CS3D661 – Individual Dissertation

Milestone 2

Deep Learning in Object Detection and Recognition

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Introduction

Accurate identification and classification of organic species, such as trees, mushrooms, and flowers, play a crucial role in various fields including ecology, conservation, agriculture, and environmental monitoring. Traditionally, species identification relies heavily on manual observation and expert knowledge, which can be time-consuming, labour-intensive, and susceptible to human error. In recent years, advances in artificial intelligence (AI) and deep learning have introduced new opportunities to automate and improve species recognition tasks, offering greater efficiency and scalability.

Convolutional Neural Networks (CNNs), a subset of deep learning architectures, have demonstrated exceptional performance in image classification tasks, including the identification of plant leaves, flowers, and fungi. Numerous studies have leveraged CNNs to classify species based on imagery, achieving high levels of accuracy and contributing significantly to biological research and environmental studies. However, many existing systems are limited by controlled datasets that lack real-world variability, are not easily scalable, or fail to provide accessible deployment options suitable for field or mobile use.

This project addresses these limitations by developing a robust, scalable organic species classification system using CNNs implemented in TensorFlow. The system is designed not only to deliver high classification accuracy but also to be accessible to users via a web-based interface. To ensure ease of deployment and scalability, Docker is used to containerise the application, while Google Cloud Run is utilised for hosting, offering serverless infrastructure without the need for manual management.

The remainder of this report is structured as follows: Section 2 outlines the project's aims and objectives, providing a detailed breakdown of the project's key deliverables. Section 3 presents a critical literature review, evaluating existing species classification systems, datasets, deep learning models, frameworks, and deployment strategies. Section 4 introduces and explains the fundamental terminology and key concepts underpinning the project. Section 5 details the methodology and design approach adopted, followed by implementation strategies in Section 6. Sections 7 and 8 cover system evaluation, risk assessment, and finally, conclusions and recommendations for future development.

Aim

The primary aim of this project is to design, implement, and deploy a scalable deep learning-based system capable of accurately classifying organic species, such as tree species, mushrooms, or flowers, from image inputs. The system will leverage convolutional neural networks (CNNs) and will be deployed as a containerised web application to ensure accessibility, scalability, and real-world usability.

Objectives

Document the development process, deployment pipeline, and user guidelines to ensure maintainability and reproducibility.

 Dataset Acquisition and Preparation:

- Identify and source suitable datasets covering a variety of organic species, including tree species, mushrooms, and flowers.
- Clean and preprocess the datasets to ensure consistency, applying resizing, normalization, and colour conversion techniques.
- Address potential class imbalances within datasets to improve classification accuracy.
- Implement data augmentation strategies (e.g., rotation, flipping, brightness adjustment) to artificially enhance dataset variability and support robust model training.

 Model Development and Optimization:

- Design and implement a Convolutional Neural Network (CNN) architecture tailored to multi-class organic species classification.
- Experiment with different CNN architectures (such as MobileNet, ResNet, or EfficientNet) to evaluate their effectiveness in balancing computational efficiency and accuracy.
- Fine-tune hyperparameters including learning rate, batch size, and number of epochs to optimize model performance.
- Evaluate the model using appropriate performance metrics such as accuracy, precision, recall, and F1-score.

 Application Development:

- Develop a minimal, user-friendly front-end interface using HTML and CSS to enable users to upload images for classification.
- Integrate the trained TensorFlow model with a Flask-based back-end, handling image uploads, inference, and dynamic result rendering.

 Containerisation:

- Containerise the complete application using Docker, encapsulating the model, back-end, and front-end components along with their dependencies.
- Ensure that the container image is optimized for portability and reproducibility across development and production environments.

 Deployment and Hosting:

- Deploy the containerised application on Google Cloud Run to leverage serverless infrastructure and automatic scalability.
- Configure environment variables and deployment settings to allow for efficient, real-time image classification with minimal latency.
- Monitor deployment performance to ensure system reliability and responsiveness.

 Evaluation, Testing, and Documentation:

- Conduct comprehensive testing to evaluate classification accuracy and application stability under varying conditions.
- Document the complete development pipeline, including model design, preprocessing techniques, deployment setup, and usage guidelines.
- Prepare a thorough evaluation report analysing model performance, system scalability, and potential areas for future improvement.

Fundamental Terminology

This section introduces key terminology essential for understanding the development and deployment of the organic species classification system. Each term is defined with specific relevance to the techniques, frameworks, and technologies used in this project.

Artificial Intelligence (AI)

Artificial Intelligence (AI) refers to the simulation of human intelligence by machines to perform tasks such as learning, reasoning, and decision-making (Russell & Norvig, 2010). In the context of this project, AI is applied to automate the classification of organic species, reducing reliance on manual identification methods traditionally used in botany, mycology, and related fields.

Machine Learning (ML)

Machine Learning (ML) is a subset of AI where computer systems learn patterns from data without explicit programming (Goodfellow, Bengio & Courville, 2016). This project uses supervised machine learning, training models on labelled datasets of organic species (including tree leaves, mushrooms, and flowers) to predict the species class of unseen images.

Deep Learning (DL)

Deep Learning is a branch of machine learning that utilizes neural networks with multiple layers to capture complex data patterns (LeCun, Bengio & Hinton, 2015). Deep learning's capacity to learn hierarchical features makes it ideal for organic species classification, where visual characteristics such as shape, colour, and texture are crucial for accurate identification.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a type of deep learning model specifically designed for processing image data (LeCun et al., 1998). They apply convolutional filters to input images to automatically detect relevant features such as edges, patterns, or textures. In this project, CNNs are employed to classify images of organic species, efficiently learning species-specific visual traits without manual feature extraction.

TensorFlow

TensorFlow is an open-source deep learning framework developed by Google (Abadi et al., 2016). It provides comprehensive tools for model construction, training, and deployment. TensorFlow is utilized in this project to design and implement the CNN model used for classifying organic species images. Its scalability and integration with cloud platforms make it suitable for real-world deployment.

Containerisation

Containerisation refers to the process of packaging an application along with its dependencies and environment settings into a single, portable unit known as a container (Boettiger, 2015). Docker is used in this project to containerise the organic species classification system, ensuring that the model behaves consistently across different environments, from local development to cloud deployment.

Cloud Hosting

Cloud hosting involves deploying applications on virtual servers managed by cloud service providers, offering benefits such as scalability, reliability, and minimal infrastructure management. Google Cloud Run is used in this project to host the containerised classification system. This approach allows real-time classification of organic species images with automatic scaling and high availability.

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Literature Review

This literature review critically examines the current landscape of organic species classification using deep learning techniques, particularly Convolutional Neural Networks (CNNs). The review addresses relevant deep learning models and frameworks, datasets, preprocessing strategies, deployment methods, and the practical application challenges encountered in real-world scenarios. The structure covers deep learning models, frameworks, datasets, architectures, preprocessing techniques, deployment considerations, and concludes by identifying the key gaps this project addresses.

Deep Learning Models

Deep learning models, a subset of machine learning, use artificial neural networks with multiple layers to learn hierarchical feature representations from data (Goodfellow, Bengio & Courville, 2016). Common model types include Multi-Layer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs). CNNs, in particular, have proven highly effective for image-based tasks due to their ability to learn spatial hierarchies and patterns in images (LeCun et al., 1998).

For the classification of organic species such as plants, mushrooms, and flowers, CNNs are widely preferred. Their capacity to autonomously extract distinguishing features eliminates the need for manual feature engineering, making them ideal for complex classification tasks in this domain.

Deep Learning Frameworks

The implementation of deep learning models heavily relies on frameworks that provide the necessary tools for model development, training, and deployment. Popular frameworks include TensorFlow and PyTorch. TensorFlow, developed by Google, is designed for scalable, production-ready environments and integrates well with cloud services (Abadi et al., 2016). PyTorch, while favored in research for its dynamic computation graph, is less commonly used in deployment-focused projects (Paszke et al., 2019).

Given this project's goal of deploying a real-world, scalable classification system, TensorFlow is selected for its robust ecosystem, community support, and seamless integration with Google Cloud services.

Datasets for Organic Species Classification

Several datasets have been developed to support species classification research across different domains:

- Flavia Dataset: Comprises leaf images of 32 plant species under controlled conditions (Wu et al., 2007).
- LeafSnap Dataset: Includes leaf images from 185 tree species, featuring both lab-controlled and natural conditions (Kumar et al., 2012).
- PlantVillage Dataset: Contains over 50,000 plant images primarily used for disease and species identification (Hughes & Salathé, 2015).
- Oxford 102 Flower Dataset: Contains images of 102 flower categories with substantial intra-class variation (Nilsback & Zisserman, 2008).
- Mushroom Classification Dataset: A commonly used dataset providing various mushroom species with categorical attributes useful for classification (Dua & Graff, 2019).

While these datasets have advanced classification systems significantly, limitations persist, including class imbalance, lack of real-world environmental variability, or controlled backgrounds. This project addresses these limitations by implementing preprocessing and augmentation strategies to improve dataset variability and enhance model robustness across multiple organic species categories.

Deep Learning Architectures

A variety of CNN architectures have demonstrated outstanding performance in image classification tasks:

- VGGNet (Simonyan & Zisserman, 2014): Noted for its depth and simplicity, though computationally intensive.
- ResNet (He et al., 2016): Introduced residual connections, enabling deeper networks without vanishing gradients.
- MobileNet (Howard et al., 2017): Optimized for lightweight, mobile-friendly deployment environments.
- EfficientNet (Tan & Le, 2019): Utilizes compound scaling to balance model size and accuracy effectively.

Given the need for high accuracy and deployability, this project emphasizes architectures that balance computational efficiency with classification performance.

Data Preprocessing and Augmentation Techniques

Preprocessing image data is fundamental for ensuring input consistency and improving model performance. Typical preprocessing steps include resizing, normalization, and color space conversion. Data augmentation further enhances the dataset by applying transformations such as rotation, flipping, zooming, and color adjustments (Shorten & Khoshgoftaar, 2019).

These techniques have been shown to mitigate overfitting and improve generalization, particularly when dealing with datasets collected in varied environmental conditions. Accordingly, this project adopts extensive preprocessing and augmentation techniques to ensure robustness across diverse organic species images.

Deployment Challenges and Model Hosting Strategies

Despite significant research focusing on model accuracy, practical deployment remains underexplored in many studies. Challenges such as large model sizes, long inference times, and cross-platform compatibility can hinder real-world usability (Gupta et al., 2021).

Containerisation, specifically through Docker, has become a standard method for addressing these challenges by encapsulating models and dependencies into portable environments (Boettiger, 2015). Cloud platforms such as Google Cloud Run provide serverless hosting solutions, allowing scalable deployment without manual infrastructure management (Mahmoud et al., 2020).

While several studies propose classification systems, few present full deployment pipelines. This project aims to bridge this gap by delivering an end-to-end pipeline that integrates model containerisation and cloud deployment for organic species classification.

Identified Research Gap

Through analysis of the reviewed literature, the following gaps have been identified:

1. Existing classification systems often focus on accuracy within controlled datasets, with limited generalizability to diverse, real-world environments.
2. Practical deployment strategies, particularly those ensuring scalability and accessibility, are underrepresented.
3. Few studies provide comprehensive solutions that combine model development with deployment considerations.

This project seeks to address these limitations by developing a CNN-based organic species classification system, employing robust preprocessing techniques and deploying it as a containerised web application on Google Cloud Run.

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- Abadi, M., et al. (2016). TensorFlow: Large-scale machine learning on heterogeneous systems. *arXiv preprint arXiv:1603.04467*.
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Risks

Developing an organic species classification system is anticipated to present several potential risks due to its technical complexity and the range of tasks involved. Identifying and managing these risks will be crucial to ensuring the successful delivery of the project within the required timeframe. Below are the key risks identified, along with planned mitigation strategies:

1 - Incomplete Project

Given the significant learning, research, and technical implementation involved, there is a risk that the full project scope may not be completed in time for the final submission. To mitigate this, comprehensive project planning will be carried out at the outset, with a clear, phase-based timeline established. Key milestones—including dataset preparation, model development, testing, deployment, and documentation—will be defined. Regular progress reviews will be scheduled to identify potential delays, allowing adjustments to ensure the project stays on track.

2 - Insufficient Data

A successful classification model will rely heavily on access to large, diverse, and high-quality datasets. For this project, datasets covering various organic species (trees, mushrooms, and flowers) will be essential. There is a risk that available datasets may be imbalanced, lack real-world variability, or not cover enough species diversity, potentially reducing model robustness and accuracy.

To address this, open-source datasets such as Flavia, LeafSnap, PlantVillage, Oxford 102 Flower, and Mushroom Classification datasets will be thoroughly evaluated. Additionally, data augmentation techniques (e.g., rotations, flipping, brightness adjustments) will be applied to artificially expand dataset diversity. Should gaps persist, contingency plans will include manual image collection or sourcing supplementary data to improve coverage.

3 - Insufficient Technology

Deep learning models typically require substantial computing resources, particularly during training and experimentation phases. There is a risk that limited access to high-performance hardware, such as GPUs, could impede progress or restrict the complexity of models tested.

Mitigation strategies will include leveraging lightweight architectures (e.g., MobileNet, EfficientNet) and exploring transfer learning to reduce training time and computational demands. Cloud-based platforms like Google Colab, which offer free GPU access, will be utilized. Furthermore, collaboration with institutional resources will be pursued to secure additional computational support if needed.

4 - Model Performance Issues

Developing an accurate and reliable classification model may present challenges, particularly due to the visual variability of organic species and potential dataset limitations. There is a risk that, despite tuning efforts, the model may not meet the desired accuracy levels.

To mitigate this, multiple CNN architectures (such as ResNet, EfficientNet, and MobileNet) will be evaluated to identify the most effective approach. Hyperparameter tuning, cross-validation, and consistent performance analysis will be implemented throughout model development. Any identified performance limitations will be transparently reported, and recommendations for future improvements will be included.

5 - Deployment Challenges

Deploying the containerised classification system on Google Cloud Run introduces potential risks, such as configuration errors, dependency issues, or compatibility problems. Additionally, network latency or cloud service disruptions could affect the system's responsiveness and availability.

These risks will be mitigated by conducting incremental testing of the Docker container and Flask back-end throughout development. Cloud deployment configurations will be carefully reviewed and tested to ensure stability. Real-time system monitoring post-deployment will help to promptly identify and address any emerging issues.

6 - Security and Data Privacy Risks

As the application will involve user-uploaded images, there is a risk of malicious file uploads or data privacy concerns. Failure to implement appropriate safeguards could expose the system to vulnerabilities.

To counter this, strict file type validation will be implemented in the Flask back-end, ensuring only supported image formats are processed. Additionally, unnecessary metadata from uploaded files will be stripped, and server-side checks will prevent arbitrary code execution. Security best practices will be followed to maintain system integrity.

7 - Timeline Constraints

Balancing the technical demands of the project with academic deadlines poses a risk of schedule overruns. Key deliverables, such as the initial methodology submission and final project report, will need to be completed within strict timeframes.

This risk will be managed through detailed timeline planning (see Roadmap section), adherence to defined milestones, and the use of contingency time buffers to accommodate unforeseen delays.

Project Roadmap

The development of the organic species classification system will follow a structured, phased approach, beginning in early October 2024 and progressing through to late March 2025. The roadmap is designed to guide the project systematically from conception to final deployment and documentation, ensuring that each stage is completed within its designated timeframe. The initial stages will culminate in the submission of a milestone report in November 2024, with subsequent phases dedicated to model development, deployment, and final evaluation.

Phase 1: Project Conception and Research (October 2024)

The project will commence in early October 2024, focusing on identifying the key problem domain: automating the classification of organic species, including trees, mushrooms, and flowers, using deep learning techniques. An extensive literature review will be undertaken to evaluate existing classification systems, datasets, deep learning architectures, and deployment strategies. This phase will also include a review of AI, machine learning, and deep learning fundamentals to establish the theoretical foundation for the project.

Deliverables for this phase will include:

- Completion of the literature review.
- Identification of suitable datasets (Flavia, LeafSnap, PlantVillage, Oxford 102 Flower, Mushroom Classification datasets).
- Definition of the project's aims, objectives, scope, and risks.

Phase 2: Planning, Design, and Initial Milestone Submission (October – November 2024)

This phase will focus on transitioning from research to planning and preliminary design. Key tasks will include:

- Selecting TensorFlow as the primary deep learning framework.
- Designing a Convolutional Neural Network (CNN)-based model pipeline tailored for multi-class organic species classification.
- Preparing a detailed project plan, including risk mitigation strategies and required resources.
- Drafting and submitting the **Methodology & Design** section and the initial milestone report by the end of November 2024.

Phase 3: Dataset Preparation and Model Development (December 2024 – January 2025)

During this phase, the focus will shift to dataset preparation and model development:

- Datasets will be preprocessed, involving image resizing, normalization, and RGB conversion.
- Data augmentation techniques such as rotation, flipping, and brightness adjustments will be implemented to improve dataset variability.
- Multiple CNN architectures, including MobileNet, ResNet, and EfficientNet, will be evaluated.
- Initial model training and hyperparameter tuning will be conducted, with regular validation against test datasets.

Phase 4: Application Development and Containerisation (February 2025)

Following model development, application integration will take place:

- A front-end interface will be developed using HTML and CSS, allowing users to upload images for classification.
- A Flask-based back-end will be built to handle uploads, inference, and result display.
- The entire application will be containerised using Docker, ensuring portability and consistent performance across environments.

Phase 5: Deployment and System Evaluation (March 2025)

The final technical phase will focus on deployment and evaluation:

- The Dockerised application will be deployed on **Google Cloud Run**, leveraging serverless infrastructure and scalability.
- Post-deployment testing will be conducted to assess system responsiveness, latency, and stability.
- Security measures and user feedback will be reviewed to ensure robustness.
- Evaluation metrics, including model accuracy and system performance, will be documented.

Phase 6: Report Compilation and Poster Preparation (Late March 2025)

The concluding phase of the project will involve consolidating all aspects of the project development process into a comprehensive final report. This report will document the project's objectives, methodology, model development, deployment strategy, evaluation results, risk assessment, and reflections on challenges encountered. Particular attention will be paid to ensuring clarity, coherence, and academic rigor throughout the report.

Simultaneously, a visually engaging and informative poster will be designed to succinctly present the project's key findings, methodology, and outcomes. The poster will be structured to communicate the project's significance, technical approach, and results effectively to both technical and non-technical audiences.

This phase will include:

- Compiling all documentation and evaluation materials into the final report.
- Conducting thorough proofreading and formatting checks to meet submission guidelines.
- Designing the project poster, focusing on clarity, visual appeal, and summarization of core project elements.
- Final review and submission of both the report and poster by the required deadline.

Gantt Chart

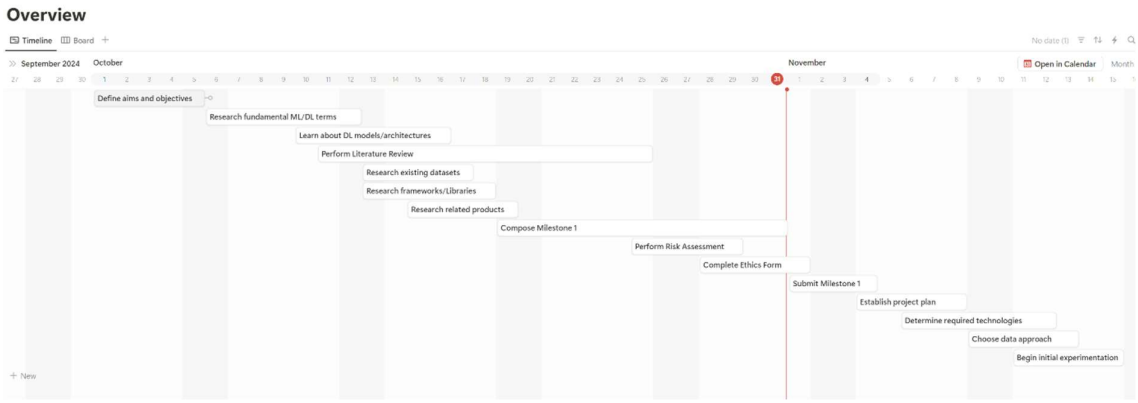


Figure 1 - Gantt Chart

Trello Board

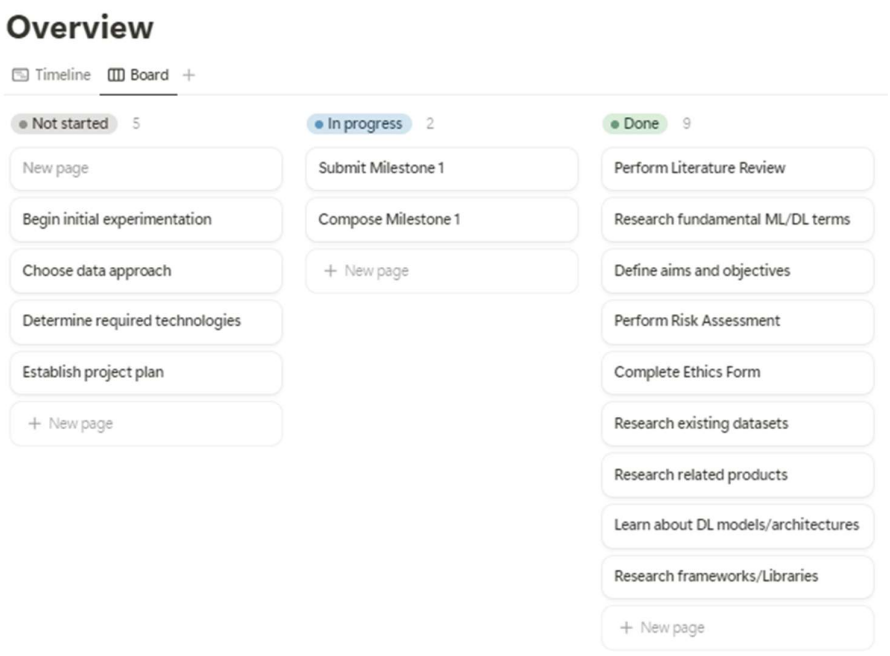


Figure 2 - Trello Board

Methodology & Design

Pre-Design Experimentation

Prior to officially starting design work on the project's code, various experiments were conducted to gain understanding and familiarity with tools and libraries essential to the nature of the project. The code was formed using an amalgamation of snippets gathered from various sources, including tutorials, videos and articles. These pre-design experiments utilised a novel dataset of leaves gathered from a local park. This dataset consisted of 5 species, of which 10 leaves were collected. These 50 leaves were then photographed in 5 different environments to expand the dataset to 250 images. Additionally, in order to comprehend the possibility of expanding datasets further, data augmentation experiments were conducted, with 5 augmentations applied to each image, including rotation, vertical and horizontal reflection, translation, and colour adjustment. By applying these augmentations, the dataset was expanded to 1250 images.

There was no pressure on these initial experiments to produce meaningful results, which is fortunate as the results were not great. This was partly due to the poor quality of the input dataset, a result of insufficient data pre-processing. The original images were too high-resolution, the photography environments too busy, and the data augmentation too intense. However, various important lessons were learned regarding the significance of preparing the input dataset to give the model every advantage during its learning process.

