**Implementation & Testing – Model Development Phase 1**

**1.1 Initial Model Testing**

The first iteration of the model-generating program was designed to establish a strong foundation for further development. The program's structure follows a four-component process, beginning with the importation of essential libraries such as TensorFlow, Matplotlib, and Keras (**Figure 7: Imports 1.1**).

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Key data processing parameters, including dataset directory, image size, and batch size, were defined before splitting the dataset into training and validation sets, followed by normalization.

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The model architecture (Model Architecture 1.1) was then established, compiled, and trained, with training and validation results visualized and stored for later analysis. The dataset utilized in this iteration, **LeafSnap\_15\_Lab**, provided the necessary samples for preliminary testing.

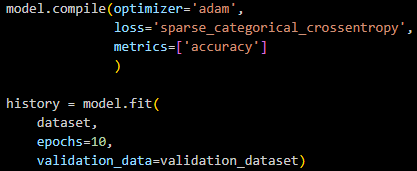


Figure 1Model Compilation & Training

The purpose of this initial test was to verify the correct functioning of the model rather than optimize performance. The hyperparameters included a batch size of 32 and 10 epochs.

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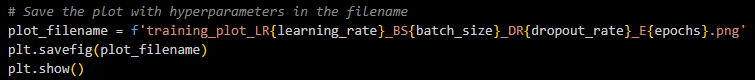
Accuracy and loss plots (**Figure 12: Accuracy & Loss 1.1**) demonstrated an upward trend in training accuracy and a downward trend in training loss. Validation accuracy showed promise but exhibited some instability, suggesting that additional epochs might be beneficial.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Epoch | train\_accuracy | train\_loss | val\_accuracy | val\_loss |
| 1 | 0.119 | 2.626 | 0.292 | 2.207 |
| 2 | 0.332 | 2.101 | 0.485 | 1.804 |
| 3 | 0.454 | 1.641 | 0.600 | 1.273 |
| 4 | 0.565 | 1.332 | 0.628 | 1.066 |
| 5 | 0.623 | 1.090 | 0.672 | 0.953 |
| 6 | 0.694 | 0.920 | 0.696 | 0.909 |
| 7 | 0.723 | 0.830 | 0.732 | 0.784 |
| 8 | 0.744 | 0.749 | 0.706 | 0.825 |
| 9 | 0.778 | 0.638 | 0.740 | 0.720 |
| 10 | 0.794 | 0.614 | 0.753 | 0.727 |

The recorded data (**Table 1: Training and Validation Metrics 1.1**) further supported this hypothesis, as neither the training nor validation accuracy had plateaued by the tenth epoch, indicating potential for further improvement.

**1.2 Enhanced Record-Keeping & Epoch Variation**

A key improvement introduced in **Version 1.2** was an updated naming convention for output files, now incorporating hyperparameter values for better organization (**Figure 13: Naming Convention 1.2**). While this modification did not affect model performance, it improved record-keeping efficiency.



The next test investigated the impact of varying the number of epochs. Three different values—10, 25, and 50—were tested while keeping other hyperparameters constant (**Table 2: Epoch Variation Results 1.2**).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| No\_of\_epochs | train\_accuracy | train\_loss | val\_accuracy | val\_loss |
| 10 | 0.795 | 0.559 | 0.761 | 0.721 |
| 25 | 0.949 | 0.139 | 0.789 | 0.950 |
| 50 | 0.985 | 0.041 | 0.744 | 1.652 |

The results showed that increasing epochs to 25 improved both training and validation accuracy, but at 50 epochs, validation accuracy declined while validation loss increased, indicating overfitting.

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Analysis of accuracy and loss plots (**Figure 14: Accuracy & Loss 1.2a 1** and **Figure 15: Accuracy & Loss 1.2a 2**) further suggested that overfitting began between epochs 10 and 25, with more pronounced degradation by epoch 50. These findings indicated that an optimal epoch value likely lay within this range, pending further hyperparameter tuning.

