of time limitations and resource restrictions.

7. Conclusion

This project successfully explored the design implementation training and evaluation process of MobileNetV3 EfficientNet-B0 and a Convolutional Autoencoder deep learning architectures when used together with CIFAR-10 dataset on the TensorFlow/Keras platform. Pre-trained CNN models received effective application of transfer learning and fine-tuning methods and the Convolutional Autoencoder excelled at unsupervised reconstruction tasks. Tuned EfficientNet-B0 delivered the best classification test results of 95.8% while the tuned CAE attained an exceptional test MSE level of 0.00075. Additional explanations of model behavior emerged from visualization methods that demonstrated learning curves, inference examples, reconstructions, latent space projections, and filters. The project encountered implementation problems with Swin Transformer but it successfully completed its objectives and delivered hands-on experience of deep learning methodologies.