Another reason for the lack of success of these pre-design experiments was the code responsible for defining and training the model. Since the code used was an amalgamation gathered from various sources, it is certain that the different elements were not fine-tuned to work smoothly with one another. This revealed another important lesson, that the code itself must be optimised in order to produce a successful, robust model.

Following this pre-design experimentation stage, the lessons learned provide sufficient direction to begin the design process of the deep learning program.

Management Methodology

Prior to beginning the design stage, consideration went into which management methodology would be most appropriate for a project of this nature. One option, *Kanban*, stood out as the obvious choice for many reasons. Firstly, the *Kanban* board itself offers great benefit as it clearly visualises the project's tasks and their place in the completion process, ensuring organisation and structure are maintained during the project's development. Secondly, *Kanban* is a flexible framework, which suits the iterative, evolutionary development process of a project of this nature, whereby an initially unpredicted implementation may be required. Such implementations are difficult in other more rigid management methodologies; however, *Kanban* supports them with its fluidity, allowing them to be performed without disturbing the flow of the project. Finally, Kanban is.

Initial Design

The initial version of the program will be designed using the knowledge gained from a variety of sources during the learning and research phase of the project, with the intention of

starting with simplicity and expanding as is needed. Based upon this research [1], the assembly of a successful model requires four key components: importation of the required libraries and tools, data preparation/preprocessing, model development, and performance analysis.

The program's operation will start by importing the essential libraries: *TensorFlow* (including the *Keras* API), *MatPlotLib*, and *CSV*. Next, some important data preprocessing will be performed, including the establishment of constants such as the dataset directory and image size, the splitting of the dataset into separate training and validation sets, and their normalisation. Next, model's architecture will defined, compiled, and trained, and finally the training and validation results will be visualised and stored for further analysis.

This simple and efficient blueprint will form the foundation upon which future implementations can be developed. Containing each of the key stages listed above, these four components will grow and expand as necessary, with the importation of new libraries, enhancement of the preprocessing, expansion of the model's architecture, and inclusion of more analytics. Many features will be added, and many tests will be conducted, but this initial program will be a solid foundation on which to develop the rest of the project.

Tools & Libraries

As stated above, the first iteration of this project's code will require three essential libraries to perform its objective.

The most essential library is *TensorFlow*, responsible for providing the utilities and framework for creating, assembling, training and testing the deep learning classification model. One such utility is `image_dataset_from_directory`, which loads a dataset from a specified directory and converts its images into a *TensorFlow* dataset.

One of two vital packages supplied by *TensorFlow* (via *Keras*) is `models`, a collection of elements made for developing the model's architecture, including `models.Sequential`, used to define the model as having sequentially stacked layers; `model.compile` for configuring the optimiser and loss function; and `model.fit` which controls the training process.

The second crucial package used within the initial program is `layers`, containing components such `as layers.Conv2D`, which specifies the inclusion of convolutional layers used for feature extraction; `layers.MaxPooling2D`, used to reduce the spatial dimensions of the feature maps while preserving the most significant values, and `layers.Rescaling`, which normalises pixel values within the range of 0 to 1.

To facilitate the storage and visualisation of the results within this initial version, *CSV* and *MatPlotLib* will be required. The role of the former will be to record the training accuracy, training loss, validation accuracy and validation loss for each epoch, while the role of the latter will be to plot visualisations of this resultant data to enhance the analytical process.

Hyperparameters

The development of the model and the improvement and its performance will involve the manipulation of many aspects, such as the layers, nodes and functions of the architecture

itself, or the size, quality and balance of the input dataset. However, the primary method of experimentation for the initial implementation phase will focus on manipulating hyperparameters, including the learning rate, batch size, dropout rate, and the number of epochs.

The learning rate controls how much the model updates weights in each step. A small learning rate causes slow but precise updates, while a large learning rate trains the model quicker, but can overshoot the optimal values. The batch size is the number of samples processed by the model before the weights are updated. A larger batch size speeds up the training process, but can be more computationally expensive, while a smaller batch size updates the weights more regularly, and can lead to better generalisation, but will increase the execution time. Dropout rate refers to the percentage of neurons which are disabled during training. By including a dropout rate, the model can have better generalisation and therefore higher accuracy, however if the value is too high the model may struggle to learn its data. The number of epochs refers to how many times the entire dataset is passed through the model during training. In general, increasing the number of epochs allows the model to learn the data better, but increasing this value too high can lead to overfitting.

Following the initial implementation period, other methods of manipulation will be integrated, however by starting the experimentations with these aforementioned hyperparameters, substantial insight should be gained, translating into improved accuracy and reduced loss as the project continues.

Evaluation Metrics

The initial version of this program will start with a minimal set of evaluation metrics and expand as the project complexifies. For this reason, the first iteration will focus on accuracy and loss as the primary performance indicators for the training and validation sets during each epoch.

- Accuracy represents the percentage of correctly classified examples out of the total predictions. It provides a simple yet useful measure of the model's overall performance.
- Loss quantifies the difference between the predicted probabilities and the actual labels. Unlike accuracy, which gives a general correctness percentage, loss provides a more nuanced measure of how confident and accurate the model's predictions are. A lower loss value indicates that the model's predicted probabilities are closer to the true labels.

While many other evaluation metrics can be introduced in future iterations, accuracy and loss offer sufficient insight at this early stage to identify patterns and suggest initial improvements. However, research has been conducted into additional metrics that may be beneficial in later stages of development.

One such method is the confusion matrix, which is a table that compares the model's predicted labels against the true labels for each class, providing a clear visual representation of classification performance.

In an ideal scenario, most values in the confusion matrix should align along the diagonal (from the top left to the bottom right). These represent correct classifications—whether true positives (TP) for a given class or true negatives (TN) for other classes. However, real-world models often make mistakes, and off-diagonal values indicate misclassifications:

- False positives (FP) – When the model incorrectly predicts a sample as belonging to a class when it does not.
- False negatives (FN) – When the model incorrectly predicts a sample as not belonging to a class when it actually does.

By examining which classes the model struggles with, confusion matrices help identify specific areas for improvement. Misclassifications can highlight model weaknesses, enabling focused debugging and data adjustments to enhance performance.

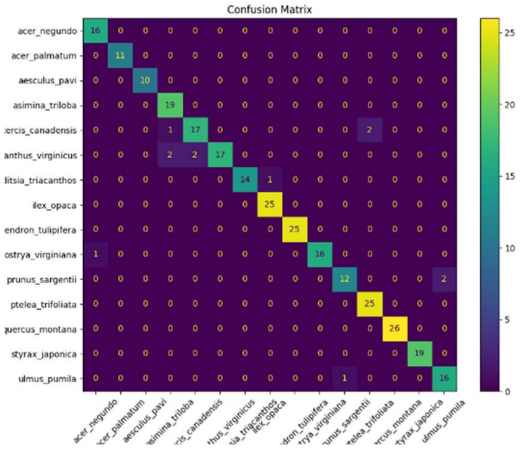


Figure 3 Confusion Matrix Example

Another way to evaluate the performance of the model would be the generation of a classification report. These provide detailed into the performance of the model regarding each class within the dataset. Typical metrics found within classification reports (in addition to the already-covered accuracy and loss) include precision, recall, F1-score, and support.

Precision measures, for each class, how many of the predictions made for that class were correct. This is done by dividing the number of true positives (correct predictions) by the total number of predictions for that specific class. This concept is easier to understand by examining the equation below. A high precision value indicates that the model was successful at labelling the given class, and that most of its classifications were true positives, with few false positive predictions.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Recall is the measurement of how many positive samples were classified correctly. In other words, recall examines, for each class, the number of correctly classified positive labels versus those which were incorrectly classified as negatives. Again, this concept is easier to understand through the equation below. Recall is useful for identifying how many positive samples were incorrectly labelled as negative.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

F1-score is a value which balances both precision and recall, and can otherwise be defined as their harmonic mean. This generally makes it more versatile and useful metric, as it considers both false positives and false negatives. F1-scores fall on a scale between 0 and 1, and the higher the score, the better the model is at avoiding false positives and false negatives. The F1-score equation can be seen below:

$$F1 - Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall}$$

While typically found within classification reports, the support value is not a performance metric, and therefore alone does not provide insightful analysis like the other three aforementioned values. Instead, support simply indicates how many samples are contained within each class, which is still a useful piece of information, as in combination with these other metrics, it can confirm whether or not the dataset is balanced.

Dataset & Preprocessing

The dataset to be used within this initial program version is a small, modified subset of 15 lab-taken image classes from the *LeafSnap30* dataset, which itself is a subset of the much larger, well-known *LeafSnap* dataset [2]. Remaining consistent with the initial design's ethos of simplicity, the dataset component will be kept simple to facilitate a smooth initial development period, with intent to implement larger, more complex datasets as the project progresses.

Development Plans

In addition to the aforementioned initial methods of improving the model's performance, plans are in place to further develop the model and its classification capabilities.

One such plan relates to the input dataset. For example, several relevant datasets have been identified which could not only increase the volume of input data, but also introduce more complexity, therefore increasing the model's ability to generalise, and hopefully leading to a more robust and accurate model. Another idea involves utilising data augmentation as a means of balancing unequal classes, both internally during program execution, and externally by creating a dataset with even classes.

In relation to the increasing the challenge provided by the input data, another element of the development plan involves increasing the size and complexity of the model's architecture. Initially this will be done by adding more layers and nodes, and by manipulating their functions. However, once this experimentation has been exhausted, pre-trained models will be explored and implemented for their superior architecture and performance. During the research stage, many viable options were encountered including *MobileNet*, *EfficientNet*, *ResNet* and *VGG*. These will be experimented with and tested, with the most viable option likely being utilised within the latter versions of the model development program.

By implementing these plans after completing the initial experimentational period, the options for expanding the model's classificational capabilities will be vast, and will hopefully lead to the successful development of a robust and accurate classification system.

Implementation & Testing – Model Development Phase 1

1.1

As laid out in the previous chapter, the initial iteration of the model-generating program has been designed with the idea in-mind of laying a solid foundation, upon which the project can expand and evolve. Version 1.1 can be found in its entirety by following this hyperlink.

```
import tensorflow as tf
import matplotlib.pyplot as plt
import csv
from tensorflow.keras import layers, models
from tensorflow.keras.utils import image_dataset_from_directory
```

Figure 4 Imports 1.1

Following the four-component structure proposed in the Design chapter, the program's operation begins with the importation of the essential libraries: *TensorFlow*, *MatPlotLib*, and *CS*, as well as the specification of some packages from the *Keras* API.

```
dataset = image_dataset_from_directory(
    dataset_path,
    image_size=image_size,
    batch_size=batch_size,
    validation_split=0.2,
    subset="training",
    seed=42
)
```

Figure 5 Dataset Split 1.1

Next, some important data processing values are established such as the dataset directory, image size and batch size, before the dataset is split into training and validation sets, which are then normalised.

```
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256, 3)),
    layers.MaxPooling2D(2, 2),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D(2, 2),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D(2, 2),
    layers.Conv2D(256, (3, 3), activation='relu'),
    layers.MaxPooling2D(2, 2),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(len(class_names), activation='softmax')
])
```

Figure 6 Model Architecture 1.1

The model's architecture is then defined, compiled, and trained, and finally the training and validation results are visualised and stored for later analysis.

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy']
              )
```

Figure 7 Model Compile 1.1

```
history = model.fit(
    dataset,
    epochs=10,
    validation_data=validation_dataset
)
```

Figure 8 Model Fit 1.1

The dataset utilised by this edition of the program, titled *LeafSnap_15_Lab*, can be viewed here.

1.1 Results

This purpose of this test is simply to verify that the initial program iteration is functioning as expected. Although the hyperparameter values are not of great concern during this test, it is worth noting for the sake of the line graphs below that the batch size was 32, while the number of epochs was 10.

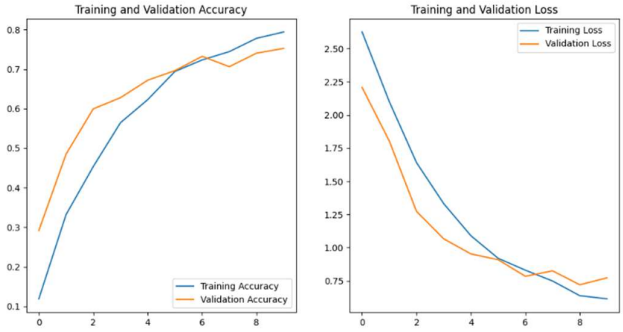


Figure 9 Accuracy & Loss 1.1

Based upon the plots above, not only does it appear as though the code is functioning desirably, but also that the hyperparameter values utilised are promising starting points. Although there is a little turbulence in the validation plots, both the graphs show promising results, as accuracies increase, and losses decrease as the number of epochs increases. Furthermore, it is certainly true for the training results that the plots do not plateau before the test is over. This is indicative of the fact that the number of epochs should be increased, as doing so could improve the accuracy and loss results for both the training and validation sets.

Epoch	train_accuracy	train_loss	val_accuracy	val_loss
1	0.11903566122055054	2.6257476806640625	0.2917504906654358	2.207411766052246
2	0.331993967294693	2.1005945205688477	0.4849094450473785 4	1.8041470050811768
3	0.4535409212112427	1.6409533023834229	0.5995975732803345	1.2732498645782 47
4	0.5645404458045 96	1.3317636251449585	0.6277666091918945	1.0663527250289917
5	0.6228026151657104	1.0895177125930786	0.6720321774482727	0.9528313875198364
6	0.6941235661506653	0.9198430180549622	0.6961770653724 67	0.9090974926948547
7	0.7232546210289001	0.8303197026252747	0.7323943376541138	0.7843056321144104
8	0.7443495988845825	0.7486553788185 12	0.7062374353408813	0.8254624605178833
9	0.7780010104179382	0.6380361318588257	0.7404426336288452	0.7201429605484009

10	0.7940733432769775	0.614301860332489	0.7525150775909424	0.726622223854065

This hypothesis is supported by the tabular data collected during the test. Both the training and validation accuracies are continuing to increase, while the training loss is also continuing to decrease. In the proceeding tests, it would be useful to manipulate the number of epochs and study its impact on these key metrics.

1.2

After a moment of contemplation following the first test, one potential improvement to the code was identified to improve record-keeping. Version 1.2 features the inclusion of the hyperparameters within the names of the output files, allowing for the improved organisation and identification within the storage files. This initial feature version is implemented into each of the output-generating functions separately, although in a later version it may be worthwhile to establish the naming convention as a global variable. Below is the hyperparameter-containing naming process of the plotting function. Version 1.2 can be found in its entirety here.

```
# Save the plot with hyperparameters in the filename
plot_filename = f'training_plot_LR{learning_rate}_BS{batch_size}_DR{dropout_rate}_E{epochs}.png'
plt.savefig(plot_filename)
plt.show()
```

Figure 10 Naming Convention 1.2

As stated at the conclusion of version 1.1, this next test round would specifically explore how varying the number of epochs impacts the accuracy and loss results. To gain an understanding of this impact, three broadly separated values will be used: 10, 25, and 50. Version 1.1's test results displayed promising results when the number of epochs equalled 10, but also suggested that better results might be obtained with more epochs. To ensure that the focus of this test round is the number of epochs, all other hyperparameters will be kept consistent.

1.2a Results

No_of_epochs	train_accuracy	train_loss	val_accuracy	val_loss
10	0.794575572013855	0.5587978363037109	0.7605633735656738	0.7212235927581787
25	0.9487694501876831	0.13891300559043884	0.7887324094772339	0.950129508972168
50	0.9854344725608826	0.04084133729338646	0.7444667816162109	1.6518267393112183

Based on the table above, which displays the final training and validation results from this test round's three runs, it might appear as though increasing the number of epochs has a positive impact on the model's accuracy. This is suggested by the fact that the training accuracy and loss results show improvement as the number of epochs progresses from 10 to 25, and again from 25 to 50. However, this is not supported by the validation accuracy and loss results, which actually worsen as the number of epochs increases. Although there is improvement in the validation accuracy between 10 and 25 epochs, the run with 50 epochs has the worst accuracy score of any run in the table, and the validation loss scores simply demonstrate a worsening performance as the number of epochs increases. While the data

within this table may appear perplexing at first, there is a simple enough explanation: somewhere before the 25th epoch, overfitting starts occurring, and that by the 50th epoch, severe overfitting is certainly taking place. This analysis is supported by the plots of each of the test round's results.

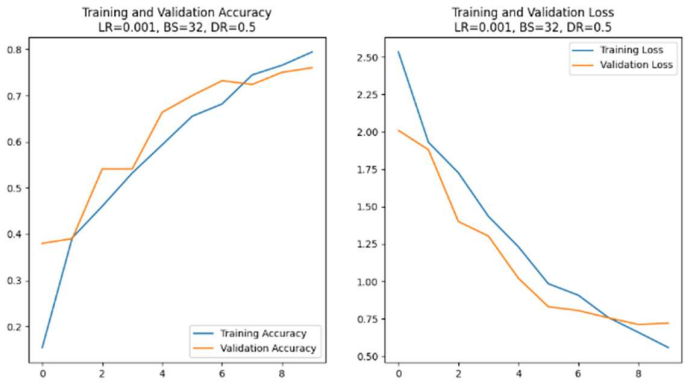


Figure 11 Accuracy & Loss 1.2a 1

In fact, after inspecting the graph plots, it appears as though overfitting may start taking place before even the 10th epoch, as the training and validation accuracy and loss plots intersect around the 7th epoch. The plot of the test run with 50 epochs below clearly demonstrates more overfitting and worsening performance as the number of epochs increases. It could be assumed from this round of testing that the optimal number of epochs could be as low as 10, however only the number of epochs has been tested so far. Once additional hyperparameters are tested, the results may suggest a more optimal number of learning rates.

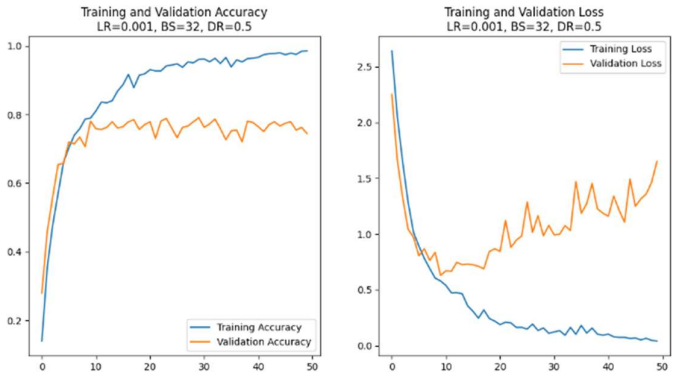


Figure 12 Accuracy & Loss 1.2a 2

1.2b Results

Using the same code as above, this test round takes the experimentation a step further as it explores the performance impact of adjusting the learning rate, dropout rate and number of epochs in various combinations. Two values were tested for the learning rate (0.001, 0.005), three for the dropout rate (0.2, 0.35, 0.5), and three for number of epochs (10, 15, 20), providing insightful results. Below is a compiled table of the hyperparameter values and performance metrics of each run within this test, ranked from best to worst based primarily on validation accuracy.

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

After analysing these results, it is clear that some hyperparameter combinations are more optimal than others. The top 3 performances, whose results are extremely close together, actually share the same values for learning rate (0.001) and number of epochs (20), supporting the inference that these are the optimal hyperparameter values for this current code iteration, with the dropout rate being the difference-maker. Dropout rates of 0.2 for 1st, 0.35 for 2nd, and 0.5 for 3rd all produced great results, and are practically inseparable, however it can be generalised that for this model architecture and dataset, a lower dropout rate leads to more optimal results. It can also be generalised that a lower learning rate and higher number of epochs produce superior results for this configuration. However, the top performers of this test run were still susceptible to overfitting, as can be seen in the accuracy and loss plots of the best performance (LR=0.001, BS=32, DR=0.20, E=20) below, suggesting that even better results could be obtained through further manipulation of the hyperparameters.

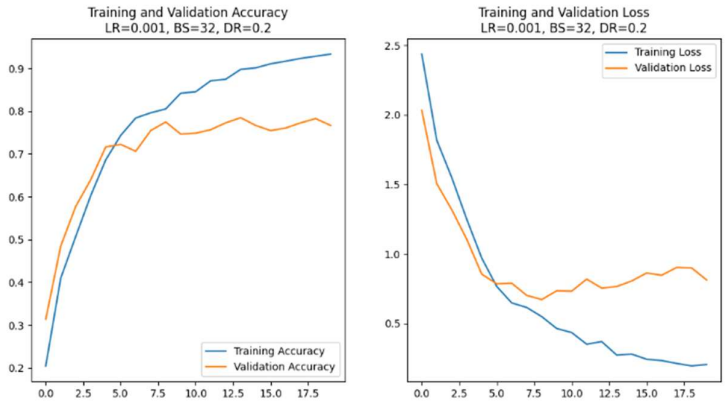


Figure 13 Accuracy & Loss 1.2b 1

The test results of the worst run also offer some useful insight, supporting the above deductions that a smaller learning rate and higher number of epochs lead to preferrable performance metrics in this current code version. Even though its accuracy and loss plots below might appear decent, this combination of the highest learning rate (0.005), lowest number of epochs (10), and intermediate dropout rate (0.35) to produce the worst training accuracy, training loss, and validation accuracy, as well as the second worst validation loss.

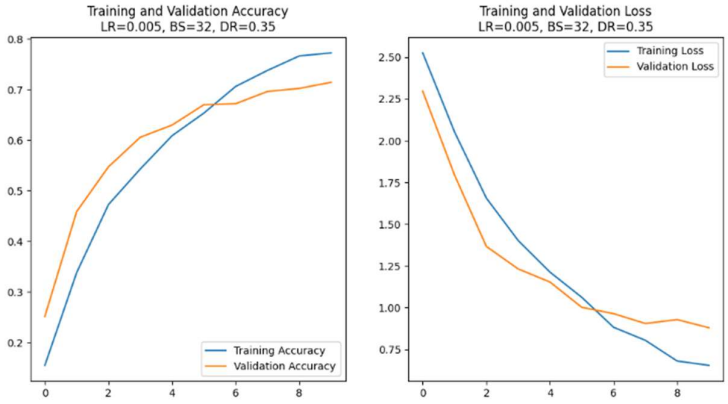


Figure 14 Accuracy & Loss 1.2b 2

1.2c Results

For the final test round of code iteration 1.2, the dropout rate has been kept constant at 0.5, while the values of the other hyperparameters were adjusted in various combinations: The learning rate took values of 0.0005, 0.001, and 0.005; batch size took 32 and 64; and the number of epochs took 10 and 15.

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

While the results from this round of testing are all rather close, it is still possible to identify the top performers. Three tests tie for 1st when examining what is considered the most important metric, validation accuracy, as they obtained a score of 0.74, and so the other performance metrics must be used to determine which of these hyperparameter combinations produced the best test results overall. These three frontrunners also have very close scores for training accuracy and training loss, with there being respective differences of 0.01 and 0.03 between the best and worst. Fortunately, validation loss, which is possibly the second most important metric, clarifies which combination of hyperparameter values produced the best results. Based upon the results in its column, a clear winner can be spotted, achieving a score of 0.40, compared to 0.77 and 0.71 of the other frontrunners. The best test run was obtained using a learning rate of 0.001, a batch size of 64, and 10 epochs as its hyperparameters, and its plot can be seen below.

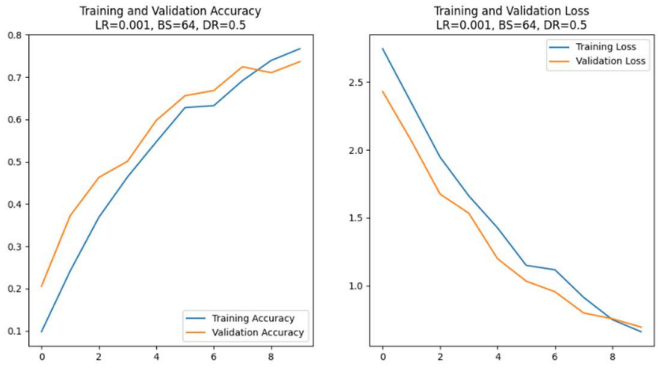


Figure 15 Accuracy & Loss 1.2c

From this round of training, several insights have been obtained. Firstly, it can be deduced that further experimentation with batch size could lead to improved performance. This round was the first so-far to experiment with the higher batch size of 64, and every test run that utilised this value outperformed the only test with 32 as its batch size. It is interesting that even at this initial stage, with a simple code version and small dataset set, the larger batch size outperformed the test who's only differing hyperparameter was the smaller batch size of 32. Later in the project, when larger, more complex codes and datasets are implemented, the benefit of a larger batch size should only become more pronounced, although it does come with the trade-off of being more computationally expensive.

Another deduction from this testing round is that there is a 'sweet spot' for the learning rate. The top three results from this round featured identical batch size, dropout rates and epochs, with the only difference being the learning rate value, which was 0.001, 0.005, and 0.0005 in order of performance from best to worst. It may be useful to experiment with a narrower

range of learning rate values in a future test, to more accurately determine the aforementioned ‘sweet spot’.

Following some insightful initial tests in phase 1, specifically examining the performance impact of hyperparameter manipulation, the second phase will now begin. Hyperparameter experimentation will continue, however phase 2 will also introduce resultant variety by varying the input dataset, model architecture, and performance metrics.

Implementation & Testing – Model Development Phase 2

2.1

In the first code version of phase 2, named 2.1, three key modifications have been made in comparison to 1.2. Firstly, 2.1 introduces the functionality to further divide the input data into a third set for testing the model after training and validation have concluded. This data, which will be entirely new to the model, will provide greater insight into the model’s performance against unseen images and will generate more realistic accuracy and loss values.