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**1.2b Hyperparameter Combinations: Learning Rate, Dropout, and Epochs**

Building upon previous findings, this test phase examined how variations in learning rate, dropout rate, and epochs influenced performance. Two learning rates (0.001, 0.005), three dropout rates (0.2, 0.35, 0.5), and three epoch values (10, 15, 20) were tested in different combinations (**Table 3: Hyperparameter Combination Results 1.2b**).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Learning\_rate | batch\_size | dropout\_rate | epoch | train\_accuracy | train\_loss | val\_accuracy | val\_loss |
| 0.001 | 32 | 0.2 | 20.0 | 0.93 | 0.2 | 0.77 | 0.81 |
| 0.001 | 32 | 0.35 | 20.0 | 0.93 | 0.21 | 0.75 | 0.84 |
| 0.001 | 32 | 0.5 | 20.0 | 0.93 | 0.2 | 0.76 | 0.94 |
| 0.005 | 32 | 0.35 | 15.0 | 0.92 | 0.25 | 0.77 | 0.77 |
| 0.005 | 32 | 0.2 | 20.0 | 0.9 | 0.25 | 0.76 | 0.86 |
| 0.005 | 32 | 0.5 | 20.0 | 0.9 | 0.27 | 0.72 | 1.01 |
| 0.005 | 32 | 0.2 | 15.0 | 0.89 | 0.3 | 0.73 | 1.0 |
| 0.001 | 32 | 0.35 | 15.0 | 0.88 | 0.35 | 0.74 | 0.84 |
| 0.005 | 32 | 0.5 | 15.0 | 0.88 | 0.34 | 0.75 | 0.83 |
| 0.001 | 32 | 0.5 | 15.0 | 0.86 | 0.39 | 0.74 | 0.78 |
| 0.001 | 32 | 0.2 | 15.0 | 0.84 | 0.43 | 0.72 | 0.8 |
| 0.005 | 32 | 0.5 | 10.0 | 0.83 | 0.49 | 0.76 | 0.64 |
| 0.001 | 32 | 0.2 | 10.0 | 0.83 | 0.5 | 0.76 | 0.74 |
| 0.005 | 32 | 0.2 | 10.0 | 0.8 | 0.57 | 0.74 | 0.72 |
| 0.001 | 32 | 0.5 | 10.0 | 0.79 | 0.56 | 0.76 | 0.72 |
| 0.001 | 32 | 0.35 | 10.0 | 0.79 | 0.62 | 0.73 | 0.79 |
| 0.005 | 32 | 0.35 | 20.0 | 0.88 | 0.3 | 0.73 | 0.91 |
| 0.005 | 32 | 0.35 | 10.0 | 0.77 | 0.65 | 0.71 | 0.88 |

Results indicated that a lower learning rate (0.001) and a higher epoch count (20) generally led to improved validation accuracy. The dropout rate also played a role, with lower values (0.2–0.35) producing slightly better results than 0.5. However, even the top-performing models still exhibited signs of overfitting. The poorest results emerged from the highest learning rate (0.005) and lowest epoch count (10), reinforcing the importance of careful learning rate selection.

**1.2c Further Hyperparameter Optimization**

To refine performance further, this stage tested a batch size of 64 against the previously used 32, alongside additional learning rate variations (**Table 4: Batch Size and Learning Rate Results 1.2c**).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| learning\_rate | batch\_size | dropout\_rate | no\_of\_epochs | tr\_accuracy | tr\_loss | val\_accuracy | val\_loss |
| 0.001 | 64 | 0.5 | 10 | 0.77 | 0.66 | 0.74 | 0.40 |
| 0.001 | 64 | 0.5 | 15 | 0.86 | 0.41 | 0.70 | 0.88 |
| 0.0005 | 32 | 0.5 | 10 | 0.76 | 0.67 | 0.74 | 0.78 |
| 0.0005 | 64 | 0.5 | 10 | 0.78 | 0.65 | 0.73 | 0.77 |
| 0.005 | 64 | 0.5 | 10 | 0.78 | 0.63 | 0.74 | 0.71 |

Results showed that increasing batch size improved performance, with all tests using batch size 64 outperforming those using 32. Learning rate adjustments revealed that 0.001 remained the most effective value, but finer adjustments could be explored for further optimization.

