



EAST WEST UNIVERSITY

Course Code : CSE366

Course Title : Artificial Intelligence

Section : 03

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Assignment Report

Submitted to :

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Computer Vision Assignment

Dataset Information:

The dataset contains 1006 leaf images grouped according to their nutritional deficiencies (Boron, Iron, Potassium, Calcium, Magnesium, Manganese, Nitrogen and others). CoLeaf dataset contains images that facilitate training and validation during the utilization of deep learning algorithms for coffee plant leaf nutritional deficiencies recognition and classification.

Class	Frequency
Boron-B	101
Calcium-Ca	162
Iron-Fe	65
Magnesium-Mg	79
Manganese-Mn	83
Nitrogen-N	64
Phosphorus-P	246
Potassium-K	96
More-deficiencies	104
Healty	6

Citation: Tuesta-Monteza, Víctor A; Mejia-Cabrera, Heber I.; Arcila-Diaz, Juan (2023), “CoLeaf DATASET”, Mendeley Data, V1, doi: 10.17632/brfgw46wzb.1

Link: <https://data.mendeley.com/datasets/brfgw46wzb/1>

Data Augmentation:

Augmentation Key factors: rotation_range=40,
width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2,
zoom_range=0.2, horizontal_flip=True, fill_mode='nearest'.

Class	Frequency
Boron-B	494
Calcium-Ca	778
Iron-Fe	321
Magnesium-Mg	379
Manganese-Mn	407
Nitrogen-N	314
Phosphorus-P	246
Potassium-K	96

Data Pre-process:

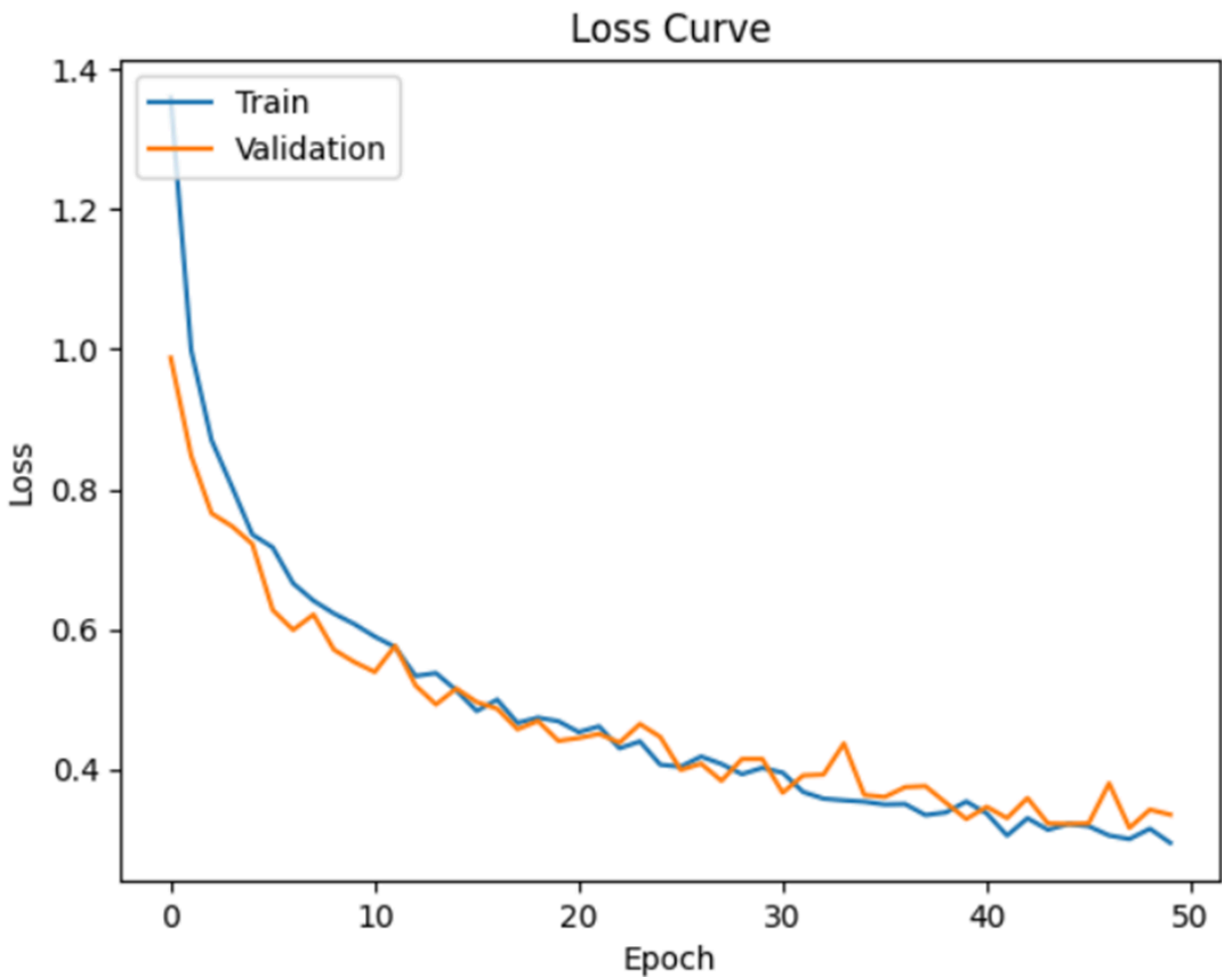
Train - 80%

Validation - 20

Model Performance

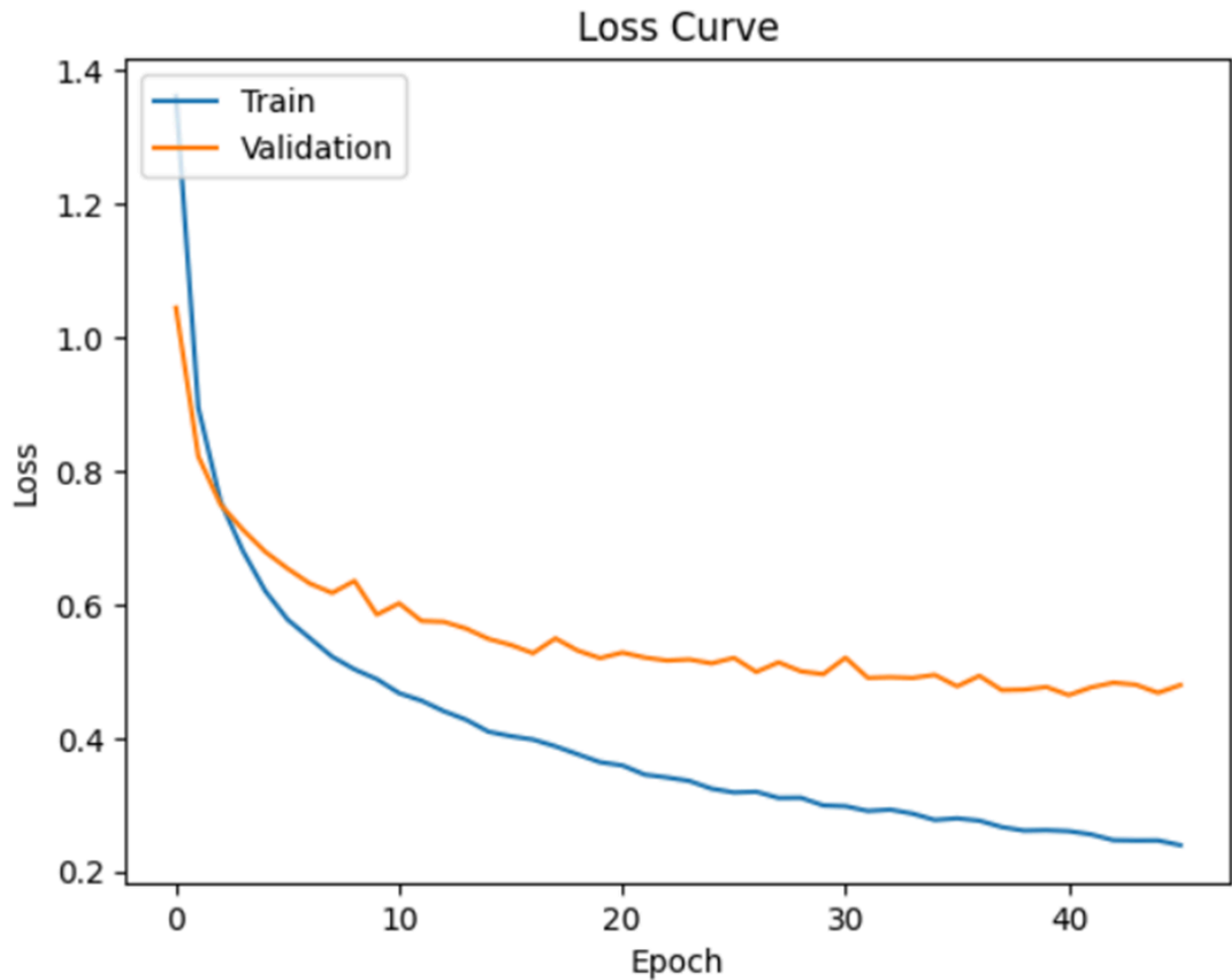
EfficientNet B3

Accuracy: 88%



DenseNet101

Accuracy 82%



Discussion of Results:

When comparing the results of the EfficientNetB3 and DenseNet121 models, both exhibit strong performance with their respective accuracies of 88% and 82%. The training loss curves of both models show a similar trend, decreasing sharply initially and then stabilizing, indicating effective learning from the training data. However, the validation loss curves display some differences. While the EfficientNetB3 model's validation loss exhibits fluctuations after approximately 30 epochs, the DenseNet121 model's validation loss plateaus after around 10 epochs. These

variations suggest potential overfitting in both models, although it appears to occur at different stages of training. Notably, both models demonstrate good generalization to unseen data, as evidenced by the minimal gap between training and validation loss.

Conclusion:

In conclusion, both the EfficientNetB3 and DenseNet121 models perform reasonably well. However, further optimization is possible to mitigate overfitting and improve generalization. Experimenting with different architectures, regularization techniques, and data augmentation strategies could enhance the models' performance and robustness. Additionally, considering early stopping and closely monitoring validation loss trends are essential steps to prevent overfitting. Overall, the models show promise but require refinement to achieve optimal performance.

Possible Future Work:

Future work could focus on exploring different scaling factors within the EfficientNet architecture and experimenting with additional architectures beyond DenseNet121. Fine-tuning the models on specific datasets to enhance recognition for classes with inaccurate predictions could further improve performance. Additionally, continuing to iterate on model evaluation and fine-tuning processes and exploring various hyperparameters are essential for ongoing improvement.