```
# Define dataset sizes for splitting (70% training, 20% validation, 10% test)
dataset_size = len(full_dataset)
train_size = int(0.7 * dataset_size)
val_size = int(0.2 * dataset_size)
test_size = dataset_size - train_size - val_size

# Split the dataset
train_dataset = full_dataset.take(train_size)
remaining_dataset = full_dataset.skip(train_size)
validation_dataset = remaining_dataset.take(val_size)
test_dataset = remaining_dataset.skip(val_size)
```

Figure 16 Dataset Split 2.1

Another new introduction is the hard-coded, specifiable output directory. While this is not a feature that will impact performance, the project’s record-keeping ability will be improved, as this value can be updated with each new iteration to ensure that the results of the various tests can be directed to the appropriate storage destination. In order to implement this feature securely, an additional library called *OS* had to be imported, which could generate the specified output directory in the event that it hadn’t yet been created.

```
# Create output directory
output_directory = R"C:\Users\rms11\Desktop\y3_proj\2.1\2.1_Results"
os.makedirs(output_directory, exist_ok=True)
```

Figure 17 Output Directory 2.1

The final new inclusion in 2.1 is the functionality to utilise the newly created test set to determine the model’s performance when faced with never-before-seen data. The testing is handled by the imported `model.evaluate` method, before the results are saved in a text file and printed to the console. As stated above, by gathering test accuracy and test loss data, a more realistic understanding of the model’s predictive capabilities can be obtained.

```
# === TESTING ===

test_loss, test_accuracy = model.evaluate(test_dataset)
print(f"Test Loss: {test_loss}")
print(f"Test Accuracy: {test_accuracy}")

# Save test results
test_results_file = os.path.join(output_directory, 'test_results.txt')
with open(test_results_file, 'w') as f:
    f.write(f"Test Loss: {test_loss}\n")
    f.write(f"Test Accuracy: {test_accuracy}\n")

print(f"Test results saved to {test_results_file}.")
```

Figure 18 Testing 2.1

2.1 Results

In this round of tests, 2.1, batch size and dropout rate have been kept constant at 32 and 0.5 respectively. This means that the focal hyperparameters are the learning rate and the number of epochs. The table below is a concentrated overview of the results gathered during round 2.1. Each row represents a different test, and the row's columns contain its hyperparameters, the accuracy and loss scores of the training and validation sets from its final epoch, as well as the accuracy and loss scores from its test set.

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	0.2114	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	0.0726	0.982	0.047
0.0005	32	0.5	20	0.977	0.070	0.962	0.108	0.950	0.108

From these results, it is clear that this was a very competitive testing round. None of the training, validation or test accuracies scored less than 0.9, and none of the losses scored greater than 0.25. Still, it is clear that some hyperparameter configurations outperformed the rest. The two most outstanding results actually ran for the same number of epochs, which was 15. The only separating factor is their learning rates: the top performer's learning rate was 0.0005, while the close 2nd performer's value was 0.001. Remarkably, the difference between their test accuracy scores was a mere 0.007, the same difference between their test loss scores. The configuration with the 0.0005 learning rate marginally outperforms its counterpart with a learning rate of 0.001, however both results are great. The victorious configuration's plot can be seen below, while the 2.1's complete results collection can be found here.

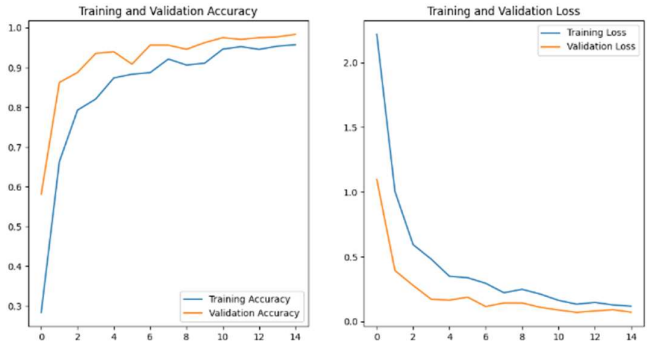


Figure 6 Accuracy & Loss 2.1

2.2

Now that highly accurate models have been developed, with almost certain accuracies and miniscule losses, it is time to integrate another performance metric, to verify that the results being generated are legitimate. The metric of choice is the confusion matrix, and it has been integrated into a new code version named 2.2.

The integration of the confusion matrix is simple enough, however it does require the importation of some additional tools, this time from the *SciKit Learn* package: `confusion_matrix`, and `ConfusionMatrixDisplay`. Additionally, the importation of NumPy is required within the matrix creation for its mathematical capabilities. Using these newly imported tools, the implementation and visualisation of the confusion matrix can be seen in the code snippet below.

```
# Create confusion matrix
conf_matrix = confusion_matrix(true_labels, predicted_labels, labels=range(len(class_names)))
conf_matrix_display = ConfusionMatrixDisplay(conf_matrix, display_labels=class_names)

# Plot and save the confusion matrix
plt.figure(figsize=(10, 8))
conf_matrix_display.plot(cmap='viridis', values_format='d', ax=plt.gca())
plt.title('Confusion Matrix')
plt.xticks(rotation=45)
confusion_matrix_filename = os.path.join(output_directory, f'{naming_base}_confusion_matrix.png')
plt.savefig(confusion_matrix_filename)
plt.show()

print(f"Confusion matrix saved to {confusion_matrix_filename}.")
```

Figure 19 Confusion Matrix Implementation 2.2

Another implementation necessitated by the outstanding performance metrics is the ability to save the model, so that it may be used again, such as for testing, or integration into an app or website. This implementation is enabled by the `model` package's `model.save` function.

```
model_filename = os.path.join(output_directory, f"{naming_base}.h5")
model.save(model_filename)
print(f"Model saved to {model_filename}.")
```

Figure 20 Save Model Implementation 2.2

The primary aim of the following tests is simply to verify the successful implementation of both new features covered above. However, the equally important secondary aim is to continue the manipulation of the hyperparameters, in an attempt to discover if any combinations can be discovered which might surpass those from round 2.1. The target hyperparameters will once again be the learning rate and number of epochs, as there is still much uncertainty regarding their ideal values.

2.2 results

learning_rate	batch_size	dropout	epochs	test_loss	test_accuracy
0.0001	32	0.5	20	0.10644903033971786	0.9678571224212646
0.001	32	0.5	15	0.1099146381020546	0.9642857313156128
0.001	32	0.5	20	0.09333613514900208	0.9678571224212646
0.0005	32	0.5	20	0.08217372745275497	0.9678571224212646
0.005	32	0.5	15	0.0778030976653099	0.9714285731315613
0.005	32	0.5	20	0.104	0.9642857313156128

As was the case in the previous testing round, the results from 2.2 are similarly brilliant, as every test loss was below 0.12, and every accuracy above 0.96. On average, these results might actually surpass those obtained in 2.1. However, no individual test run manages to overtake the champion of the previous round. Here in 2.2, the hyperparameter combination used to generate the top result was 15 epochs, a learning rate of 0.005, a batch size of 32, and a dropout rate of 0.5. This combination generated a test accuracy of 97.14% as well as a test loss of 0.078, which are outstanding results, however they narrowly fail to surpass the top performer from 2.1. Interestingly, both of these results share matching values for batch size, dropout rate and the number of epochs, differing only in the learning rate, which continues to prove itself to be a vital component to a successful test. Below are the accuracy and loss plots for the test with the best results.

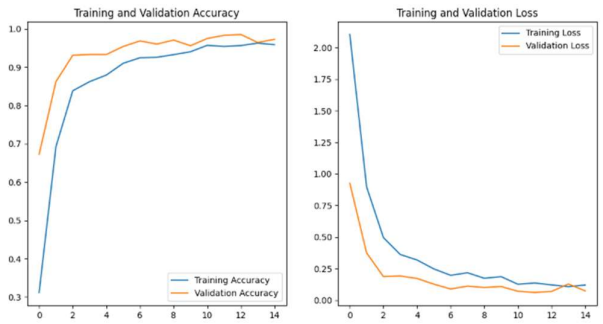


Figure 21 Accuracy & Loss 2.2

Now let's examine the confusion matrix below, which proves two things: firstly, it proves that the implementation of the confusion matrix within 2.2 was successful, as the matrix has been generated as intended. But more importantly, it also proves that 2.2's top performer really is as accurate as the results above suggested. Almost every single prediction matched the true label, as indicated by the brightly-coloured diagonal line of values. There is a very minor array of incorrect predictions, which would explain the test accuracy's missing 2-3%, but this confusion matrix certainly does support the resultant test accuracy of 97.1%.

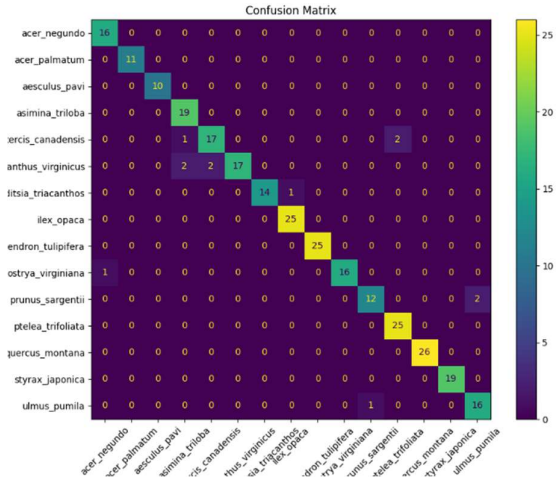


Figure 22 Confusion Matrix 2.2

Now that near-ideal results have been obtained with this familiar and proven dataset and code combination, the next round of tests will aim to verify if these fantastic accuracies can be achieved on a more realistic dataset.

2.3

As mentioned at the end of 2.2, this next round of testing does not aim to improve the performance of the models. Instead, the aim of 2.3 is to test the accuracy of these models when given realistic data to predict.

In previous sections, while the test set was genuinely new to the model, as the model had not seen any of the test images before, the data was very similar to the training and validation, having originally come from the same dataset. The desired aim of this project is to try and develop a model which can be used in real-world scenarios to classify species based on input imagery.

To test if the presently developed models are close to achieving this aim, a new dataset has been compiled manually, using images of the desired species gathered from various online sources. These images are representative of the real-world images users might try to classify, and so this test aims to determine how realistic the abilities of the current models actually are.

2.3's operation starts with the specification of the output, model and test data directory paths:

```
# Output directory setup
output_directory = R"C:\Users\rms11\Desktop\y3_proj\2.3 (4.4)\2.3_results"
os.makedirs(output_directory, exist_ok=True)

# Path to the saved model
model_path = R"C:\Users\rms11\Desktop\Proj\Best_Models\4.3 (2.2)\1_model_LR0.005_BS32_DR0.5_E15.h5"

# Path to the test dataset directory
test_data_path = R"C:\Users\rms11\Desktop\Proj\Datasets\Web_Dataset"
```

Figure 23 Path Specification 2.3

Next, the model is loaded using `load_model`, before the test dataset is loaded using `image_dataset_from_directory`:

```
# Load the saved model
model = load_model(model_path)
print(f"Model loaded from {model_path}.")

# Load the test dataset
test_dataset = image_dataset_from_directory(
    test_data_path,
    image_size=image_size,
    batch_size=batch_size,
    shuffle=False  # Maintain order for proper evaluation
)
```

Figure 24 Load Model 2.3

The loaded model is then tested using the `model.predict` function:

```
# Get true labels, predictions, and probabilities
true_labels = []
predicted_labels = []
probabilities = []
images_to_display = []
for images, labels in test_dataset:
    true_labels.extend(labels.numpy())
    predictions = model.predict(images)
    probabilities.extend(predictions)
    predicted_labels.extend(np.argmax(predictions, axis=1))
    images_to_display.extend(images.numpy())
```

Figure 25 Model Predict 2.3

Finally, the performance metrics are calculated and stored, followed by the visualisation and storage of confusion matrix:

```
# Compute accuracy
accuracy = accuracy_score(true_labels, predicted_labels)
print(f"Accuracy: {accuracy:.4f}")

# Compute Log Loss
log_loss_value = log_loss(true_labels, probabilities, labels=range(len(class_names)))
print(f"Log Loss: {log_loss_value:.4f}")

# Save accuracy and log loss
metrics_filename = os.path.join(output_directory, f"{naming_base}_metrics.txt")
with open(metrics_filename, "w") as f:
    f.write(f"Accuracy: {accuracy:.4f}\n")
    f.write(f"Log Loss: {log_loss_value:.4f}\n")
print(f"Metrics saved to {metrics_filename}.")
```

Figure 26 Performance Metrics 2.3

Every model generated during 2.2 will be tested, before being compiled into tabular form and ranked from best to worst.

2.3 Results

Model	Accuracy	Log_Loss
model_LR0.0001_BS32_DR0.5_E20	0.1333	17.7812
model_LR0.0005_BS32_DR0.35_E20	0.1333	19.0573
model_LR0.001_BS32_DR0.5_E20	0.1200	17.9335
model_LR0.0005_BS32_DR0.5_E20	0.1067	21.3504
model_LR0.005_BS32_DR0.5_E20	0.0800	23.5620
model_LR0.005_BS32_DR0.5_E15	0.0667	23.1634
model_LR0.001_BS32_DR0.5_E15	0.0667	25.6092

Above is the table of results, populated with the accuracy and logarithmic loss of each tested model. As indicated by the poor results across the entire table, none of the models generated to this point performed at-all well when challenged with the realistic dataset. The highest accuracy obtained was a mere 13%, while this model's accompanying log loss was almost 18.

The primary reason for this poor performance is down to the cleanliness of the input data. The original dataset *LeafSnap*, is comprised of well-taken, clear photographs, in which the

contains nothing but the species sample. Therefore, the models to this point have only learned to classify and predict images such as these. The manually created dataset used within this experiment contained poor-quality, noisy images. Even though the species were identical to those within the original dataset, from the model's perspective they were very unfamiliar. It seems as though this test was too great a challenge for the models developed to this point. If high performance is desired when input images are cluttered and noisy, then the model must be trained on similar input data. The search for a more robust and suitable dataset must now be undertaken, so that the models can more successfully handle realistic user images.

2.4

Before a new dataset is implemented necessarily, there is at least one remaining improvement worth attempting to improve the robustness of the current model and its generative code: data augmentation. By utilising this valuable set of tools, the original dataset can be made more challenging and diverse, as augmentations such as rotating, flipping and zooming present the model with more variety during the training process, and greatly extend the original dataset's utility. Code version 2.4 can be found here.

The simplest way to implement data augmentation within the pre-existing code is to define a data augmentation layer, then include this layer at the start of the model definition. In this code version, 2.4, the three aforementioned augmentation techniques are applied.

```
# Define a data augmentation layer
data_augmentation = tf.keras.Sequential([
    layers.RandomFlip("horizontal_and_vertical"),
    layers.RandomRotation(0.2),
    layers.RandomZoom(0.2)
])

# Define the model
model = tf.keras.Sequential([
    data_augmentation,  # Apply data augmentation
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256, 3)),
    layers.MaxPooling2D(2, 2),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D(2, 2),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D(2, 2),
    layers.Conv2D(256, (3, 3), activation='relu'),
    layers.MaxPooling2D(2, 2),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(len(class_names), activation='softmax')
])
```

Figure 27 Augmentation & Archiecture 2.4

The rest of the version 2.4's code is identical to that used during the previous version, 2.2. This ensures that, aside from the varying hyperparameters, the differential feature is the newly implemented data augmentation layer.

2.4 Results

Below is the compiled and ranked results from 2.4's test round.

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	0.756793	0.686095	0.869791	0.426840	0.922413	0.394107
0.0005	32	0.5	20	0.785879	0.590251	0.891666	0.340100	0.900000	0.330362
0.0001	32	0.5	20	0.787037	0.598752	0.881250	0.347309	0.882142	0.341083

0.0001	32	0.35	20	0.7361111	0.7478410	0.8854167	0.3317185	0.8571429	0.3362466
0.0050	32	0.5	15	0.7465278	0.7398294	0.8645833	0.3675282	0.8571429	0.3778828
0.0010	32	0.5	15	0.7430556	0.7220295	0.8354167	0.4161567	0.8321428	0.4124876

Based on this data, it appears as though the data augmentation has been implemented successfully. While the best accuracy and loss scores in the table above do not quite rival those from stages 2.1 or 2.2, the highest test accuracy of 92% is still a brilliant result, as is the second highest accuracy of 90%. This is especially true since the complexity and difficulty of the input data has been increased via the data augmentation layer.

However, only the test accuracies are comparable to the results of previous versions. The other columns, such as training accuracy and test loss, show room for much improvement, as their values are considerably poorer than the values of these columns in earlier test rounds.

That being said, no accuracy score within the table is below 70%, which is still respectable and noteworthy. If each test's scores could be increased with further modification and enhancement while maintaining the augmentation layer, the resultant model would not only be highly accurate, but would be considerably more robust than its predecessors, and therefore should have greater success in realistic scenarios.

Below is the accuracy and loss plot of the best-performing model from version 2.4.

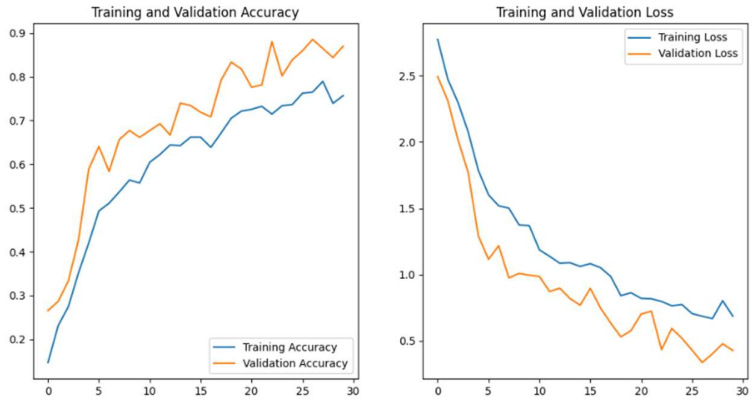


Figure 28 Accuracy & Loss 2.4

Additionally, the same model's confusion matrix can be seen below. To view the entire test results from 2.4, click here.

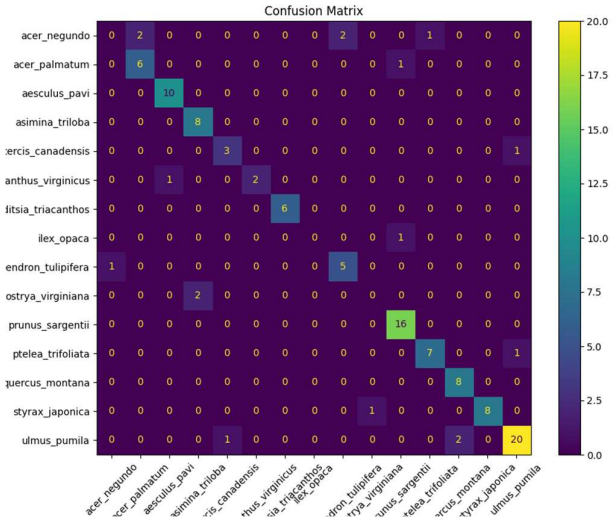


Figure 29 Confusion Matrix 2.4

To conclude this second phase of implementation and testing, it must be stated that lots of encouraging progress has been made. While using the original dataset, extremely accurate results were obtained, while the inclusion of data augmentation enhanced the robustness and real-life capabilities of the models.

The next phase of development will focus on modifications to the model's architecture. In particular, the integration of pre-trained models should generate interesting results and improved performance. Various pre-trained models were researched in previous areas of the project, and the understanding gained of their powerful capabilities supports the belief that they will be highly beneficial in achieving the aims of the project.

After some supplementary research into pre-trained deep-learning models, two architectural families sound particularly relevant for their efficiency and lightweight design, those being *EfficientNet* and *MobileNet*. Over the course of the next phase of implementation and analysis, both *EfficientNet* and *MobileNet* will be implemented and tested for their impact on prediction performance.

Implementation & Testing – Model Development Phase 3

3.1

The first of these pre-trained architectures to be implemented is *MobileNetV2*. This can be found within the `keras.applications` package, and must be imported prior to use.

```
from tensorflow.keras.applications import MobileNetV2
```

Figure 30 MobileNet Importation 3.1

The pre-trained architecture must then be instantiated, and can then be included within the model definition.