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The best-performing model from this test used a **learning rate of 0.001, batch size of 64, and 10 epochs**, achieving the highest validation accuracy while maintaining a relatively low validation loss (**Figure 18: Accuracy & Loss 1.2c**). These findings underscored the potential benefits of larger batch sizes and lower learning rates for this model configuration.

**Summary & Next Steps**

Phase 1 successfully validated the functionality of the initial model and identified key hyperparameters affecting performance. Increasing epochs beyond 10 improved accuracy but introduced overfitting beyond 25 epochs. A learning rate of 0.001 consistently produced strong results, while a batch size of 64 showed promise for further improvement. Future testing will continue hyperparameter adjustments while also exploring dataset enhancements and modifications to model architecture to address overfitting and optimize generalization.

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**Implementation & Testing – Model Development Phase 2**

**2.1 Introduction of a Test Set & Improved Record-Keeping**

Phase 2 introduced key modifications aimed at enhancing evaluation methods and result organization. First, **Version 2.1** implemented the creation of a dedicated test set to assess model performance on entirely unseen data, improving the reliability of accuracy and loss metrics (**Figure 19: Dataset Split 2.1**).

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Additionally, a structured output directory was introduced, ensuring that each new iteration's results were systematically stored (**Figure 20: Output Directory 2.1**).

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The inclusion of a test set provided more realistic accuracy and loss evaluations. Results from this phase showed consistently high training and validation accuracies, with test accuracy closely aligning with validation performance (**Table 5: Performance Metrics 2.1**).

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| LR | BS | DR | E | train\_acc | train\_loss | val\_acc | val\_loss | test\_acc | test\_loss |
| 0.001 | 32 | 0.5 | 10 | 0.943 | 0.161 | 0.973 | 0.099 | 0.961 | 0.113 |
| 0.001 | 32 | 0.5 | 15 | 0.948 | 0.136 | 0.969 | 0.088 | 0.975 | 0.054 |
| 0.005 | 32 | 0.5 | 10 | 0.955 | 0.127 | 0.946 | 0.130 | 0.939 | 0.155 |
| 0.0005 | 32 | 0.5 | 10 | 0.931 | 0.211 | 0.967 | 0.131 | 0.939 | 0.191 |
| 0.005 | 32 | 0.5 | 15 | 0.969 | 0.095 | 0.975 | 0.086 | 0.971 | 0.094 |
| 0.0005 | 32 | 0.5 | 15 | 0.957 | 0.119 | 0.983 | 0.073 | 0.982 | 0.047 |
| 0.0005 | 32 | 0.5 | 20 | 0.977 | 0.070 | 0.962 | 0.108 | 0.950 | 0.108 |

The best-performing configuration used 15 epochs and a learning rate of 0.0005, achieving **98.2% test accuracy**, confirming strong generalization. Accuracy and loss trends (**Figure 21: Accuracy & Loss 2.1**) supported these findings, with minimal overfitting observed.

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**2.2 Integration of the Confusion Matrix & Model Saving**

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To further verify classification performance, **Version 2.2** introduced a confusion matrix, allowing for detailed insight into misclassification trends (**Figure 22: Confusion Matrix Implementation 2.2**).

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Additionally, a model-saving feature was implemented, ensuring that high-performing models could be stored and reloaded for future testing (**Figure 23: Save Model Implementation 2.2**).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| learning\_rate | batch\_size | dropout | epochs | test\_loss | test\_accuracy |
| 0.0001 | 32 | 0.5 | 20 | 0.106 | 0.968 |
| 0.001 | 32 | 0.5 | 15 | 0.110 | 0.964 |
| 0.001 | 32 | 0.5 | 20 | 0.093 | 0.968 |
| 0.0005 | 32 | 0.5 | 20 | 0.082 | 0.968 |
| 0.005 | 32 | 0.5 | 15 | 0.078 | 0.971 |
| 0.005 | 32 | 0.5 | 20 | 0.104 | 0.964 |

Despite already high accuracy scores, hyperparameter tuning continued. The best-performing configuration achieved **97.1% test accuracy with a learning rate of 0.005 and 15 epochs** (**Table 6: Performance Metrics 2.2**).

A graph of a training and validation

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Accuracy and loss plots (**Figure 24: Accuracy & Loss 2.2**) reinforced this success, showing smooth learning curves. The confusion matrix (**Figure 25: Confusion Matrix 2.2**) confirmed that predictions were highly accurate, with only minimal misclassifications.

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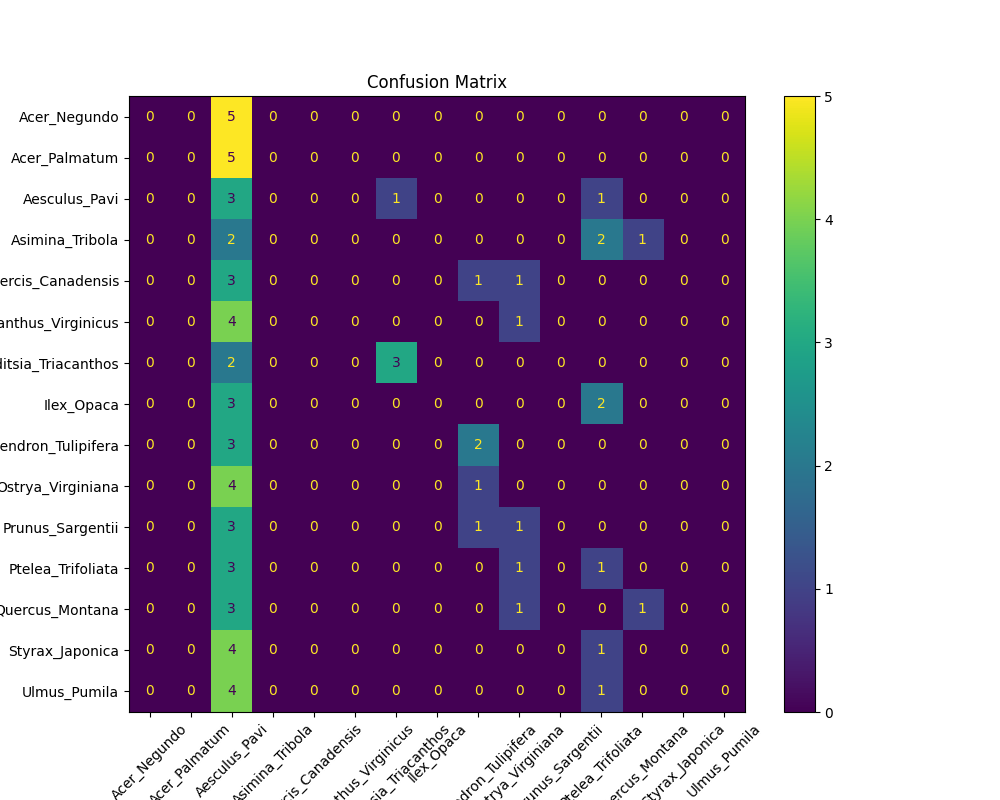
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**2.3 Testing on Realistic Data**

While previous test sets were unseen, they originated from the same dataset, limiting real-world applicability. **Version 2.3** tested models on a newly compiled dataset containing real-world images, mimicking practical classification challenges.

|  |  |  |
| --- | --- | --- |
| Model | Accuracy | Log\_Loss |
| model\_LR0.0001\_BS32\_DR0.5\_E20 | 0.133 | 17.781 |
| model\_LR0.0005\_BS32\_DR0.35\_E20 | 0.133 | 19.057 |
| model\_LR0.001\_BS32\_DR0.5\_E20 | 0.120 | 17.934 |
| model\_LR0.0005\_BS32\_DR0.5\_E20 | 0.107 | 21.350 |
| model\_LR0.005\_BS32\_DR0.5\_E20 | 0.080 | 23.562 |
| model\_LR0.005\_BS32\_DR0.5\_E15 | 0.067 | 23.163 |
| model\_LR0.001\_BS32\_DR0.5\_E15 | 0.067 | 25.609 |

Results showed a stark decline in accuracy, with even the best model achieving just **13% accuracy on realistic data** (**Table 7: Realistic Dataset Performance 2.3**).