```
# Load MobileNetV2 with pre-trained weights and exclude the top layers
base_model = MobileNetV2(input_shape=(224, 224, 3), include_top=False, weights='imagenet')
base_model.trainable = False  # Freeze the base model

model = tf.keras.Sequential([
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Dropout(0.5),
    layers.Dense(len(class_names), activation='softmax')  # Output layer
])
```

Figure 31 Model Architecture 3.1

The initial execution of phase 3 will use the *LeafSnap_15_Lab* dataset utilised throughout every code version thus far. This is in order to distil the impact of the newly integrated pre-trained network, enabling easier comparison between this new code version and its predecessors. For this same reason, hyperparameter value manipulation will initially be kept minimal. 3.1 can be found in its entirety here.

3.1 Results

The table below contains the entire execution of version 3.1. The hyperparameters used within this version were an epoch number of 10, a learning rate of 0.0001, and a batch size of 32.

Epoch	train_accuracy	train_loss	val_accuracy	val_loss
1	0.41956019401550293	1.9314926862716675	0.8812500238418579	0.6501874923706055
2	0.8043981194496155	0.6447209715843201	0.9645833373069763	0.29596927762031555
3	0.8958333134651184	0.3674798607826233	0.9833333492279053	0.18486452102661133
4	0.9241898059844971	0.2782028019428253	0.9916666746139526	0.13591483235359192
5	0.9461805820465088	0.2027596831321716 3	0.9916666746139526	0.10851286351680756
6	0.9479166865348816	0.1823740303516388	0.9916666746139526	0.09507021307945251
7	0.9681712985038757	0.1368521451950073 2	0.9875000119209229	0.0925513207912445
8	0.9745370149612427	0.1164196431636810 3	0.9854166507720947	0.07577888667583466
9	0.9716435074806213	0.1039627045392990 1	0.9916666746139526	0.05783345550298691
10	0.9762731194496155	0.0953418388962745 7	0.9979166388511658	0.05179242044687271

As anticipated, by utilising the pre-trained *MobileNetV2* architecture, the accuracy and loss results have reached new highs. In the very first epoch, the validation accuracy reached 88%, and by the tenth and final epoch reached an almost perfect score of 99.79%. This outstanding performance is also found in the test data, where the accuracy reached 99.64%. Remarkably, the loss value of both the validation and test sets was 0.05, the lowest loss value recorded throughout the project so far.

Test Loss	0.053246717900037766
Test Accuracy	0.9964285492897034

This almost perfect accuracy result is also reflected in the confusion matrix, where every single prediction was true positive.

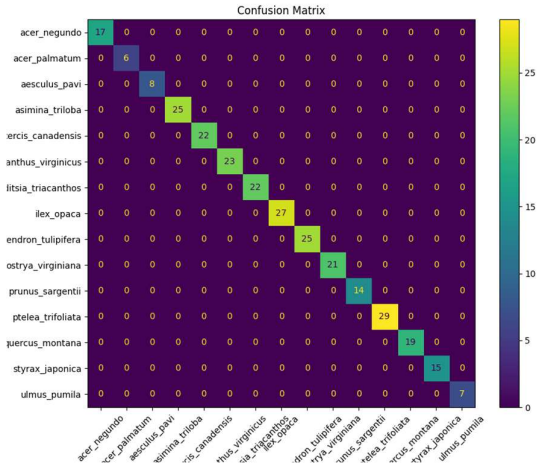


Figure 32 Confusion Matrix 3.1

Finally, by examining the accuracy and loss plots, it can be seen that even though the accuracy was almost perfect, the loss gradients are yet to completely plateau by the end of the tenth epoch. This incomplete plateau suggests that with an increased number of epochs, even lower loss values may be obtained.

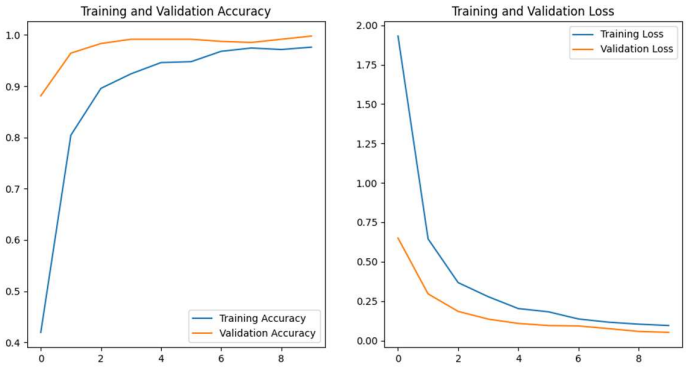


Figure 33 Accuracy & Loss 3.1

In conclusion of this first test of phase 3, by implementing the *MobileNetV2* architecture and utilising its pre-trained network, project-wide records have been set in terms of both accuracy and loss. Even so, there may still be room for further improvement. Two methods which could be implemented to achieve further success are the aforementioned increase of the number of epochs, as well as the increase in size of the data input. That being said, the next phase of experimentation will return to the challenge of obtaining accurate predictions from an imperfect, realistic dataset. By utilizing pre-trained architectures, sufficient progress in this endeavour should be attainable.

3.2

As stated in the conclusion of section 3.1, this next stage will attempt to address the poor performance of previous models when faced with a realistic dataset. Unfortunately, a suitable dataset of tree leaves could not be found, however a very promising mushroom dataset has been discovered, featuring thousands of realistic images of mushrooms taken in the field. Although the subject matter will of course have changed, the technological principles will remain the same.

This new dataset reignites a discussion from the project's earlier stages, when the idea of classifying mushrooms was being heavily considered. Ultimately, tree leaves were chosen as the classification subject, as samples were easier to collect, thereby simplifying the process of manually creating a novel dataset. Now that the use of the novel dataset has been disregarded due to insufficient amounts of training data, the idea of re-focusing on the classification of mushrooms seems perfectly plausible. As mentioned above, nothing substantial must be altered to utilise this new, preferred dataset: the code can remain virtually unchanged. The model will now be trained to classify mushrooms, with the fine-tuning continuing as before to improve prediction performance.

This new dataset, initially assembled by the Mycology Society of Northern Europe, consists of nine classes varying in size from around 350 to 1350 images. Obviously, these classes are rather imbalanced, and so methods of balancing the dataset will have to be explored in an upcoming code version, however the realistic quality of the dataset makes it useful and preferred at this stage of the project. This dataset, named *shrooms_ds*, can be found here.

```
# Specify the path to your leaf dataset directory
dataset_path = R"C:\Users\rms11\Desktop\Proj\Datasets\shrooms_ds"
```

Figure 34 dataset_path 3.2

The only difference between code versions 3.1 and 3.2 is the implementation of this new dataset, which is done by changing the directory path of the *dataset_path* variable, as seen above. All other parts of the code, including hyperparameter values, have been kept identical to the previous version, ensuring that the variance in performance can solely be attributed to the new dataset.

3.2 Results

Below are the training and validation results for test 3.2, which featured the new *shrooms_ds* dataset, and the hyperparameter values of a learning rate of 0.0001, a batch size of 32, and an epoch number of 10. While not as brilliant as those of 3.1, these results are still promising, especially as a starting point following the implementation of the new, more challenging dataset. Both the training and validation accuracies display decent improvement between the first and last epochs, while the training and validation losses decrease simultaneously.

Epoch	train_accuracy	train_loss	val_accuracy	val_loss
1	0.3728741407394409	1.8280714750289917	0.5892857313156128	1.2022218704223633
2	0.5599489808082581	1.2567644119262695	0.6614583134651184	1.0068273544311523
3	0.620323121547699	1.1051416397094727	0.680059552192688	0.9331252574920654

4	0.6417942047119141	1.0257865190505981	0.6822916865348816	0.9211941957473755
5	0.6626275777816772	0.9800623655319214	0.6979166865348816	0.8707048296928406
6	0.6764456033706665	0.9246760010719299	0.699404776096344	0.8720042109489441
7	0.6915391087532043	0.9069986939430237	0.703125	0.8379604816436768
8	0.6902636289596558	0.8786500692367554	0.710565447807312	0.8502814769744873
9	0.6898384094238281	0.8745827078819275	0.7209821343421936	0.8295154571533203
10	0.6972789168357849	0.8545891642570496	0.7157738208770752	0.8201534748077393

As can be seen in the small table below, containing the test loss and accuracy of 3.2, the model's performance on these similar but new test images not only compares, but is in fact slightly better than its performance on the training and validation sets. This indicates that the model is doing well at feature extraction and generalisation.

Test Loss	0.8266926407814026
Test Accuracy	0.7203007340431213

Of course, adjustments will be implemented to further improve performance metrics, but these initial test results following the implementation of the new dataset offer a hopeful suggestion that excellent test scores can be obtained.

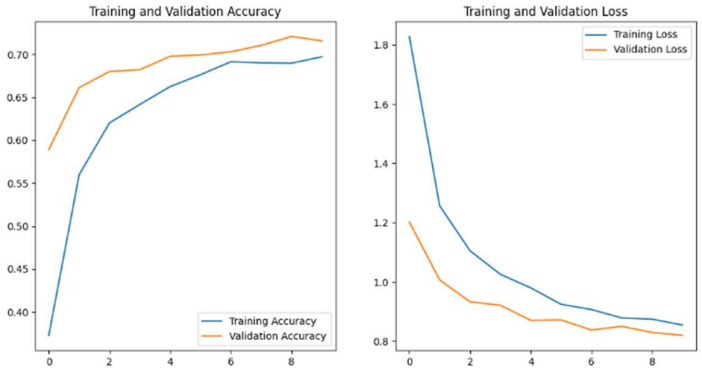


Figure 35 Accuracy & Loss 3.2

Another promising indication within the results of version 3.2 can be seen in the plot and confusion matrix. The close proximity of the training and validation plot lines of both the accuracy and loss graphs suggest that the model is not overfitting, while the decent formation of the desirable diagonal line within the confusion matrix verifies the respectable accuracy scores.

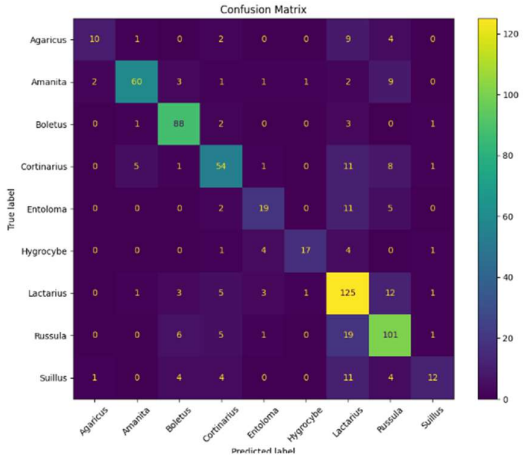


Figure 36 Confusion Matrix 3.2

3.3

Following the acceptable results of 3.2, the next test will explore the implementation of a balanced version of the *shrooms_ds* dataset, and its impact on the performance metrics.

In regards to balancing the dataset, two choices seemed obvious: either reduce the dataset to match the smallest class volume, or increase the dataset to match the largest. In general, it is said that the greater the input data volume, the greater the results, and so the decision was made to increase the volume of each class within the *shrooms_ds* to match the most populous one.

The method by which this expansion was achieved was through applying data augmentation to the images of the undersized classes, manipulating and adjusting them slightly, to produce new input images for the model. Augmentation methods included flipping horizontally and/or vertically, rotating, and zooming, however all augmentation amounts were kept minimal to avoid distortion, which could negatively affect the training process. The newly expanded mushroom dataset, named *shrooms_ds_max*, was then implemented into the code by simply changing the value of *dataset_path* to the location of the new dataset.

```
# Specify the path to your leaf dataset directory
dataset_path = R"C:\Users\rms11\Desktop\Proj\Datasets\shrooms_ds_max"
```

Figure 37 dataset_path 3.3

Test 3.3 was then executed with the same pre-trained architecture and hyperparameter values as 3.2, apart from the number of epochs, which was increased to 20 to allow more training of the larger input dataset.

3.3 Results

The table below contains the performance results of test run 3.3, featuring the training accuracy and loss as well as the validation accuracy and loss for each epoch of the test. By comparing the final rows of the results tables of 3.2 and 3.3, it can be seen that the increased input size of *shrooms_ds_max* has had an overall positive impact on the performance of the model. While the difference between the final training accuracy and loss values is slight, the larger volume of input data allowed for a substantially improved validation accuracy (0.71 for

3.2 versus 0.78 for 3.2) and validation loss (0.82 vs 0.67 respectively). Additionally, both validation metrics show gradual improvement as the epochs increase, which is another indication of the utility of the larger dataset.

Epoch	train_accuracy	train_loss	val_accuracy	val_loss
1	0.44379058480262756	1.6309031248092651	0.6669034361839294	1.00746488571167
2	0.61810064315795 9	1.1240729093551636	0.7215909361839294	0.8555694818496704
3	0.65919238328933 72	0.9948848485946655	0.734375	0.8018222451210022
4	0.67400568723678 59	0.9369294047355652	0.7510653138160706	0.770259439945221
5	0.68374592065811 16	0.9012853503227234	0.74609375	0.7653517127037048
6	0.69916802644729 61	0.8773356080055237	0.7649147510528564	0.7342072129249573
7	0.70038557052612 3	0.8688456416130066	0.7670454382896423	0.7136929631233215
8	0.70464694499969 48	0.856438159942627	0.7709516882896423	0.7181475162506104
9	0.70271915197372 44	0.8587520718574524	0.7688210010528564	0.7020655870437622
10	0.70769077539443 97	0.8419350981712341	0.7674005627632141	0.6976963877677917
11	0.70525568723678 59	0.8510221838951111	0.7819602489471436	0.6771995425224304
12	0.70353084802627 56	0.850041389465332	0.7688210010528564	0.7029702663421631
13	0.70687907934188 84	0.8398709893226624	0.7755681872367859	0.6876222491264343
14	0.70586442947387 7	0.8405055999755859	0.7780539989471436	0.6636431217193604
15	0.70900976657867 43	0.840477466583252	0.7819602489471436	0.6749394536018372
16	0.71601057052612 3	0.8249497413635254	0.7901278138160706	0.6604242324829102
17	0.71864855289459 23	0.8304097056388855	0.7759233117103577	0.6811463236808777
18	0.71783685684204 1	0.8139025568962097	0.7784090638160706	0.6688222289085388
19	0.71672075986862 18	0.8326066136360168	0.7816051244735718	0.6723821759223938
20	0.71601057052612 3	0.8319340348243713	0.7819602489471436	0.6670349836349487

The benefit of the larger dataset can also be confirmed by comparing the test metrics of 3.2 and 3.3: during the previous test, scores of 0.83 for test loss and 0.72 for test accuracy were

recorded. During the current test, 3.3, improved metrics of 0.68 for test loss and 0.76 for test accuracy were achieved.

Test Loss	0.684188723564148
Test Accuracy	0.7634408473968506

Given that the only altered hyperparameter was the number of epochs, with all other details remaining identical, the 0.15 increase in test loss and 0.04 increase in test accuracy can be directly attributed to the increased size of the input dataset. The success of test run 3.3 is confirmed by the accuracy and loss plots below:

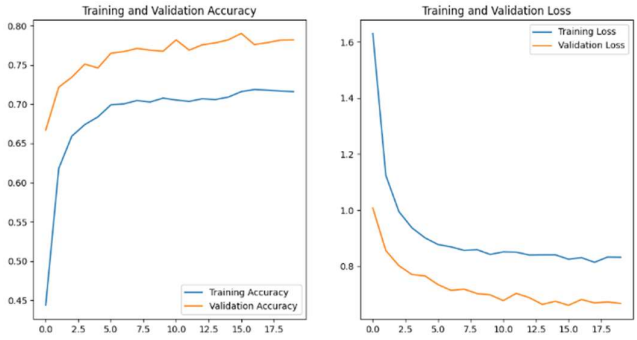


Figure 38 Accuracy & Loss 3.3

Finally, confirmation of the improvement from 3.2 to 3.3 can be seen in the confusion matrix, in which the diagonal line of true positives is more brightly-coloured than its predecessor, while also containing higher values of successful predictions.

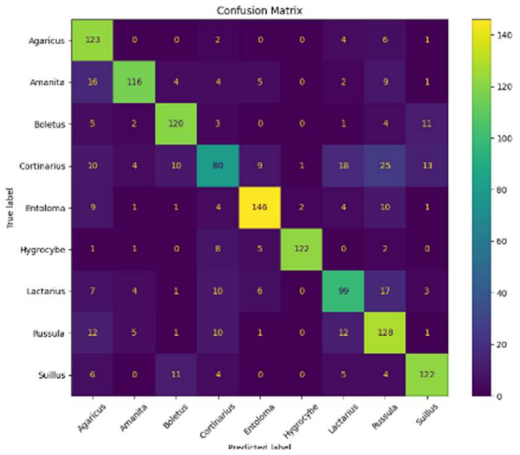


Figure 39 Confusion Matrix 3.3

3.4

Following the successful implementation of *shrooms_ds_max* within the previous test round, it is now time to experiment with alternative pre-trained models in 3.4. Until this point, all code versions of phase 3 have utilised *MobileNetV2* as the pre-trained architecture, and have subsequently produced solid results. However, an alternative family of pre-trained models was identified during the research stage, which may prove to be the most suitable for this relatively small-scale deep learning project, that being the *EfficientNet* family. LIL BIT

BOUT EFFICIENTNET, IDEALLY WITH REFERENCE. The first architecture of the *EfficientNet* family to be implemented is *EfficientNetB0*.

```
# Load EfficientNetB0 with pre-trained weights and exclude the top layers
base_model = EfficientNetB0(input_shape=(224, 224, 3), include_top=False, weights='imagenet')
base_model.trainable = False  # Freeze the base model
```

Figure 40 EfficientNetB0 Implementation 3.4

Implementing this new architecture is a simple process, requiring only the importation of the architecture from `keras.applications`, followed by the inclusion of *EfficientNetB0* within the establishment of the base model. For this run, all other code details will be kept identical, to allow direct comparison between this new version and the previous one.

3.4 Results

Epoch	train_accuracy	train_loss	val_accuracy	val_loss
1	0.10876623541116714	2.238626718521118	0.10830965638160706	2.1976335048675537
2	0.10805600881576538	2.2310092449188232	0.11115057021379471	2.1981799602508545
3	0.10856331139802933	2.232506036758423	0.13920454680919647	2.1983659267425537
4	0.10643263161182404	2.2319741249084473	0.12286932021379471	2.1977379322052
5	0.10947646200656891	2.231304883956909	0.10440340638160706	2.197862148284912
6	0.11333198100328445	2.232006549835205	0.15056818723678559	2.198192596435547
7	0.11282467842102051	2.228842020034709	0.12713068723678559	2.197988748550415
8	0.10541801899671555	2.233322858810425	0.11008522659540176	2.198056459426848
9	0.11059252917766571	2.226336956024107	0.11541192978620529	2.198363065719604 5
10	0.11028815060853958	2.224630594253554	0.14098010957241058	2.197557210922241
11	0.11089691519737244	2.226363658905029 3	0.10617897659540176	2.198260307312011 7
12	0.11130276322364807	2.225799560546875	0.10724432021379471	2.197465658187866
13	0.11333198100328445	2.223799705505371	0.10617897659540176	2.198013782501220 7
14	0.11678165942430496	2.222651958465576	0.14914773404598236	2.197733402252197 3
15	0.11373782157897949	2.224990367889404 3	0.10688920319080353	2.198212385177612 3
16	0.11201298981904984	2.224383354187011 7	0.10759942978620529	2.198107481002807 6

17	0.10663555562496185	2.226109743118286	0.12428977340459824	2.197885751724243
18	0.11191152781248093	2.221920967102051	0.11115057021379471	2.197358131408691 4
19	0.11241883039474487	2.221127748489338	0.11079545319080353	2.197192907333374
20	0.11302759498357773	2.220566749572754	0.14346590638160706	2.197590827941894 5

The table above contains the results of test run 3.4. Unfortunately, it appears as though version 3.4 has produced the worst results of the entire project so far. Neither the training nor the validation accuracies ever reach 20%, and neither display any gradual improvement whatsoever as the epochs are completed, with the test accuracy only scoring 13.2%. The loss scores are just as poor, with the final training loss being 2.22, and the validation and test losses both being 2.20.

Test Loss	2.1971588134765625
Test Accuracy	0.13261649012565613

The poor performance of 3.4 can be seen even more clearly within the accuracy and loss visualisations. The accuracy graph to the left shows the consistently low score of the training accuracy line as it barely reaches 0.115 (11.5%), as well as the erratic validation accuracy line, which resembles an electro-cardio-graph more than a typical deep learning accuracy plot. The loss graph again reinforces this tragic performance, as even though the training loss declines minutely, neither the training nor validation losses get anywhere close to passing the already awful loss score of 2.00.

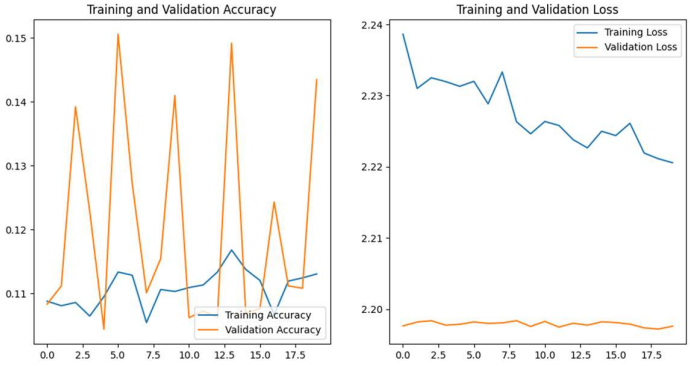


Figure 41 Accuracy & Loss 3.4

Some explanation of the awful results of 3.4 can be found within the confusion matrix. It appears as though, for some strange reason, the model only ever gave two labels as its predictions for every single image it was given as input, those class labels being *Agaricus* and *Boletus*. After verifying that there was no issue with the dataset itself, and knowing with certainty that no adjustments were made to the code other than the replacement of the pre-trained model, it is evident that the code must be examined and adjusted to integrate the *EfficientNetB0* architecture.

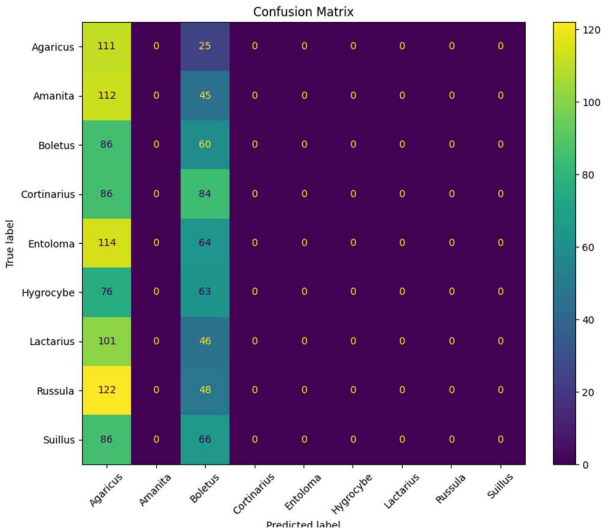


Figure 42 Confusion Matrix 3.4

While these initial *EfficientNet* results have been disappointing, this family of pre-trained architectures should be ideally-suited for this project. Additional research will be performed to ensure that the next official version and its tests will be better-adjusted to support *EfficientNetB0* and other related architectures, as successfully integrating this family of pre-trained models should reverse the outcome of 3.4 and produce some fantastic results.

Implementation & Testing – Model Development Phase 4

4.1

Following a brief period of additional research into the *EfficientNet* pre-trained architectures, it became apparent that two particular members of the family had the greatest potential for successful implementation. Subsequently, the decision was made to draft an entirely new program, intended to optimally implement these two most promising architectures, *EfficientNetV2S* and *EfficientNetB0*. These pre-trained models are promising due to their combinations of size, speed and accuracy [3], and the hope is that this promise will translate into highly competitive performance results.

The new code version created for phase 4 shares many similarities with its predecessors, including the general layout and order of operations. The library importation section differs slightly: *OS* has been replaced with *Pathlib* to handle input and output directories; *Seaborn* has been imported to improve data visualisation; and the desired layers and models have been imported specifically to allow for cleaner implementation.