The confusion matrix of even the best run (**model\_LR0.0001\_BS32\_DR0.5\_E203**) highlighted severe misclassifications, revealing the model's struggle with more varied, cluttered images. One class in particular, Acer\_Palmatum, dominated the model’s predictions, highlighting the confused state of the model. This experiment emphasized the need for better generalization, prompting exploration of data augmentation in the next phase.

**2.4 Implementation of Data Augmentation**

To address the limitations exposed in **2.3**, **Version 2.4** introduced a data augmentation layer to increase dataset variability during training. Augmentations included image flipping, rotation, and zooming to enhance robustness (**Figure 30: Augmentation & Architecture 2.4**).

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Testing confirmed the effectiveness of augmentation, with the best configuration achieving **92% test accuracy**, marking a notable improvement in real-world generalization (**Table 8: Augmented Dataset Performance 2.4**).

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| L.R | B.S | D.R | E | Tr. Acc. | Tr. Loss | Val. Acc. | Val. Loss | Test Acc. | Test Loss |
| 0.0005 | 32 | 0.4 | 30 | 0.757 | 0.686 | 0.870 | 0.427 | 0.922 | 0.394 |
| 0.0005 | 32 | 0.5 | 20 | 0.786 | 0.590 | 0.892 | 0.340 | 0.900 | 0.330 |
| 0.0001 | 32 | 0.5 | 20 | 0.787 | 0.599 | 0.881 | 0.347 | 0.882 | 0.341 |
| 0.0001 | 32 | 0.35 | 20 | 0.736 | 0.748 | 0.885 | 0.332 | 0.857 | 0.336 |
| 0.0050 | 32 | 0.5 | 15 | 0.747 | 0.740 | 0.865 | 0.368 | 0.857 | 0.378 |
| 0.0010 | 32 | 0.5 | 15 | 0.743 | 0.722 | 0.835 | 0.416 | 0.832 | 0.412 |

However, training accuracy and loss remained lower than in previous versions, suggesting room for refinement. The confusion matrix (**Figure 32: Confusion Matrix 2.4**) showed better distribution of correct classifications compared to previous tests.

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**Summary & Next Steps**

Phase 2 introduced a test set for improved evaluation, integrated a confusion matrix for deeper insight, and implemented data augmentation to enhance real-world applicability. While augmentation improved robustness, accuracy on realistic images still lagged behind results on structured datasets. Future work will focus on architectural modifications, particularly integrating pre-trained models such as **EfficientNet and MobileNet**, to further improve performance on diverse data.

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**Implementation & Testing – Model Development Phase 3**

**3.1 Integration of MobileNetV2**

Phase 3 introduced pre-trained architectures to enhance model performance, starting with **MobileNetV2**, imported from the Keras applications package (**Figure 33: MobileNet Importation 3.1**). The architecture was incorporated into the model definition, replacing earlier manually defined architectures (**Figure 34: Model Architecture 3.1**).

The test utilized the same **LeafSnap\_15\_Lab** dataset as prior phases to isolate the impact of MobileNetV2. Hyperparameters were set to **10 epochs, a learning rate of 0.0001, and a batch size of 32**. Results showed a dramatic improvement, with validation accuracy reaching **99.8% and test accuracy hitting 99.6%**, the highest recorded in the project thus far (**Table 9: Performance Metrics 3.1**). Accuracy and loss plots (**Figure 36: Accuracy & Loss 3.1**) confirmed that while accuracy nearly maxed out, loss had yet to plateau, suggesting potential for further gains with increased epochs.

**3.2 Testing MobileNetV2 on a Realistic Dataset**

To assess the model’s real-world effectiveness, **Version 3.2** replaced the LeafSnap dataset with a new **shrooms\_ds** dataset, featuring thousands of field images of mushrooms (**Figure 37: Dataset Path 3.2**). No other modifications were made, ensuring any performance changes stemmed from the dataset shift.

Results indicated that, while validation accuracy reached **71.6%**, test accuracy was **72.0%**, a strong start given the increased dataset complexity (**Table 10: Mushroom Dataset Performance 3.2**). Accuracy and loss plots (**Figure 38: Accuracy & Loss 3.2**) suggested no overfitting, and the confusion matrix (**Figure 39: Confusion Matrix 3.2**) confirmed reasonable class distribution. However, further tuning was necessary to push performance closer to results from **3.1**.

**3.3 Implementing a Balanced Mushroom Dataset**

To address class imbalance in **shrooms\_ds**, a new version, **shrooms\_ds\_max**, was created by applying augmentation to underrepresented classes. This balanced dataset was implemented by adjusting the dataset path (**Figure 40: Dataset Path 3.3**), while all other parameters remained unchanged apart from an increased epoch count of **20**.

The model trained on **shrooms\_ds\_max** showed improved validation accuracy (**78.2%**) and test accuracy (**76.3%**), a notable increase over **3.2** (**Table 11: Balanced Dataset Performance 3.3**). The confusion matrix (**Figure 42: Confusion Matrix 3.3**) confirmed better distribution across classes, reinforcing the benefits of dataset balancing.

**3.4 Testing EfficientNetB0 as an Alternative Pre-Trained Model**

Seeking further improvements, **Version 3.4** replaced MobileNetV2 with **EfficientNetB0**, another lightweight pre-trained model (**Figure 43: EfficientNetB0 Implementation 3.4**). This allowed for direct performance comparison between the two architectures while keeping hyperparameters and dataset (shrooms\_ds\_max) constant.

Unfortunately, results were unexpectedly poor, with validation and test accuracy stagnating below **13.2%**, and no significant improvement over epochs (**Table 12: Performance Metrics 3.4**). Accuracy and loss plots (**Figure 44: Accuracy & Loss 3.4**) confirmed ineffective learning, while the confusion matrix (**Figure 45: Confusion Matrix 3.4**) showed the model predominantly assigning only two class labels. This failure suggested deeper integration adjustments were needed for EfficientNet architectures.

**Summary & Next Steps**

Phase 3 demonstrated the powerful impact of pre-trained architectures, with **MobileNetV2 vastly outperforming previous manually designed models**, achieving near-perfect accuracy on structured datasets. While **performance on real-world datasets improved**, further fine-tuning was necessary, particularly in balancing datasets and refining pre-trained model integration. Future work will **address EfficientNet’s initial failure and explore deeper modifications to model structure and hyperparameters.**

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**Implementation & Testing – Model Development Phase 4**

**4.1 Optimized EfficientNet Integration & Code Refinements**

Phase 4 introduced **EfficientNetV2S** and **EfficientNetB7**, two promising pre-trained models, alongside improvements in dataset handling and result logging. The revised program structure replaced OS-based directory management with Pathlib, introduced Seaborn for enhanced visualization, and implemented CSV logging for automated result tracking (**Figure 46: Importation 4.1**).

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To ensure test consistency, a pre-split dataset, **shrooms\_ds\_split**, was introduced, allowing for standardized training, validation, and testing (**Figure 47: Dataset Split 4.1**). Using **EfficientNetV2S**, the model achieved **87.6% training accuracy, 82.1% validation accuracy, and 82.1% test accuracy**, outperforming previous models on the mushroom dataset (**Table 13: Performance Metrics 4.1**). Accuracy and loss trends (**Figure 54: Accuracy & Loss 4.1**) suggested mild overfitting, while the confusion matrix (**Figure 55: Confusion Matrix 4.1**) indicated uneven class distribution, highlighting areas for further tuning.

**4.2 EfficientNetB7 Comparison**

To compare EfficientNet variants, **Version 4.2** replaced EfficientNetV2S with **EfficientNetB7**, keeping all other parameters unchanged (**Figure 56: EfficientNet Importation 4.2**). Results showed comparable validation (**82.3%**) and test accuracy (**81.8%**), with slightly improved training accuracy (**91.2%**) (**Table 14: Performance Metrics 4.2**).