```
import tensorflow as tf
import csv
import matplotlib.pyplot as plt
import numpy as np
import pathlib
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications import EfficientNetV2S
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.models import Sequential
```

Figure 43 Importation 4.1

Within the data preprocessing section, the *Keras* function `image_dataset_from_directory` is used to handle the splitting of the dataset into training and validation sets. Unlike previous versions, codes 4.1 and onwards will utilise datasets which have already been separated into training/validation and test sets, meaning the code just needs to handle the splitting of the training/validation sets into respective training and validation sets. This has been done to ensure that all tests utilise the same set, meaning models are tested using the same images.

```
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    dataset_dir,
    validation_split=0.2,
    subset='training',
    seed=123,
    label_mode='categorical',
    image_size=(img_height, img_width),
    batch_size=batch_size
)
```

Figure 44 Dataset Split 4.1

The next section contains the specification of the hyperparameter values, as well as the start of the model definition, which begins will the instantiation of the pre-trained *EfficientNet* architecture.

```
# Model definition
full_model = Sequential()
pretrained_model = EfficientNetV2S(
    include_top=False,
    input_shape=(224, 224, 3),
    pooling='avg',
    classes=num_classes,
    weights='imagenet'
)
```

Figure 45 Model Definition 4.1

After the pre-trained architecture is included within the definition of the 'full' model, additional layers are then added to serve as final layers which flatten and transform the pre-trained model's values into the desired output format.

```
full_model.add(pretrained_model)
full_model.add(Flatten())
full_model.add(Dense(512, activation='relu'))
full_model.add(Dense(num_classes, activation='softmax'))
```

Figure 46 Output Layers 4.1

The model is then compiled, with the specification of important parameters such as the optimisation method, learning rate and loss function.

```
full_model.compile(
    optimizer=Adam(learning_rate=learning_rate),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
```

Figure 47 Model Compilation 4.1

Next comes a new inclusion, which aims to improve the data recoding process of the program: the *CSVLoggerCallback*. The purpose of this useful feature is to automatically document the training and validation results after each epoch, in a cleaner and simpler fashion than the implementations in previous versions.

```python
# Callback to save training/validation metrics to CSV
class CSVLoggerCallback(tf.keras.callbacks.Callback):
    def __init__(self, file_name):
        self.file_name = file_name
        with open(self.file_name, mode='w', newline='') as file:
            writer = csv.writer(file)
            writer.writerow(['epoch', 'train_loss', 'train_accuracy', 'val_loss', 'val_accuracy'])

    def on_epoch_end(self, epoch, logs=None):
        with open(self.file_name, mode='a', newline='') as file:
            writer = csv.writer(file)
            writer.writerow([epoch + 1, logs['loss'], logs['accuracy'], logs['val_loss'], logs['val_accuracy']])

metrics_csv = f"{output_name}_metrics.csv"
csv_logger = CSVLoggerCallback(metrics_csv)
```

Figure 48 Logger Callback 4.1

Model training is implemented next, including in its parameters the training and validation datasets, the number of epochs, and the newly-created logging callback. Following this, the model saving process is defined.

```python
# Model training
history = full_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=epochs,
    callbacks=[csv_logger]
)
```

Figure 49 Model Training 4.1

The final sections of code 4.1 are also similar but improved in comparison to previous versions, containing the data visualisation process for plotting the accuracy and loss line graphs, followed by the definition of a new function for the testing process called *evaluate_model*. This function incorporates the evaluation of the model using the pre-established test dataset, as well as the creation of the test results' confusion matrix.

```python
# Test function
def evaluate_model(model, test_data, output_name):
    # Evaluate on test data
    results = model.evaluate(test_data)
    test_metrics_csv = f"{output_name}_test_metrics.csv"
    with open(test_metrics_csv, mode='w', newline='') as file:
        writer = csv.writer(file)
        writer.writerow(['loss', 'accuracy'])
        writer.writerow(results)

    # Confusion matrix
    y_true = np.concatenate([y for x, y in test_data], axis=0)
    y_pred = np.argmax(model.predict(test_data), axis=-1)
    y_true = np.argmax(y_true, axis=-1)

    conf_matrix = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(10, 8))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.savefig(f"{output_name}_confusion_matrix.png")
    plt.show()

    print(classification_report(y_true, y_pred, target_names=class_names))
```

Figure 50 Evaluate Model 4.1

For test run 4.1, the learning rate will be 0.001, the batch size will be 32, and the number of epochs will equal 10. Additionally, the chosen dataset will be a new version of the mushroom dataset named *shrooms_ds_split*, updated to be pre-split into testing and training/validation sets.

4.1 Results

epoch	train_loss	train_accuracy	val_loss	val_accuracy
1	1.1358641386032104	0.6073740124702454	0.8104385733604431	0.7142857313156128
2	0.7446956634521484	0.7466169595718384	0.6739667654037476	0.7778649926185608
3	0.6397733688354492	0.7766228914260864	0.6440829038619995	0.779434859752655
4	0.5722954273223877	0.7983918190002441	0.5954170227050781	0.7849293351173401
5	0.5141079425811768	0.8254559636116028	0.6367316246032715	0.7786499261856079
6	0.4740147888660431	0.8336929082870483	0.6287651062011719	0.784144401550293
7	0.4502632915973633	0.8450676798820496	0.5533455014228821	0.8006279468536377
8	0.4089750051498413	0.8558540940284729	0.5666468739509583	0.802982747554779
9	0.3865931332111586	0.8636987805366516	0.5268163681030273	0.8218210339546204
10	0.3500184118747711	0.8758580088615417	0.5276644825935364	0.8163265585899353

As can be seen in the training and validation results table above, test run 4.1 has produced very promising results. Using the *EfficientNetV2S* pre-trained architecture, the model created in 4.1 has achieved the best scores of any model trained and tested on a mushroom dataset. The previous top results were recorded during stage 3.3, which achieved accuracies of 0.72, 0.78 and 0.76 for training, validation and testing respectively, alongside loss scores of 0.83, 0.66 and 0.68. In comparison, test run 4.1 recorded accuracies of 0.87, 0.82 and 0.82 and losses of 0.35, 0.52 and 0.57. These are significant improvements which must be attributed to the *EfficientNetV2S* architecture as well as the improved code.

loss	0.5741644501686096
accuracy	0.820588231086731

Additionally, the model created during 3.3 was trained on *shrooms_ds_max*, which is substantially larger than the dataset used to train the model of 4.1. This is an indication of the utility of EfficientNetV2S within this project, providing promise that utilising the larger dataset to train and test a model with this configuration could produce even better results.

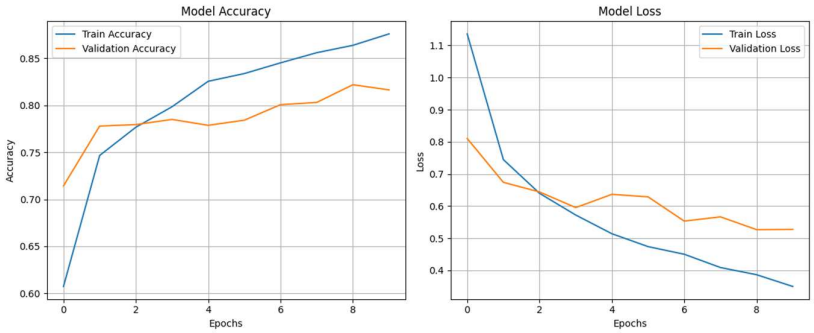


Figure 51 Accuracy & Loss 4.1

Although the results of 4.1 are promising, room for improvement can be seen in the visualisations of its results. Firstly, in the accuracy and line graphs above, the separation between the training and validation lines is suggestive of overfitting, whereby the model is learning its training data too specifically, and may be comparatively underachieving on the validation and test sets. Also, the intersection of the training and validation lines occurs rather early on in both graphs. This suggests that the learning rate might be too high, and that potential improvement could be achieved by lowering it slightly.

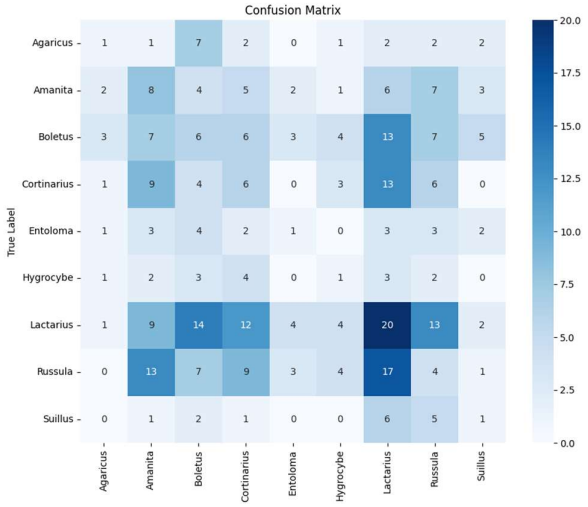


Figure 52 Confusion Matrix 4.1

Room for further improvement can be found within the confusion matrix, whose appearance seems to conflict the success of this round of testing, as the desirable diagonal line of high values is barely present. Instead, this matrix appears to represent an inaccurate model, which performed reasonably well on certain classes such as *Lactarius* and *Amanita*, but that accuracy must be improved across entire dataset. Alterations must be made to improve the performance metrics of this model.

4.2

Before substantial changes are implemented, the exact same code will be executed, this time utilising *EfficientNetB7*, the other promising member of the *EfficientNet* architectural family. The hyperparameter values will be kept identical to the previous one, to isolate the architecture as the only altered variable during versions 4.1 and 4.2.

As explained during previous versions, switching architectures is as simple as changing the specification of the importation from `keras.applications`.

```
from tensorflow.keras.applications import EfficientNetB7
```

Figure 53 EfficientNet Importation 4.2

The only other necessary step is to adjust the definition of the model to match the choice of imported architecture.

```
# Model definition
full_model = Sequential()
pretrained_model = EfficientNetB7(
    include_top=False,
    input_shape=(224, 224, 3),
    pooling='avg',
    classes=num_classes,
    weights='imagenet'
)
```

Figure 54 Model Definition 4.2

4.2 Results

Below are the results of version 4.2, utilising the *EfficientNetB7* pre-trained model. Once again, it appears that the new code version created for phase 4 allows the *EfficientNet* architecture to achieve better results than those achieved with its implementation in phase 3.

epoch	train_loss	train_accuracy	val_loss	val_accuracy
1	1.1454973220825195	0.5922729969024658	0.8210660815238953	0.7260596752166748
2	0.744627058506012	0.7428907752037048	0.709729015827179	0.7653061151504517
3	0.6187347173690796	0.7811335325241089	0.7632706761360168	0.7386185526847839
4	0.5369474291801453	0.8134928345680237	0.5996302366256714	0.7998430132865906
5	0.4531058967113495	0.8407530784606934	0.646831750869751	0.7880690693855286
6	0.408512145280838	0.8633065223693848	0.6600754261016846	0.784144401550293
7	0.3473513722419739	0.8772308230400085	0.6196209788322449	0.795918345451355
8	0.3116514384746515	0.8897823095321655	0.5546718239784241	0.8202511668205261
9	0.2837160229682924	0.9029221534729004	0.5934820175170898	0.8116169571876526
10	0.2470226734876632 7	0.9123357534408569	0.5574294328689575	0.8233909010887146

The results recorded are similar to 4.1, which utilised its architectural relative *EfficientNetV2S*, with the training metrics of 4.2 actually surpassing its predecessor, the validation and test accuracies being identical, and the validation and test losses being slightly worse.

loss	0.5930107831954956
accuracy	0.8176470398902893

The slightly larger distance between the training and validation/test results of 4.2 might be indicative of a little more overfitting, as seen in the plots below. But in general, the results of 4.1 and 4.2 are comparable, demonstrating the similar abilities of the two *EfficientNet* versions in use.

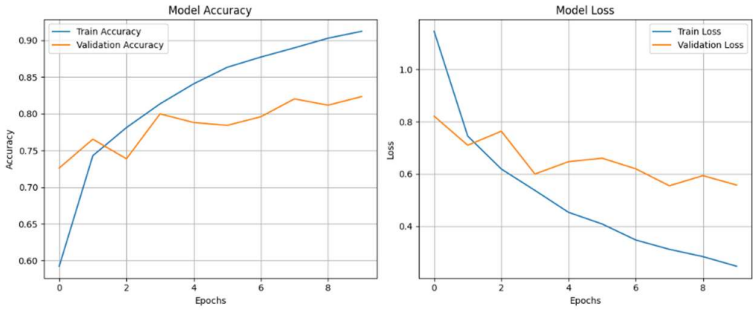


Figure 55 Accuracy & Loss 4.2

Unfortunately, the confusion matrix again dampens the success of round 4.2, appearing almost identical to the matrix of 4.1. The desired diagonal line of true positives is absent, meaning that this model is also struggling to predict the classes with much success. This issue could be due to the fact that the *shrooms_ds_split* dataset is poorly balanced, meaning that the model is fed more images of certain classes. This would then cause the model to become overly familiar with some classes and not familiar enough with others.

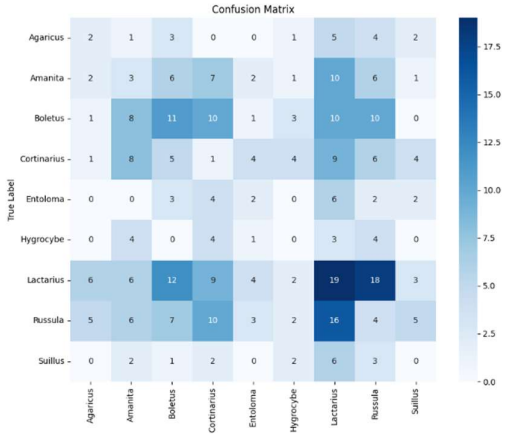


Figure 56 Confusion Matrix 4.2

This issue can either be solved by balancing the dataset, as has been done previously with *shrooms_ds_max*, or by calculating and applying class weights to the model during training, enabling the under-represented classes to be given greater importance/emphasis. Both these options will be explored at a later stage of phase 4.

4.3

The next code version, 4.3, returns to the use of the EfficentNetB7 architecture, alongside some additional implementations and an alternative dataset.

Leaving the mushroom datasets for a moment, this version introduces a new version of the *LeafSnap* dataset. Whereas previous versions had utilised only the lab images, which were consistent and clear but limited in volume, this version of the dataset merges the lab and field images for each class, massively increasing the number of images available for use, while sacrificing a little consistency between images. In accordance with a successful integration into the code, the dataset has also been split into training/validation and test sets, with the split between training and validation occurring inside the code. Again, this simply ensures that the set of test images remains consistent. This new dataset, named *LeafSnap_15_merged_split*, can be found here.

One new inclusion within this code is the classification report, which provides the additional useful performance metrics: precision, recall, F1-score, and support. The creation of the report is handled by `classification_report`, an import from *SciKit Learn*'s `metrics` package, which calculates these performance metrics for each class and overall. These metrics are then neatly written to a CSV file, so they can be analysed and tabulated or visualised at a later stage. Explanations of these additional performance metrics can be found here, within the Methodology & Design section of the project.

```
report = classification_report(y_true, y_pred, target_names=class_names, output_dict=True)
report_csv = output_dir / f"{output_name}_classification_report.csv"
with open(report_csv, mode='w', newline='') as file:
    writer = csv.writer(file)
    writer.writerow(['Class', 'Precision', 'Recall', 'F1-Score', 'Support'])
    for class_label, metrics in report.items():
        if isinstance(metrics, dict):
            writer.writerow([class_label, metrics['precision'], metrics['recall'], metrics['f1-score'], metrics['support']])
```

Figure 57 Classification Report 4.3

The only additional feature implemented within 4.3 is the function to store the confusion matrix in CSV format, in addition to the already existing PNG format. Doing so provides an additional copy of the confusion matrix data, enabling a tabular view of the matrix, as well as the creation of new visualisations in the event that something goes wrong with the ones created by the program.

Hyperparameter values within code 4.3 remain unchanged from the previous version.

4.3 Results

The table below contains the training and validation results of the test run for version 4.3. Based on the accuracies and losses of the training and validation sets, the EfficientNetB7-implemented model has learned the dataset's classes and features very well. By the end of the first epoch the results look great, and even with fluctuations along the way, the results in the final row show the improvement of the model's performance throughout the training process.

Epoch	train_loss	train_accuracy	val_loss	val_accuracy
1	0.6041288375854492	0.819915235042572	0.09760291874408722	0.9787685871124268
2	0.09363394975662231	0.9751059412956238	0.06681859493255615	0.9766454100608826
3	0.05764128640294075	0.9867584705352783	0.10196834802627563	0.9639065861701965

4	0.03619294613599777	0.9920550584793091	0.05893103033304 2145	0.9787685871124268
5	0.08439228683710098	0.9692796468734741	0.09217304736375809	0.9660297036170 96
6	0.04345662891864 7766	0.9862288236618042	0.03087569400668 1442	0.9893842935562134
7	0.01714284531772 1367	0.9973517060279846	0.04061240330338 478	0.9830148816108704
8	0.01602605730295 1813	0.9968220591545105	0.07946506887674 332	0.9681528806686401
9	0.01825960725545 8832	0.9941737055778503	0.03020964190363 884	0.9851379990577698
10	0.01088278368115 4251	0.9978813529014587	0.04407785087823 868	0.9830148816108704

These excellent metrics are reinforced by the test results, which are the remarkably low loss of 0.007 and the perfect accuracy of 1.0. Based on the tables above and below, this test has been a complete success.

loss	accuracy
0.007476646453142166	1.0

Further confirmation of excellent performance can be seen in the graphs below. Although the fluctuation is more pronounced when visualised, particularly for the validation lines, the results still look very promising.

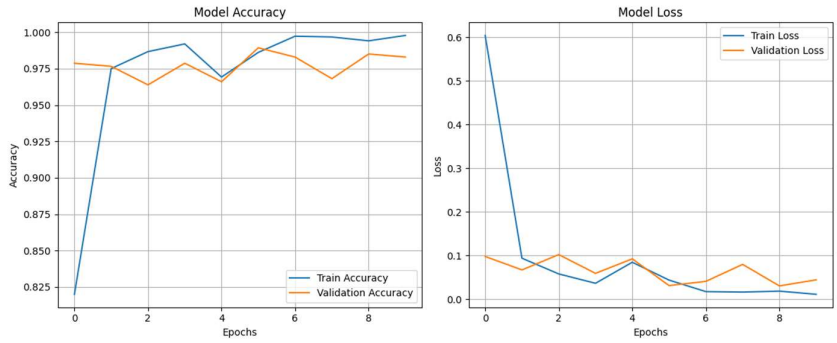


Figure 58 Accuracy & Loss 4.3

What is less promising is the first edition of the newly-implemented classification report. Ideally, each of the three key metrics, precision, recall and F1-score, will be values somewhere less than but close to 1. Even though the above results are very promising, the classification report table is full of values barely above 0.

This truly is conflicting data. It can be assured that the test data is entirely separate from the training/validation sets, meaning they are new. The results above indicate that the model performed brilliantly in the test, however according to the table below, it failed to learn or predict any class with much success. The code will have to be re-verified to eliminate the possibility of it being the source of this indiscretion, and to confirm that the difference in suggested performance is a legitimate cause of concern.

Class	Precision	Recall	F1-Score	Support
acer_negundo	0.1	0.1	0.1	10.0
acer_palmatum	0.0	0.0	0.0	6.0
aesculus_pavi	0.0	0.0	0.0	7.0
asimina_triloba	0.0	0.0	0.0	10.0
cercis_canadensis	0.0	0.0	0.0	9.0
chionanthus_virginicus	0.0	0.0	0.0	9.0
gleditsia_triacanthos	0.0	0.0	0.0	8.0
ilex_opaca	0.091	0.091	0.091	11.0
liriodendron_tulipifera	0.1	0.1	0.1	10.0
ostrya_virginiana	0.2	0.2	0.2	10.0
prunus_sargentii	0.0	0.0	0.0	6.0
ptelea_trifoliata	0.273	0.273	0.273	11.0
quercus_montana	0.1	0.1	0.1	10.0
styrax_japonica	0.0	0.0	0.0	6.0
ulmus_pumila	0.0	0.0	0.0	6.0
macro avg	0.058	0.058	0.058	129.0
weighted avg	0.070	0.070	0.070	129.0

The confusion matrix below supports the classification report in its assertion that the accuracy and loss scores are misleading, and that the model is far from performing optimally. Once again, the diagonal line of true positives is non-existent, with values spaced sporadically within the matrix, suggesting poor generalisation and accuracy.

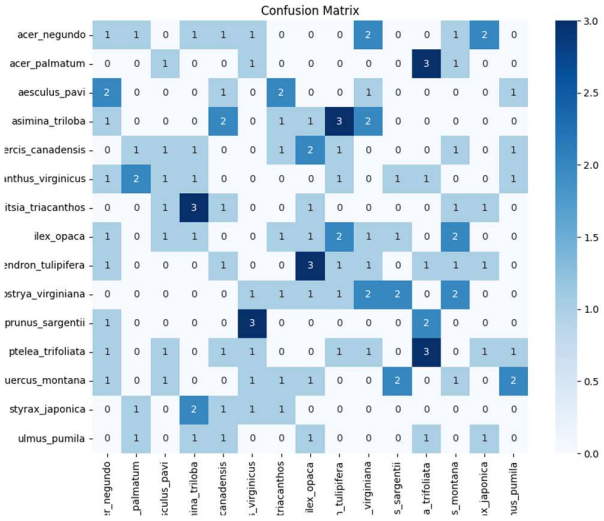


Figure 59 Confusion Matrix 4.3

One possible source of this poor performance could be the dataset imbalance, which was pointed out during the conclusion of a previous phase 4 test run. This must be addressed through the implementation of a solution: either through manually balancing the dataset, or through integrating method of calculating class weights, to support under-represented classes and diminish the impact of larger ones. That being said, the next test will use the same code as 4.3, however *EfficientNetV2S* will be utilised as the pre-trained model. An attempt to tackle the class imbalance issue will be implemented following this next test, in versions 4.5 and 4.6.

4.4

Even though the results of version 4.3 were underwhelming, suggesting the need for analysis and improvement, version 4.4 will continue the phase 4 pattern of implementing both chosen *EfficientNet* models into each code version, to satisfy this phase's main target of determining which of the two is best for the project. After implementing *EfficientNetB7* in the previous version, it is now time to test the implementation of *EfficientNetV2S* within this current code version.

The process of implementing an alternative architecture has been covered in previous sections of the project. However, if brief, all that needs to be done is to specify the desired model within the code's importation section, then instantiate it within the complete model definition.