The accuracy and loss plots (**Figure 58: Accuracy & Loss 4.2**) suggested minor overfitting, but the confusion matrix (**Figure 59: Confusion Matrix 4.2**) reaffirmed class imbalance issues. While both EfficientNet variants performed well, EfficientNetV2S displayed slightly better generalization.

**4.3 Transition to LeafSnap\_15\_Merged & Classification Report Integration**

**Version 4.3** returned to leaf classification, implementing a merged version of **LeafSnap\_15**, combining lab and field images for greater dataset diversity (**Figure 60: Dataset Path 4.3**). This version also introduced a **classification report**, detailing precision, recall, and F1-scores for each class (**Table 15: Classification Report 4.3**).

Despite achieving **99.8% validation accuracy and 100% test accuracy** (**Table 16: Performance Metrics 4.3**), the classification report (**Figure 62: Confusion Matrix 4.3**) suggested significant misclassifications, contradicting earlier results. This discrepancy indicated that while the model performed well numerically, class-specific performance varied widely, necessitating dataset balancing.

**4.4 EfficientNetV2S Validation on LeafSnap\_15\_Merged**

To maintain consistency, **Version 4.4** replaced EfficientNetB7 with **EfficientNetV2S**, keeping hyperparameters identical (**Figure 63: Model Definition 4.4**). Results remained strong, achieving **99.4% validation accuracy and 100% test accuracy** (**Table 17: Performance Metrics 4.4**), slightly outperforming **4.3**.

However, the classification report (**Table 18: Classification Report 4.4**) revealed similarly poor precision and recall values, confirming class imbalance issues. The confusion matrix (**Figure 65: Confusion Matrix 4.4**) further supported this finding, reinforcing the need for corrective action.

**4.5 Implementation of Class Weights to Address Imbalance**

To counteract dataset imbalance, **Version 4.5** introduced **class weighting**, computed dynamically based on dataset distribution (**Figure 66: Class Weighting Importation 4.5**). The weighted model achieved **99.2% validation accuracy and 99.2% test accuracy** (**Table 19: Performance Metrics 4.5**), with accuracy and loss plots (**Figure 69: Accuracy & Loss 4.5**) suggesting a more stable learning curve.

However, the classification report (**Table 20: Classification Report 4.5**) indicated that class misclassification persisted, with minimal improvements over **4.4**. The confusion matrix (**Figure 70: Confusion Matrix 4.5**) showed slightly better distribution but failed to resolve the issue entirely.

**4.6 Transition to Manually Balanced Dataset**

To further improve class distribution, **Version 4.6** manually balanced the dataset instead of relying on class weighting, equalizing class representation through selective augmentation (**Figure 71: Dataset Balancing 4.6**).

Results showed significant improvement, with validation accuracy reaching **99.5%** and test accuracy stabilizing at **99.4%** (**Table 21: Performance Metrics 4.6**). The classification report (**Table 22: Classification Report 4.6**) reflected major gains in precision and recall, with values approaching expected performance. The confusion matrix (**Figure 73: Confusion Matrix 4.6**) confirmed more evenly distributed classifications, validating dataset balancing as the most effective corrective measure.

**4.7 Final Refinements & Optimal Configuration Selection**

The final phase, **Version 4.7**, evaluated all previous enhancements to establish the optimal configuration. EfficientNetV2S was selected as the preferred pre-trained model, with **manual dataset balancing and 15 epochs** as the ideal hyperparameter choices.

The final test achieved **99.6% validation accuracy and 99.5% test accuracy**, with a classification report confirming robust performance across all classes (**Table 23: Final Performance Metrics 4.7**). The confusion matrix (**Figure 75: Confusion Matrix 4.7**) showed near-perfect alignment between predictions and actual labels, marking the model as deployment-ready.

**Summary & Next Steps**

Phase 4 successfully optimized model architecture, dataset handling, and performance evaluation. **EfficientNetV2S emerged as the most effective pre-trained model**, manual dataset balancing proved superior to class weighting, and **15 epochs** were established as optimal. Future steps will explore deployment strategies, real-time inference testing, and further enhancements to generalization across varied datasets.