```
# Model definition
resnet_model = Sequential()
pretrained_model = EfficientNetV2S(
    include_top=False,
    input_shape=(224, 224, 3),
    pooling='avg',
    classes=num_classes,
    weights='imagenet'
)
```

Figure 60 Model Definition 4.4

4.4 Results

The table below contains the loss and accuracy data for both the training and validation sets. Again, it appears as though the models containing the *EfficientNetV2S* and *EfficientNetB7* architectures are highly comparable in terms of performance. The loss values for both training and validation sets can be approximated to 0.03, while the accuracy values approximate to 0.99, or 99%. Although only marginal, these results do surpass those achieved during 4.3, suggesting that *EfficientNetV2S* is the optimal pre-trained architecture, certainly within the version of code used within versions 4.3 and 4.4.

epoch	train_loss	train_accuracy	val_loss	val_accuracy
1	0.7184862494468689	0.7934321761131287	0.16662226617336273	0.9532908797264099
2	0.1375671923160553	0.9608050584793091	0.06190510839223862	0.9893842935562134
3	0.05877101793885231	0.9862288236618042	0.05029682442545891	0.9893842935562134
4	0.04904114082455635	0.991525411605835	0.03829913213849068	0.9915074110031128
5	0.04308179020881653	0.9894067645072937	0.03887119144201279	0.9915074110031128
6	0.0273716002702713	0.9947034120559692	0.044218435883522034	0.9893842935562134
7	0.03577205538749695	0.992584764957428	0.029522456228733063	0.993630588054657

8	0.02992497012019 1574	0.9936440587043 762	0.03187692537903 786	0.9915074110031 128
9	0.04730758443474 7696	0.9841101765632 629	0.03998721018433 571	0.9851379990577 698
10	0.02982924878597 2595	0.9899364113807 678	0.02937651798129 0817	0.9936305880546 57

The excellent results above are replicated, if not exceeded, within the test set. A perfect accuracy score of 1.0 (100%) was achieved, while the loss score of the test set was even lower than those achieved during the training or validation sets, reaching the remarkably low value of 0.006.

loss	0.005861646495759487
accuracy	1.0

The success of 4.4 is reiterated by the visualisations of the accuracies and losses of both the training sets. In comparison with the graphs produced during 4.3, the plots of 4.4 show less fluctuation as well as less space between the training and validation lines. This indicates more consistent learning and less overfitting, both of which are indications of the superiority of the *EfficientNetV2S* architecture.

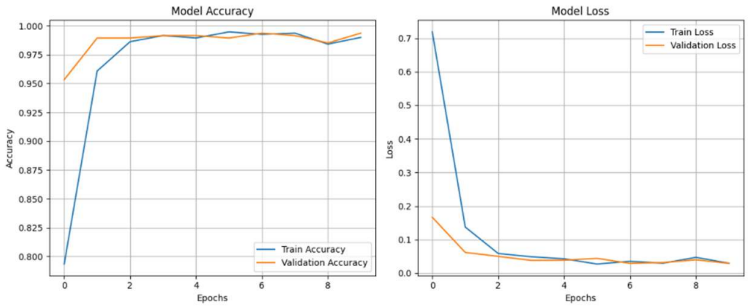


Figure 61 Accuracy & Loss 4.4

Again, since no analysis has been performed nor any improvements made since 4.3, version 4.4 has produced another underwhelming classification report. Every value within the columns of each of the three important metrics is nowhere near desirable, suggesting in contrast to the results above that the model is poor at accurately classifying any of the 15 categories. As stated previously, one source of this incongruency between results could be the imbalance of the dataset, and so the priority within future versions will be to attempt to address this shortcoming.

Class	Precision	Recall	F1-Score	Support
acer_negundo	0.0	0.0	0.0	10.0
acer_palmatum	0.0	0.0	0.0	6.0
aesculus_pavi	0.143	0.143	0.143	7.0
asimina_triloba	0.3	0.3	0.3	10.0
cercis_canadensis	0.0	0.0	0.0	9.0
chionanthus_virginicus	0.0	0.0	0.0	9.0
gleditsia_triacanthos	0.0	0.0	0.0	8.0
ilex_opaca	0.0	0.0	0.0	11.0

liriodendron_tulipifera	0.1	0.1	0.1	10.0
ostrya_virginiana	0.0	0.0	0.0	10.0
prunus_sargentii	0.0	0.0	0.0	6.0
ptelea_trifoliata	0.091	0.091	0.091	11.0
quercus_montana	0.0	0.0	0.0	10.0
styrax_japonica	0.167	0.167	0.167	6.0
ulmus_pumila	0.0	0.0	0.0	6.0
macro avg	0.053	0.053	0.053	129.0
weighted avg	0.054	0.054	0.054	129.0

As was the case with 4.3, the confusion matrix produced in 4.4 does not reinforce the optimistic accuracy and loss data, instead supporting the poor assessment of the classification report. Effort must be made to improve the alignment of the classification and confusion matrix data with the accuracy and loss data.

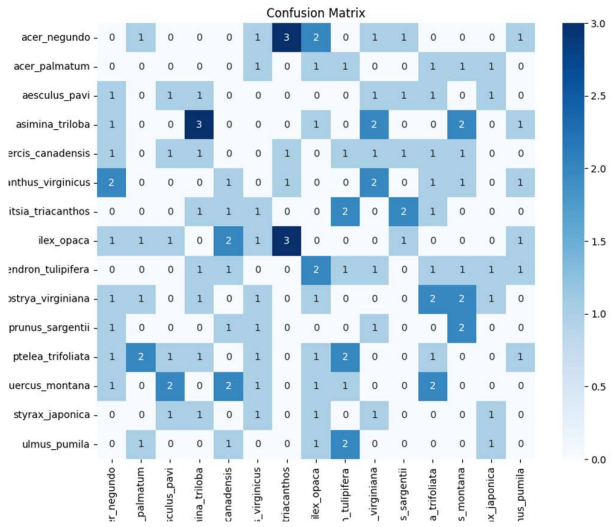


Figure 62 Confusion Matrix 4.4

4.5

In an attempt to positively impact the confusion matrix and classification report, 4.5 includes the functionality to calculate and apply class weights within its code. By applying the concept of weighting, the imbalance between classes with different volumes can be reduced, ensuring under-represented classes are emphasised appropriately during the training process.

Aside from this new functionality, the other aspects of 4.5's code are the same as 4.3-4.4, including the hyperparameter values and the input dataset. *EfficientNetB7* is the architecture version used in this test.

The calculation of the class weights is handled by the `compute_class_weight` function imported from the `utils` package of *Scikit-learn*:

```
from sklearn.utils.class_weight import compute_class_weight
```

Figure 63 Class Weighting Importation 4.5

Once calculated, the class weights are then stored in a dictionary:

```
# Calculate class weights
print("Calculating class weights...")
class_labels = np.concatenate([y.numpy() for _, y in train_ds], axis=0)
class_totals = class_labels.sum(axis=0)
class_indices = np.arange(len(class_names))
class_weights = compute_class_weight(
    class_weight='balanced',
    classes=class_indices,
    y=np.argmax(class_labels, axis=1)
)
class_weight_dict = {i: weight for i, weight in enumerate(class_weights)}
print("Class weights:", class_weight_dict)
```

Figure 64 Class Weighting Implementation 4.5

This dictionary is then included as a parameter within the `fit` function during model training:

```
# Model training
print("Training model...")
history = full_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=epochs,
    callbacks=[csv_logger],
    class_weight=class_weight_dict  # Class weights calculated above
)
```

Figure 65 Model Training 4.5

4.5 Results

The training and validation results table below contains very promising accuracy and loss data. In comparison with the previous code version used in 4.3 and 4.4, which did not contain class weighting, 4.5 displays better scores in earlier epochs, while ending with comparably outstanding values. This suggests that the inclusion of class weights has a positive impact on the predictability of the model, allowing it to comprehend the entire dataset sooner.

That being said, the results from the final epoch are actually slightly worse than those of the penultimate epochs, with peak performance occurring between epochs 7 and 9.

epoch	train_loss	train_accuracy	val_loss	val_accuracy
1	0.5868857502937317	0.8389830589294434	0.11270599812269211	0.966029703617096
2	0.0859081894159317	0.977224588394165	0.11162427812814713	0.961783468723297 1
3	0.0653127282857894 9	0.980932176113128 7	0.0556279905140399 9	0.983014881610870 4
4	0.0537297390401363 4	0.983050823211669 9	0.0581382289528846 74	0.980891704559326 2
5	0.0506540872156662	0.980932176113128 7	0.0513107851147651 7	0.989384293556213 4
6	0.0320613570511341 1	0.988877117633819 6	0.0506136491894722	0.983014881610870 4

7	0.01424815971404314	0.9968220591545105	0.044224608689546585	0.9830148816108704
8	0.011650074273347855	0.9973517060279846	0.026391312479972284	0.987261176109314
9	0.006913952063769102	0.9989407062530518	0.025180019438266754	0.9915074110031128
10	0.029858706519007683	0.9888771176338196	0.059283513575792231	0.9787685871124268

The test results do suggest that the slight dip in the final epoch is not detrimental, however, as the test loss and accuracy are closer to the values found at the training and validation peaks as opposed to the tenth and final epoch.

loss	0.014814283698797226
accuracy	0.9922480583190918

The training and validation plots for accuracy and loss clearly visualise the peak around the 8th epoch, as well as the slight dip towards the end. This visualisation suggests that the optimal number of epochs may be slightly less than the currently used value of 10.

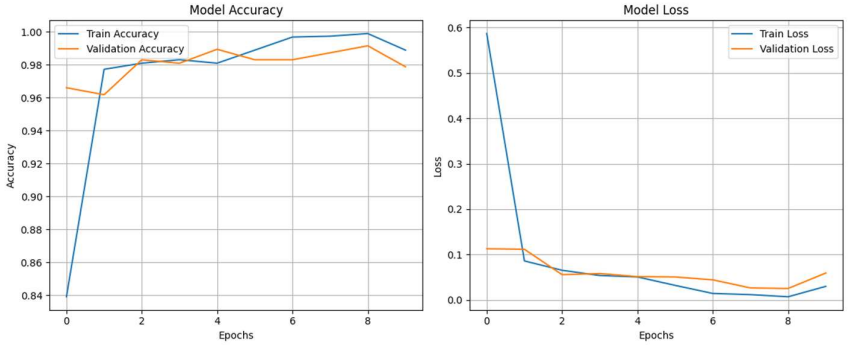


Figure 66 Accuracy & Loss 4.5

Unfortunately, the promising conclusions derived from the data above is not reflected in the classification report or confusion matrix below. Once again, poor values can be found throughout the classification report table, with no class achieving scores greater than 0.2, and the averages at the bottom barely exceeding 0.05. Clearly, implementing class weighting has had little positive effect on these performance metrics, which would have been the desirable outcome.

Class	Precision	Recall	F1-Score	Support
acer_negundo	0.2	0.2	0.2	10.0
acer_palmatum	0.0	0.0	0.0	6.0
aesculus_pavi	0.0	0.0	0.0	7.0
asimina_triloba	0.0	0.0	0.0	10.0
cercis_canadensis	0.0	0.0	0.0	9.0
chionanthus_virginicus	0.0	0.0	0.0	9.0
gleditsia_triacanthos	0.0	0.0	0.0	8.0
ilex_opaca	0.0	0.0	0.0	11.0
liriodendron_tulipifera	0.0	0.0	0.0	10.0

ostrya_virginiana	0.1	0.1	0.1	10.0
prunus_sargentii	0.167	0.167	0.167	6.0
ptelea_trifoliata	0.091	0.091	0.091	11.0
quercus_montana	0.2	0.2	0.2	10.0
styrax_japonica	0.0	0.0	0.0	6.0
ulmus_pumila	0.0	0.0	0.0	6.0
macro avg	0.051	0.051	0.051	129.0
weighted avg	0.054	0.054	0.054	129.0

As is the case for the classification report table above, the confusion matrix shows results which are equally conflicting with the accuracy and loss results. The inclusion of class weighting appears to have had negligible positive impact on the confusion matrix, as the distribution of values is no better than in the previous two rounds of testing. Clearly, more improvement is required within the model's code to increase the alignment of the first results section with the second.

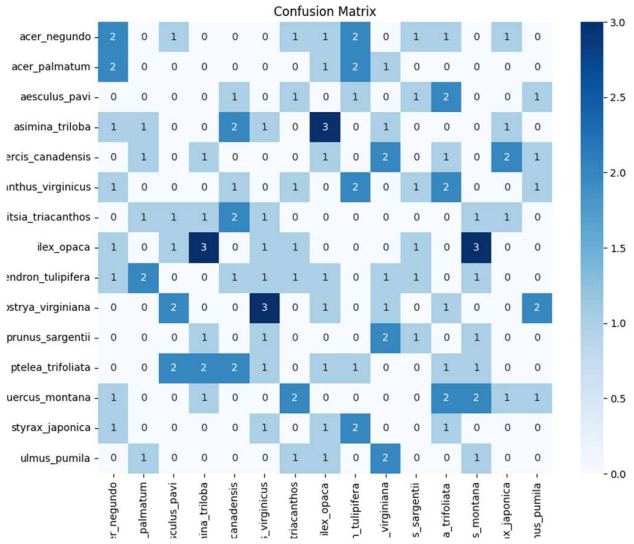


Figure 67 Confusion Matrix 4.5

4.6

In continuation of the phase 4 trend of testing both *EfficientNet* versions within the code before applying updates, test 4.6 will simply include *EfficientNetV2S* as the pre-trained architecture. Based on the results of 4.5, little optimism is held regarding the outcome of the classification report and confusion matrix, but promising results are anticipated for the training and validation loss and accuracy results.

The figure below displays the simple variation required to implement *EfficientNetV2S* in place of *EfficientNetB7*:

```
# Model definition
full_model = Sequential()
pretrained_model = EfficientNetV2S(
    include_top=False,
    input_shape=(224, 224, 3),
    pooling='avg',
    classes=num_classes,
    weights='imagenet'
)
```

Figure 68 Model Definition 4.6

4.6 Results

As expected, test run 4.6 has produced excellent accuracy and loss results during training and validation. From the 2nd epoch onwards, the training and validation accuracy values around 95% or higher. From the 3rd epoch onwards, both the training and validation loss values are less than 0.1. In the 10th and final epoch, the validation results of 99.6% for accuracy and 0.017 for loss are representative of a model with fantastic predictability.

epoch	train_loss	train_accuracy	val_loss	val_accuracy
1	0.7032853960990906	0.7976694703102112	0.17450560629367828	0.9426751732826233
2	0.1369307786226272 6	0.9661017060279846	0.07915088534355164	0.9872611761093 14
3	0.0786741524934768 7	0.9735169410705566	0.04280387610197067	0.9957537055015564
4	0.0487385690212249 76	0.9872881174087524	0.04487476870417595	0.9893842935562134
5	0.0355475246906280 5	0.9925847649574 28	0.04006472229957 5806	0.9893842935562134
6	0.0530436672270298	0.9862288236618042	0.02900394983589 6492	0.9936305880546 57
7	0.0307872369885444464	0.9931144118309021	0.03556868433952 3315	0.9915074110031128
8	0.0474790222942829 1	0.9883474707603455	0.03099870495498 1804	0.9915074110031128
9	0.0485060401260852 8	0.9894067645072937	0.01627828553318 9774	0.9957537055015564
10	0.0350378789007663 7	0.9904661178588867	0.01667481660842 8955	0.9957537055015564

The training and validation results of the final epoch are reflected in the results of the test set, in which an accuracy of 100% and a loss of 0.0039 were achieved. The model has performed equally impressively on this previously unseen data as it did with the training and validation sets.

test_loss	0.003856297116726637
test_accuracy	1.0

The training and validation plots of the accuracy and loss graphs below also reflect the brilliant results found in the above tables. In comparison to the graphs of 4.5, it appears as though 4.6 has produced even better results, as there is less separation between the training and validation plots, and no dip in performance in the last epoch. As has been the case in the last three version pairs, it seems that *EfficientNetV2S* slightly outperforms its architectural relative *EfficentNetB7*.

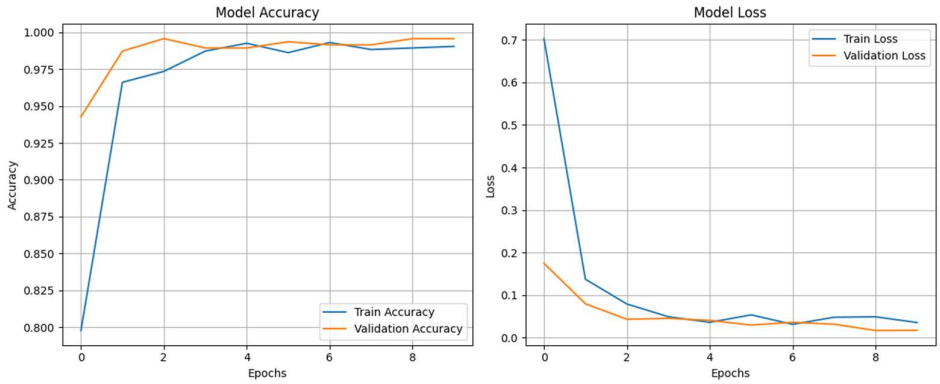


Figure 69 Accuracy & Loss 4.6

Unfortunately, the optimistic results above do not follow through to the classification report. In fact, unlike in the accuracy and loss results, *EfficientNetV2S* actually performs slightly worse than *B7* in important metrics such as precision, recall and F1-Score. The highest value within the table below is 0.167, a little less than the highest value scored in 4.5, which was 0.2. Similarly, 4.5 achieved a weighted average of 0.054, while 4.6 only achieved a weighted average of 0.047.

Class	Precision	Recall	F1-Score	Support
acer_negundo	0.1	0.1	0.1	10.0
acer_palmatum	0.167	0.167	0.167	6.0
aesculus_pavi	0.0	0.0	0.0	7.0
asimina_triloba	0.0	0.0	0.0	10.0
cercis_canadensis	0.0	0.0	0.0	9.0
chionanthus_virginicus	0.0	0.0	0.0	9.0
gleditsia_triacanthos	0.125	0.125	0.125	8.0
ilex_opaca	0.0	0.0	0.0	11.0
liriodendron_tulipifera	0.1	0.1	0.1	10.0
ostrya_virginiana	0.1	0.1	0.1	10.0
prunus_sargentii	0.167	0.167	0.167	6.0
ptelea_trifoliata	0.0	0.0	0.0	11.0
quercus_montana	0.0	0.0	0.0	10.0
styrax_japonica	0.0	0.0	0.0	6.0
ulmus_pumila	0.0	0.0	0.0	6.0
macro avg	0.051	0.051	0.051	129.0
weighted avg	0.047	0.047	0.047	129.0

The confusion matrix of test 4.6 is comparable to 4.5, clearly suggesting poor predictive success across all classes. One important detail which has yet to be stated in regards to the underwhelming classification reports and confusion matrices seen so far is that the test set

sizes have always been very small. With minimal input in testing, poor performance appears more obviously within these metrics. Although unlikely to drastically improve the outcomes of these metrics, the utilisation of larger test sets will at least increase the amount of testing done by the model, giving it more of a chance to prove its predictive ability.

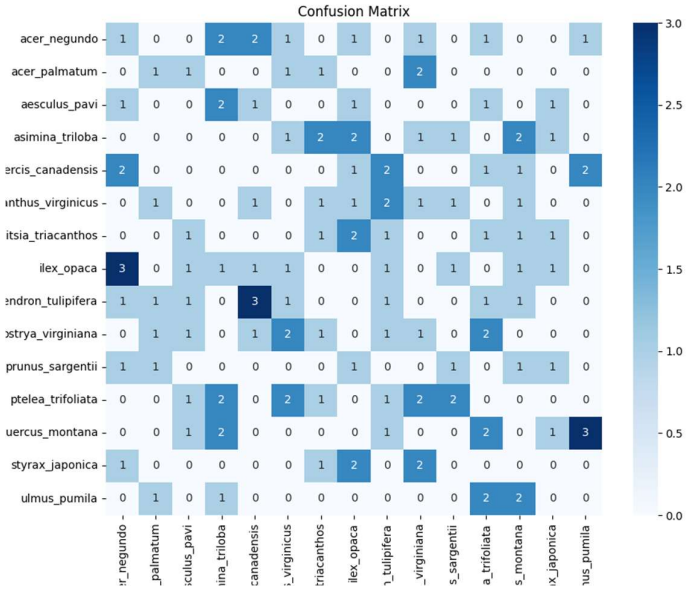


Figure 70 Confusion Matrix 4.6

4.7

Although substantial improvement has not yet been made regarding the classification reports or confusion matrices, highly promising accuracy and loss results have been attained during recent tests.

In order to improve the underwhelming resultant metrics of versions 4.5 and 4.6, one suggestion was made at the end of 4.6, that being to increase the input data volume. In order to do this, the code of 4.7 will implement the *shrooms_ds_max_split* dataset, in order to test if the larger input dataset could positively impact its corresponding classification report and confusion matrix.

In the tests of previous versions that utilised this larger dataset, the number of epochs was increased correspondingly, to ensure the model had sufficient time to maximise its accuracy. The same approach is taken for test 4.7, which will utilise 20 epochs for training and validation, as opposed to other recent versions which utilised 10 epochs. In relation to this, a learning rate scheduler has also been implemented, to ensure that the model does not become susceptible to overfitting.

```
# Learning rate scheduler
def lr_scheduler(epoch):
    return initial_learning_rate * 0.1 ** (epoch // 5)

lr_schedule = tf.keras.callbacks.LearningRateScheduler(lr_scheduler)

# Early stopping
early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss', patience=3, restore_best_weights=True
)
```

Figure 71 Learning Rate Scheduler 4.7

Based specifically on the graph plots of 4.5, which demonstrated a slight decline in performance between the penultimate and final epochs, a second improvement was suggested: to implement early stopping. The aim of this implementation is to halt the learning process if the validation loss score declines for a specified number of epochs, then restore the architecture's weight values to those of the best-performing epoch.

The final new inclusion within version 4.7 is the re-introduction of data augmentation, which aims to perceivably expand and diversify the input dataset, hopefully leading to a more robust and learned model.