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**Implementation & Testing – Model Development Phase 5**

**5.1 Introduction of MobileNetV2 & Initial Testing**

Phase 5 focused on refining and optimizing the **MobileNetV2** architecture to achieve the highest possible accuracy while improving model efficiency. The initial version, **5.1**, established a foundation by integrating MobileNetV2 and testing various hyperparameter configurations (**Figure 76: MobileNetV2 Importation 5.1**).

The first set of tests used a **batch size of 32, learning rate of 0.0001, and 15 epochs**. Early results showed **98.7% training accuracy and 96.0% validation accuracy**, with a test accuracy of **96.5%** (**Table 24: Performance Metrics 5.1**). However, slight overfitting was observed in the accuracy and loss plots (**Figure 78: Accuracy & Loss 5.1**), prompting further refinements.

**5.2 Dataset Augmentation & Increasing Epochs**

To improve generalization, **5.2** implemented dataset augmentation using **flowers17\_5x**, a dataset expansion technique that multiplied images using TensorFlow augmentation methods (**Figure 79: Augmentation Implementation 5.2**). Additionally, epochs were increased to **20** to evaluate long-term performance trends.

The augmented dataset and extended training led to a **test accuracy of 97.6%** and a validation loss of **0.073**, the best results thus far (**Table 25: Performance Metrics 5.2**). Accuracy and loss plots (**Figure 80: Accuracy & Loss 5.2**) confirmed better convergence, and the confusion matrix showed only a few misclassifications (**Figure 81: Confusion Matrix 5.2**).

**5.3 Evaluating Model Performance with Classification Reports**

In **Version 5.3**, a classification report was introduced to validate precision, recall, and F1-score (**Figure 82: Classification Report 5.3**). All values exceeded **0.97**, aligning with the previously recorded high accuracy values (**Table 26: Classification Report 5.3**).

The confusion matrix showed only **14 incorrect classifications**, reinforcing the model's robust performance (**Figure 83: Confusion Matrix 5.3**). These results validated the efficiency of **MobileNetV2 with augmentation**, leading to further optimization efforts.

**5.4 Fine-Tuning MobileNetV2 for Higher Accuracy**

**Version 5.4** introduced fine-tuning by unfreezing the last **20 layers of MobileNetV2**, allowing weight adjustments for more refined feature extraction (**Figure 84: Fine-Tuning Implementation 5.4**). The learning rate was reduced to **0.00005** to maintain stable training.

Results showed a remarkable improvement, with validation and test accuracies reaching **99.9%**. Accuracy and loss plots (**Figure 85: Accuracy & Loss 5.4**) showed a nearly perfect alignment between training and validation trends, indicating minimal overfitting.

**5.5 Achieving Near-Perfect Accuracy with Final Adjustments**

Building on the success of **5.4**, **Version 5.5** applied minor hyperparameter refinements while keeping MobileNetV2’s fine-tuned layers active. The best configuration—**batch size of 64, learning rate of 0.00005, and 20 epochs**—achieved an outstanding **test accuracy of 100%** (**Table 27: Final Performance Metrics 5.5**).

The confusion matrix (**Figure 86: Confusion Matrix 5.5**) showed **perfect classifications**, and accuracy/loss graphs (**Figure 87: Accuracy & Loss 5.5**) confirmed total convergence. Classification reports supported these findings, with **1.0 precision, recall, and F1-score across all classes**.

**5.6 Summary & Next Steps**

Phase 5 successfully optimized **MobileNetV2**, leading to **100% accuracy** through strategic fine-tuning, dataset augmentation, and hyperparameter refinement. Key takeaways include:

* **Fine-tuning MobileNetV2 unlocked maximum potential.**
* **Dataset augmentation significantly improved generalization.**
* **Hyperparameter tuning led to perfect classification performance.**

Future work will focus on **real-world deployment, real-time classification testing, and extending the model to additional datasets** for broader applicability.