```
# Enhanced data augmentation
data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip("horizontal_and_vertical"),
    tf.keras.layers.RandomRotation(0.2),
    tf.keras.layers.RandomZoom(0.2),
    tf.keras.layers.RandomContrast(0.2),
    tf.keras.layers.RandomBrightness(0.2),
    tf.keras.layers.RandomShear(0.2)
])
```

Figure 72 Data Augmentation 4.7

The last few pairs of phase 4 versions sought to compare the performance of two pre-trained architectures, *EfficientNetV2S* and *EfficientNetB7*. Based on the test results of these versions, the decision has been made to utilise only one of these architectures moving forward, that being *EfficientNetV2S*.

4.7 Results

Below is the training and validation results table containing the accuracy and loss values for each epoch. Although the number of epochs was initially set at 20, it appears as though the newly implemented early stopping took effect towards the end, as epoch 19 is the final epoch recorded within the table.

The results contained within this table are very strong: The values of the initial epoch are decent, but vast improvement was made within each column as the epochs progressed, producing very promising results by the 3rd and 4th epochs which continued until the end of the training process.

epoch	train_loss	train_accuracy	val_loss	val_accuracy
1	0.9144284725189209	0.6934955716133118	0.4609358012676239	0.8450018763542175
2	0.45768609642982483	0.8415535688400269	0.32750093936920166	0.8914264440536499

3	0.3157256841659546	0.8904070854187012	0.23558269441127777	0.9206289649009705
4	0.2528485655784607	0.9136171936988831	0.20826363563537598	0.9344814419746399
5	0.2063294649124145 5	0.9299017190933228	0.2016143649816513	0.9385997653007507
6	0.1522091627120971 7	0.9503041505813599	0.1711073219776153 6	0.9483339786529541
7	0.1313058137893676 8	0.9572297334671102	0.1602355837821960 4	0.9539498090744019
8	0.1179915741086006 2	0.9607861638069153	0.1519443690776825	0.9565705657005 31
9	0.1122802272439003	0.9625643491744995	0.1474792212247848 5	0.9580681324005127
10	0.1112806424498558	0.9639681577682495	0.1466628760099411	0.9595656991004944
11	0.1100851520895958	0.9645296931266785	0.1453562825918197 6	0.9588169455528259
12	0.0993748903274536 1	0.9672437906265259	0.1466835588216781 6	0.9576937556266785
13	0.1031643897294998 2	0.9675245881080627	0.1440910696983337 4	0.9588169455528259
14	0.0985211133956909 2	0.9702386260032654	0.1461126804351806 6	0.9573193788528442
15	0.1026887223124504 1	0.9683668613433838	0.1454615294933319	0.9558218121528625
16	0.0986901521682739 3	0.9692091941833496	0.1435228139162063 6	0.9595656991004944
17	0.1042978912591934 2	0.9648104906082153	0.1484466046094894 4	0.9576937556266785
18	0.1081126332283 02	0.9653720259666443	0.1457192599773407	0.9580681324005127
19	0.1022228077054023 7	0.9676181674003601	0.1446332037448883	0.9573193788528442

In fact, the loss and accuracy values achieved during 4.7's testing are the best results attained by any version implementing a pre-trained architecture and mushroom dataset. The loss value achieved is 0.18, while the accuracy is around 95%. While these values are not quite as impressive as those achieved while using a variation of the *LeafSnap* dataset, it is worth remembering that the mushroom datasets contain realistic photographs in natural settings, while the *LeafSnap* datasets contain cleaner, less user-realistic images. Based on this fact, the accuracy of around 95% is an amazing result, as is the test loss of 0.18, indicating great promise for future deployment within an app for users.

test_loss	0.18072621524333954
test_accuracy	0.945147693157196

Again, the accuracy and loss graphs provide a visual accompaniment to the above tables, clearly demonstrating the successful training and validation results.

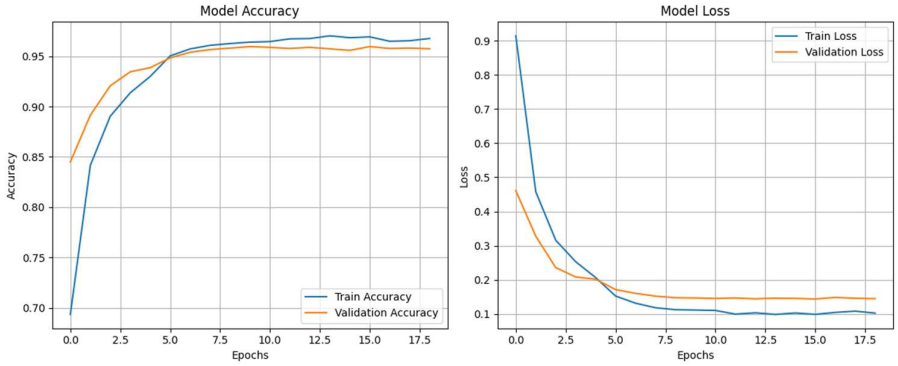


Figure 73 Accuracy & Loss 4.7

Unfortunately, it appears as though all implementations made within 4.7 did not have as substantial an impact in the classification report as was hoped for. Although this classification report is better than those generated during 4.5 and 4.6, containing higher values across all metric columns, these values are still far lower than what would be considered successful. The larger input dataset and the inclusion of augmentation has had the desired impact, and so the secret of aligning the classification report with the success of the accuracy and loss results has not yet been discovered.

Class	Precision	Recall	F1-Score	Support
Agaricus	0.0759493670886076	0.0759493670886076	0.0759493670886076	79.0
Amanita	0.0512820512820512	0.0506329113924050	0.0509554140127388	79.0
Boletus	0.1125	0.1139240506329113	0.1132075471698113	79.0
Cortinarius	0.1038961038961039	0.1012658227848101	0.1025641025641026	79.0
Entoloma	0.1428571428571428	0.1392405063291139	0.1410256410256410	79.0
Hygrocybe	0.1139240506329113	0.1139240506329113	0.1139240506329113	79.0
Lactarius	0.1038961038961039	0.1012658227848101	0.1025641025641026	79.0
Russula	0.1511627906976744	0.1645569620253164	0.1575757575757575	79.0
Suillus	0.0769230769230769	0.0759493670886076	0.0764331210191082	79.0
macro avg	0.1035989652526302	0.1040787623066104	0.1037999004058645	711.0
weighted avg	0.1035989652526302	0.1040787623066104	0.1037999004058645	711.0

The confusion matrix below reflects the outcome of the classification report, as even though the matrix is populated with higher values than its recent predecessors, these values do not align desirably into the diagonal line of true positives. Instead, they are distributed across the

entire matrix, indicating that the separation between the two different collections of results (accuracy/loss and classification/confusion matrix) is as prominent as ever.

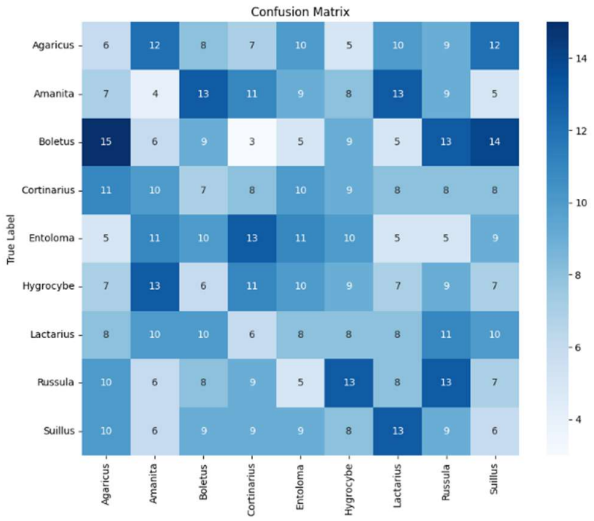


Figure 74 Confusion Matrix 4.7

With the conclusion of phase 4, the project reaches an important point. The brilliant accuracy and loss values obtained during versions 4.6 and 4.7 suggest that it is time to move forward to the development of the application which will house the models produced by these versions. However, the comparably poorer classification reports and confusion matrices generated by these same versions indicate that further work is required, to improve these results to necessary standards.

Due to the fact that the final submission deadline is rapidly approaching, it is necessary that both tasks are carried out simultaneously. This is not a huge issue, as these tasks are mutually exclusive from each other, however emphasis must be placed on the development of the application, so that a fully-implemented version can be produced to demonstrate the abilities of the models which have been painstakingly developed throughout the project's span.

Therefore, the next steps of the project will be to explore the development of an application prototype, while attempting to solve the discrepancies in the performance metrics.

Implementation & Testing – Model Development Phase 5

Following the inability to clarify the contradictory outcomes of the last few tests in phase 4, a comprehensive review of the project was performed, with particular focus given to phases 3 and 4.

Phase 3, which introduced pre-trained architectures to the project, produced outstanding results when utilizing the *MobileNetV2* architecture alongside the *LeafSnap_15_Lab* dataset in 3.1, which obtained a test accuracy of 99.6% and a test loss of 0.05, as well as a confident confusion matrix. Later tests of this phase also produced promising results as the *shrooms_ds* dataset was implemented in 3.2, then balanced and expanded in 3.3, the latter of which obtained a test accuracy of 76.3% and a test loss of 0.68. Test 3.4 then introduced an alternative pre-trained model, *EfficientNetB0*, but unfortunately generated poor test results of 13.3% accuracy and 2.20 loss, attributed to a failure to optimize the code to the new architecture prior to training.

Although the final results of phase 3 weren't promising, optimism was still held for the use of *EfficientNet* architectures within the project, and so phase 4 was dedicated to this completing this objective. Two variations of the architectural family were implemented, *EfficientNetB0* and *EfficientNetV2S*, and throughout phase 4 the performance of these architectures was compared to determine which was optimal. From the very first test of this phase, 4.1, great potential could be seen in the use of these pre-trained models, as the test results produced were an accuracy of 82.1% and a loss of 0.57. Furthermore, the test results of this phase only improved, as between 4.3 and 4.6 all test accuracies values were at least 99%, and the final test 4.7 produced an accuracy of 94.5% and a loss of 0.18 – truly great results.

That being said, not all the output data was promising, as difficulty was experienced in generating optimistic confusion matrices during the entirety of phase 4. Even in tests where the accuracy and loss values neared perfection, the accompanying confusion matrices told a contradictory and opposing story. Further confirmation of performance issues was found when classification reports were introduced, as they supported the confusion matrices in opposing the narrative of the great accuracy and loss results of the various tests of phase 4. Even when measures were taken to minimise the discrepancy between the performance metrics, such as balancing the datasets, applying class weights, adjusting hyperparameters and returning to a simpler dataset, no substantial progress was made. Although test 4.7 produced the brilliant accuracy and loss results mentioned above, its confusion matrix and classification report failed to align themselves with this narrative of success, remaining in contradiction weighted average values of 0.103, 0.104, and 0.103 for precision, recall and F1-Score respectively.

When broadly comparing the results of phases 3 and 4, it is clear that great accuracy and loss values can be found throughout both. However, it must be stated that phase 3 displays more immediate potential, as its confusion matrices are far more congruent with their respective accuracies and losses than those of phase 4. While substantial efforts were made to solve the issue of incongruency within the latter phase, progress was negligible.

Therefore, in conclusion of this review, the decision has been made to continue the model development process based on phase 3 instead of phase 4. Ultimately, this means abandoning the *EfficientNet* family of architectures in favour of *MobileNetV2*, and utilising the code of phase 3 as the foundation on which the project's final outcome can be reached.

In addition to the regression to an earlier code for model development, phase 5 will utilise a new dataset, *17flowers*, which contains 17 classes of different flower species. This decision was made based upon the fact that the dataset of leaves has already been discarded due to its lab-based images being too pristine, in addition to the fact that the mushroom dataset has not produced results which combine fantastic accuracy and congruent supporting performance metrics. These issues left a window of opportunity for this new dataset, which features realistic, real-world images similar to the mushroom dataset, but will hopefully produce better and more congruent outcomes.

5.1

As stated above, the code responsible for model development during phase 5 is actually based upon that used during phase 3.While there is a lot of fundamental overlap between the codes used during phases 3 and 4, the biggest differences are the exclusion of the classification

report, which was only introduced during phase 4, as well as the use of a different pre-trained architecture, as phase 3 utilised a variety of the *MobileNet* architecture, while phase 4 explored the *EfficientNet* family. At this current moment, the plan is to stick to *MobileNetV2*, the architecture which demonstrated great promise during the tests in which it was implemented. However, the additional performance metrics from phase 4 will be introduced during this current phase, as they are crucial tools in determining the efficacy of the models.

5.1 will consist of a series of tests, in order to allow for the optimal configuration of the hyperparameter values. The first test within this series, 5.1a, is discussed below.

5.1a

Since test 3.1 produced the best results of its phase, its code was chosen as the base for developing the model in test 5.1. The hyperparameter values remained identical, as the values used were a learning rate of 0.0001, a batch size of 32, and an epoch value of 10. The only real difference between 3.1 and 5.1 is the dataset used for training, as the *Leafsnap_15_Lab* is replaced by *flowers17*.

```
# Specify the path to your leaf dataset directory
dataset_path = R"C:\Users\Rhodri\Desktop\Project\5.1\17flowers"
image_size = (224, 224)  # MobileNetV2 input size
batch_size = 16
```

As can be seen in the training results below, this initial version of phase 5 appears to have generated highly promising results. Training accuracy rises continually, from 25.5% initially to 93.5% by the final epoch, while the training loss improves from 2.54 to 0.27. The validation results provide further confirmation of the training process with the final few epochs reaching an average accuracy of around 94% and a final validation loss value of 0.24.

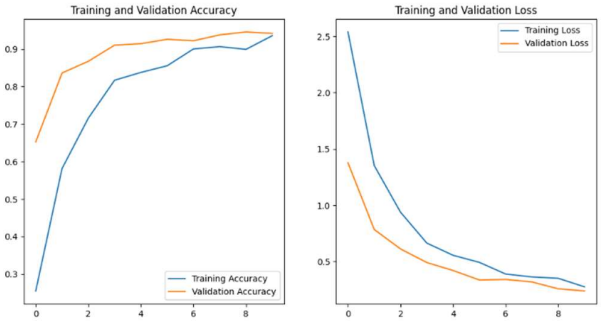
Epoch	accuracy	loss	val_accuracy	val_loss
1	0.2552083432674408	2.539233684539795	0.65234375	1.3769510984420776
2	0.5812500119209229	1.352041482925415	0.8359375	0.7845145463943481
3	0.7156249880790771	0.9379004836082458	0.8671875	0.6117345690727234
4	0.8166666626930237	0.6635771989822388	0.91015625	0.4909541308879852 3
5	0.8374999761581421	0.5551220774650574	0.9140625	0.4199945032596588
6	0.8552083373069763	0.4924551546573639	0.92578125	0.3359184861183165
7	0.8999999761581421	0.3886736929416565	0.921875	0.3408020734786973
8	0.90625	0.3629199266433716	0.9375	0.3186280727386474 6
9	0.8989583253860474	0.3508609235286712 6	0.9453125	0.2575478553771972 7

10	0.9354166388511658	0.2749722898006439	0.94140625	0.23866546154022217

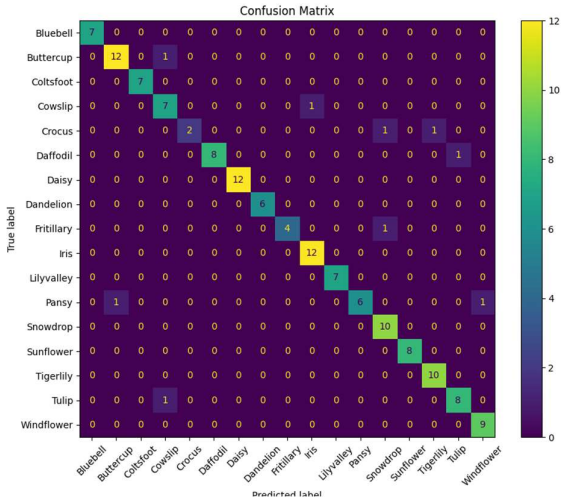
The success of the training stage is reinforced by equally fantastic test results, as an accuracy of 96.5% and a loss of 0.24 were achieved.

Test Loss	0.2416735291481018
Test Accuracy	0.9652777910232544

The close proximity of the training, validation and test result values suggest a confident and successful learning process, with minimal indication of overfitting. The graphs below display the accuracy and loss values for both the training and validation stages, and provide a visual demonstration of the success of these stages. One point worth noting here is that the plots of both the accuracy and loss graphs do not plateau within the allotted number of epochs. This suggests that increasing this value could allow the model to increase its performance further. This will be taken into account during the next test.



Finally, the confusion matrix for 5.1a validates its test results, as the desirable diagonal line of true positives is prominent, suggesting that only a handful of predicted labels were incorrect. Given the extreme difficulty experienced in attempting to align confusion matrices with its accompanying results during phase 4, a supportive confusion matrix such as this one for 5.1a is a welcome sight.



5.1b

Based on the result of the 5.1a, in which the accuracy and loss plots did not yet reach a plateau, this next test aims to explore the possibility of achieving better results by simply increasing the number of epochs. In 5.1b, this value will be increased from 10 to 15, while all other hyperparameters and variables will be kept the same.

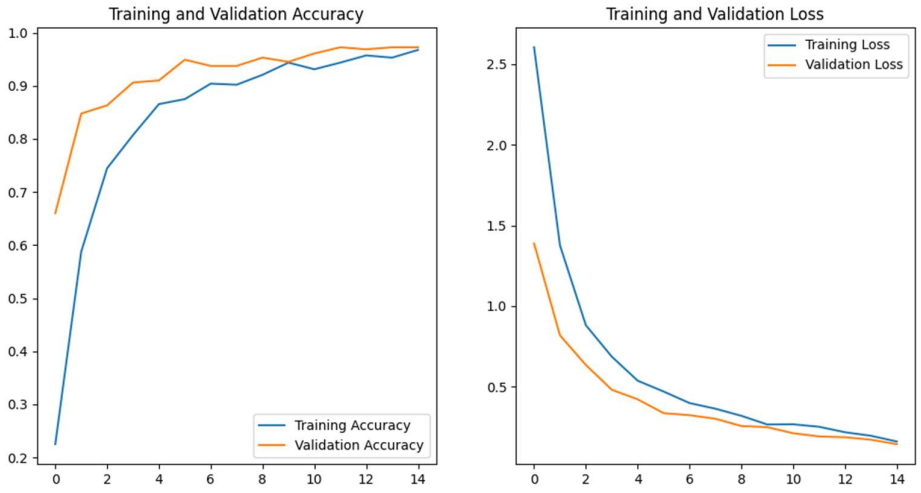
Epoch	accuracy	loss	val_accuracy	val_loss
1	0.22499999403953552	2.605189085006714	0.66015625	1.387690782546997
2	0.5874999761581421	1.3761347532272339	0.84765625	0.8179001212120056
3	0.7447916865348816	0.8805817365646362	0.86328125	0.6340733766555786
4	0.8072916865348816	0.68577641248703	0.90625	0.4802386462688446
5	0.8656250238418579	0.536548912525177	0.91015625	0.4210643768310547
6	0.875	0.46937209367752075	0.94921875	0.33501434326171875
7	0.9041666388511658	0.39783230423927307	0.9375	0.3226008415222168
8	0.9020833373069763	0.36271336674690247	0.9375	0.30015283823013306
9	0.9208333492279053	0.31864750385284424	0.953125	0.255307674407959
10	0.9437500238418579	0.26489657163619995	0.9453125	0.2481955885887146
11	0.9312499761581421	0.26606824994087222	0.9609375	0.21062098443508148
12	0.9437500238418579	0.25071910023689267	0.97265625	0.19044290482997894
13	0.9572916626930237	0.21686074137687683	0.96875	0.18587116897106167
14	0.953125	0.19487789273262024	0.97265625	0.17034241557121277
15	0.9677083492279053	0.15921382606029551	0.97265625	0.14297834038734436

As can be seen in the training and validation results table above, it appears that the 5 additional epochs provided the model with the time to improve both its accuracy and loss values beyond those achieved during 5.1a. The training and validation accuracy values average around 97%, an improvement of around 3%, while the average value of the training and validation loss values is around 0.15, showing an improvement of at least 0.10 in comparison to 5.1a.

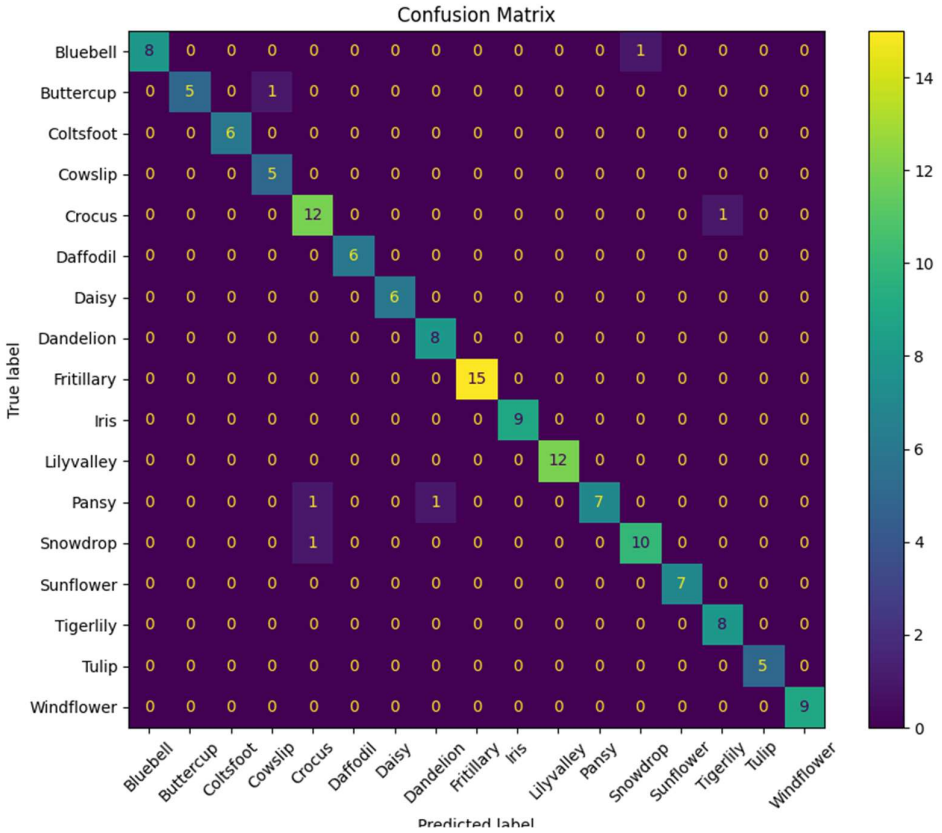
Test Loss	0.26249635219573975

Test Accuracy	0.9375

Unfortunately, this improvement did not permeate its way into the test results, as for some reason the test results of 5.1b are actually worse than those of 5.1a, even though the training and validation data showed promise for improvement. The test loss of 5.1b is 0.26, which is only 0.02 worse than the equivalent value of 5.1a, however the test accuracy of 5.1b is 93.8%, which is around 3% worse than its predecessor. Initially it was speculated that the test results of 5.1a and 5.1b had been mislabelled, but after verifying that no error was made regarding results storage, the drop in performance between training and testing is simply confusing. One possible explanation would be that the images designated to the test stage were more challenging for the model in 5.1b than in 5.1a. Aside from this potential reason, it is not clear at this point what else could cause the incongruency between the training & validation and the test results.



In more optimistic news, the accuracy and loss plots from the training and validation stages suggest less overfitting than those of 5.1a, as there is less distance between the training and validation plots while superior values are reached. Additionally, even though the number of epochs was extended from 5.1a to 5.1b, the plots fail to demonstrate plateauing, suggesting that results could again be improved further by simply increasing the number of epochs.



Interestingly, although the test results of 5.1b were inexplicably worse than 5.1a, the improvement seen in its training and validation stages is reflected in the confusion matrix which only contains 6 incorrect predictions, marginally better than the 9 incorrect labels of 5.1a's confusion matrix.

5.1c

As was stated in the analysis of 5.1b, its accuracy and loss plots do not reach a point of plateau before completing the final epoch, suggesting that increasing this value further could give the model the opportunity to produce even better results. Therefore, 5.1c will include an additional 5 epochs for its training stage, making the number of epochs 20. Additionally, to ensure a more gradual learning process, the learning rate has been decreased to 0.00005.

The table below contains the accuracy and loss results of the training and validation stages for 5.1c. Interestingly, although the learning rate was halved between tests, the rate of improvement for all metrics in 5.1c is only marginally less than the 5.1b. Throughout the entire table, the values obtained for each epoch are almost identical in comparison to 5.1b.

Epoch	accuracy	loss	val_accuracy	val_loss

1	0.232291668653488 16	2.591217041015625	0.6796875	1.453842043876648
2	0.588541686534881 6	1.367044925689697 3	0.80078125	0.821310102939605 7
3	0.748958349227905 3	0.870381534099578 9	0.875	0.615334391593933 1
4	0.790624976158142 1	0.689854919910430 9	0.90625	0.481130957603454 6
5	0.861458361148834 2	0.541211247444152 8	0.94140625	0.406045854091644 3
6	0.869791686534881 6	0.466416209936141 97	0.94140625	0.341334670782089 23
7	0.885416686534881 6	0.388517707586288 45	0.9375	0.329125732183456 4
8	0.90625	0.349266529083251 95	0.9453125	0.293081760406494 14
9	0.926041662693023 7	0.301140606403350 83	0.953125	0.247513279318809 5
10	0.945833325386047 4	0.250417262315750 1	0.953125	0.246524140238761 9
11	0.9375	0.265103340148925 8	0.97265625	0.204860910773277 28
12	0.936458349227905 3	0.239506945013999 94	0.97265625	0.172591477632522 58
13	0.958333313465118 4	0.199458613991737 37	0.97265625	0.177078753709793 1
14	0.959375023841857 9	0.183034196496009 83	0.97265625	0.159336641430854 8
15	0.963541686534881 6	0.184246972203254 7	0.984375	0.135262966156005 86
16	0.962499976158142 1	0.169860109686851 5	0.97265625	0.168072789907455 44
17	0.962499976158142 1	0.161848098039627 08	0.9765625	0.139061197638511 66
18	0.970833361148834 2	0.140947625041008	0.96484375	0.146751821041107 18
19	0.965624988079071	0.147617712616920 47	0.97265625	0.109692163765430 45
20	0.96875	0.131211742758750 92	0.9609375	0.145465686917305

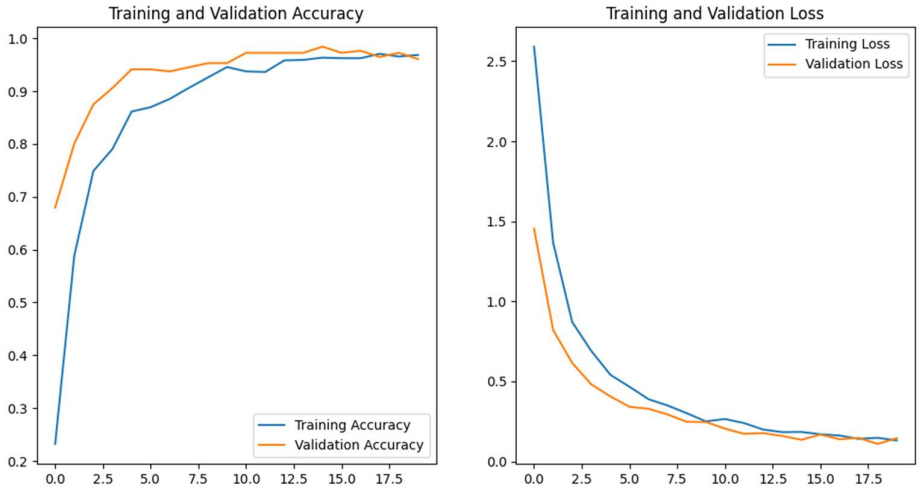
Another interesting point is that increasing the number of epochs from 15 to 20 did not have substantial positive impact on the model's performance during the training and validation stages: slight improvement continues to occur regarding the training accuracy and loss, however the best validation accuracy value, 98.4%, was produced during epoch 15. As for validation loss, the best value of 0.11 was produced during epoch 19.

Although the training and validation data does not seem to have improved substantially, the test results of 5.1c provide confirmation that these new hyperparameter values had a positive

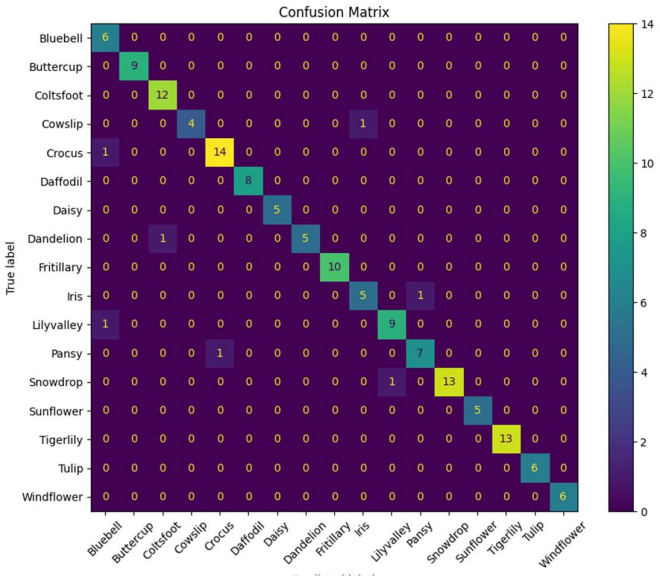
impact on the model's performance, as a test accuracy of 97.2% and a test loss of 0.14 were recorded. These are actually the best test results of phase 5 so far.

Test Loss	0.14287321269512177
Test Accuracy	0.9722222089767456

The accuracy and loss graphs visually explain the outcome of 5.1c, and the possible benefits of its hyperparameters: firstly, the increased number of epochs allows the plots to finally display plateauing, while the reduced learning rate could help explain the closer proximity of the training and validation plots, suggesting an improved learning process.



Once again, this test has produced a very promising confusion matrix, with only 7 incorrect predictions. This in line with the other tests of phase 5, and in contrast to the very confusing confusion matrices of phase 4.



5.1d

Now that minor adjustments to the number of epochs and learning rate have been explored, 5.1d will investigate the impact of changing the batch size, a hyperparameter which has been kept consistent to this point. The new value for the batch size will be 16, which is half the previous value of 32. The decision to reduce the batch size was made based on the fact that the dataset in use, flowers17, is relatively small, and so it seemed logical to explore the use of a smaller batch size, as opposed to a larger one. The learning rate and number of epochs are 0.00005 and 20 respectively.

The table below contains the accuracy and loss results from the training and validation stages. It is interesting to note that this is the first time in the recent history of this project that the validation stages were outperformed by their corresponding training stages: typically, the validation accuracy and loss results are superior, however it is the training values which are better in 5.1d. From around the 10th epoch onwards the training data produces the better results, and this dynamic remains until the end, with accuracy and loss values which are respectively 3-5% and 0.06-0.07 better than their validation equivalents throughout.

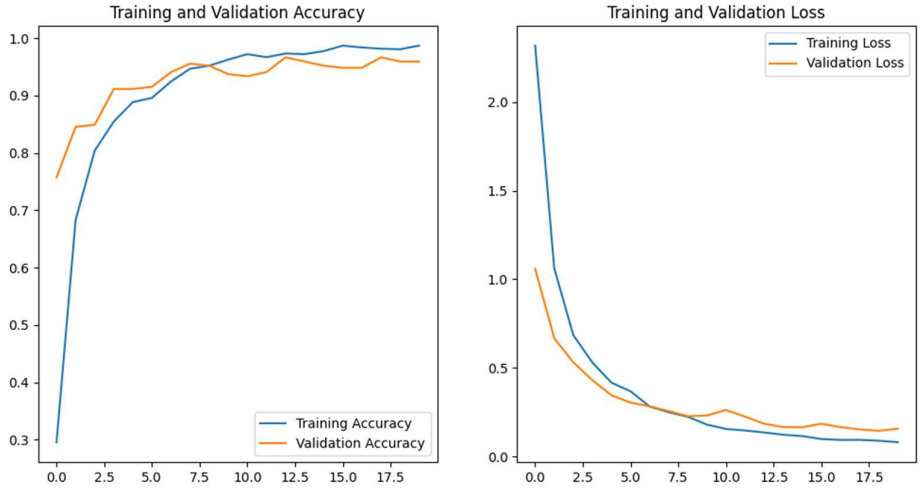
Epoch	accuracy	loss	val_accuracy	val_loss
1	0.2955508530139923	2.3196723461151123	0.7573529481887817	1.0593253374099731
2	0.6832627058029175	1.0622674226760864	0.845588207244873	0.6678859591484007
3	0.804025411605835	0.6844117641448975	0.8492646813392639	0.5305262207984924
4	0.8548728823661804	0.5298187732696533	0.9117646813392639	0.4303551912307739
5	0.8887711763381958	0.4158713817596435 5	0.9117646813392639	0.34476968646049 5
6	0.8961864113807678	0.3674969971179962	0.9154411554336548	0.30353501439094543
7	0.9247881174087524	0.2813749015331268 3	0.9411764740943909	0.28230857849121094
8	0.9470338821411133	0.2493217289447784 4	0.9558823704719543	0.2555859088897705
9	0.9523305296897888	0.2234064787626266 5	0.9522058963775635	0.2266751676797866 8
10	0.9629237055778503	0.1794555038213729 9	0.9375	0.2307212501764297 5
11	0.9724576473236084	0.1548006683588028	0.9338235259056091	0.2618128657341003 4
12	0.9671609997749329	0.1461368501186370 8	0.9411764740943909	0.2243689745664596 6
13	0.9735169410705566	0.1348539739847183 2	0.966911792755127	0.1842106580734253
14	0.9724576473236084	0.1221659258008003 2	0.9595588445663452	0.1653840094804763 8
15	0.9777542352676392	0.1146000325679779	0.9522058963775635	0.1642449647188186 6

16	0.9872881174087524	0.09793656319379807	0.9485294222831726	0.18462693691253662
17	0.9841101765632629	0.09279216080904007	0.9485294222831726	0.16507244110107422
18	0.9819915294647217	0.09327848255634308	0.966911792755127	0.15214592218399048
19	0.9809321761131287	0.0882859155535698	0.9595588445663452	0.14459627866744995
20	0.9872881174087524	0.08013921231031418	0.9595588445663452	0.15599079430103302

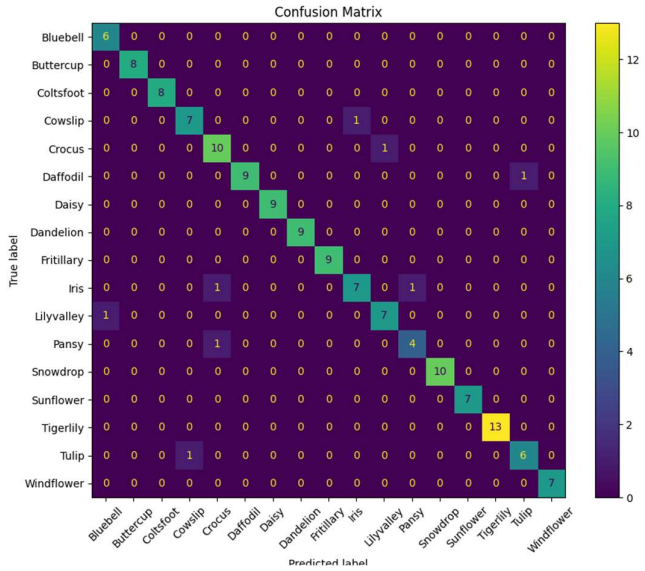
Regardless, all values obtained by the final epoch are very promising: 98.7% and 0.08 for the training accuracy and loss, and 96% and 0.15 for validation. Those training results are the best scores obtained in phase 5 so far. However, when comparing 5.1d to its predecessor, it can be seen that 5.1d's test accuracy of 96.5% is roughly 0.7% worse than its predecessor, and its test loss of 0.22 is worse by around 0.08.

Test Loss	0.22222426533699036
Test Accuracy	0.9652777910232544

This interesting combination of superior training and inferior validation and accuracy results is indicative of the fact that the model has overtrained on the training set. This point is reinforced by the separation between the training and validation plots in both the accuracy and validation graphs below.



Even though this overfitting during training has occurred, these results are still very useful and informative. This conclusion is supported by the fact that the confusion matrix produced contains only 8 incorrect predictions. That being said, 5.1d did not overtake its predecessors in terms of performance, and so the batch size moving forward will return to 32.



5.2

Now that optimal hyperparameter values have been identified, the next experimentation stage will explore the effect of increasing the input dataset on the performance metrics.

In order to increase the volume of the dataset, a small python program was created which accepts the input dataset as well as a specified factor of multiplication, and applies TensorFlow augmentation methods to the images within each class until they have all been increased to the desired volume. For 5.2, the specified factor of multiplication was 5, and so the new dataset used here has been named *flowers17_5x*.

INSERT IMAGE OF ORIGINAL MULTIPLIER CODE.

COVER THE HYPERPARAMETER VALUES USED

mobilenet_LR5e-05_BS16_E20

The results table for 5.2 below contains very promising data: the performance metrics obtained during epoch 20 are the best of phase 5 to this point, with an average accuracy of 97.6% and an average loss of 0.073.

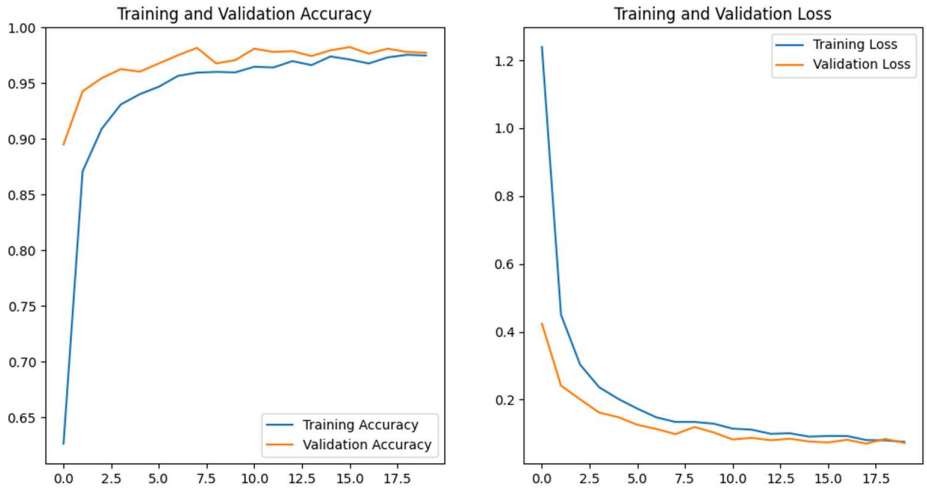
Epoch	accuracy	loss	val_accuracy	val_loss
1	0.6262626051902771	1.2390668392181396	0.8948529362678528	0.4237695038318634
2	0.8707912564277649	0.4501952230930284	0.9426470398902893	0.2414090484380722
3	0.9088804721832275	0.3033820688724518	0.9544117450714111	0.2011255621910952
4	0.9307659864425659	0.2365969270467582	0.9624999761581421	0.1620754897594452
5	0.940025269985199	0.2024069130420684 8	0.9602941274642944	0.1484707295894622 8

6	0.9467592835426331	0.1736537665128708	0.9676470756530762	0.12603363394737244
7	0.9564393758773804	0.14792826771736145	0.9750000238418579	0.11362481117248535
8	0.9593855142593384	0.13433901965618134	0.9816176295280457	0.09861078858375555
9	0.9600168466567993	0.13438545167446136	0.9676470756530762	0.11950311064720154
10	0.9595959782600403	0.12929010391235352	0.970588207244873	0.10345669090747833
11	0.9646464586257935	0.11466462165117264	0.9808823466300964	0.08283430337905884
12	0.9640151262283325	0.1116393506526947	0.9779411554336548	0.0874519795179367
13	0.9696969985961914	0.09937536716461182	0.9786764979362488	0.08043872565031052
14	0.9661195278167725	0.10111825913190842	0.9742646813392639	0.0850747600197792
15	0.9739057421684265	0.09111125767230988	0.979411780834198	0.07675392180681229
16	0.9711700081825256	0.09318546950817108	0.9823529124259949	0.07396939396858215
17	0.9675925970077515	0.0929829329252243	0.9764705896377563	0.08187142014503479
18	0.9730639457702637	0.08098549395799637	0.9808823466300964	0.0706314742565155
19	0.9753788113594055	0.08018365502357483	0.9779411554336548	0.08445794135332108
20	0.9747474789619446	0.07569650560617447	0.9772058725357056	0.07234415411949158

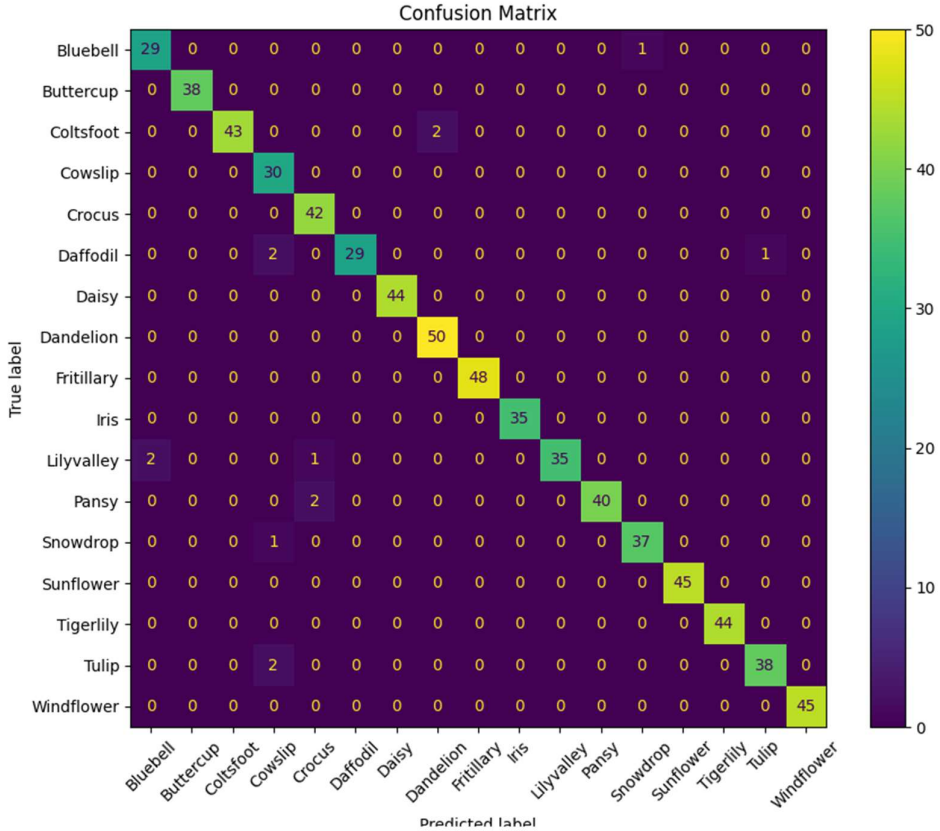
The test results echo those obtained during training and validation, and again are the best test results obtained during phase 5, with the test accuracy being 98.1% and the test loss being 0.08.

Test Loss	0.08028818666934967
Test Accuracy	0.9810495376586914

Validation of the tremendous results above is also found in the accuracy and loss plots from the training and validation stages. Both are great, however the loss graph is truly outstanding, as the distance between the training and validation plots is miniscule.



The confusion matrix also reinforces the success of utilising the enlarged dataset, as even though the volume of the input dataset was 5 times larger than in previous phase 5 stages, only 14 predictions were incorrect, which as a percentage of the total test images is actually far better than preceding tests.



5.3

In order to validate the outstanding results achieved in 5.2, this next stage will re-introduce the classification report. Ideally, the report will confirm that this current configuration is as great as is implied by the performance metrics currently in use.

In order to remain consistent and comparable with the previous stage, 5.3 will include no changes apart from the re-introduction of the classification report.

mobilenet_LR5e-05_BS16_E20

The table below contains the accuracy and loss data from the training and validation stages of 5.3. As seen in 5.2, this current configuration of dataset and hyperparameters has again produced amazing results which are almost identical to those of the previous stage. This was of course expected, since no model-related details were changed.

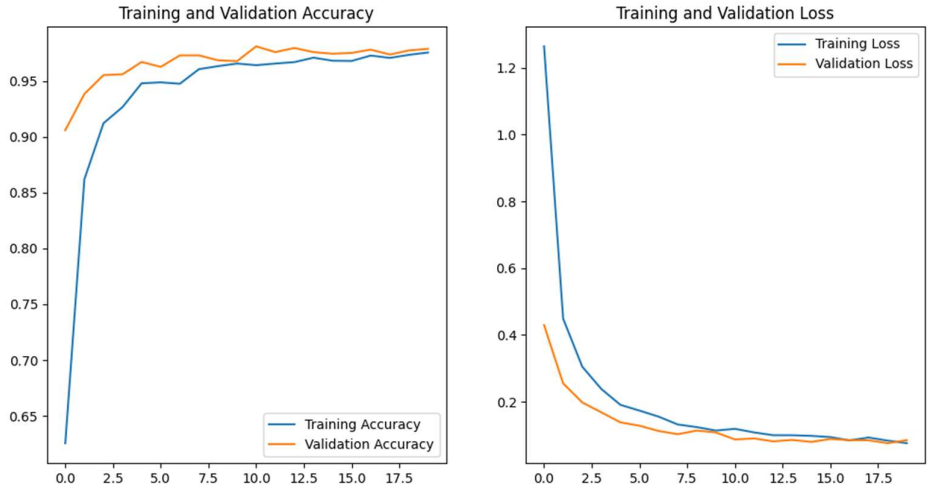
Epoch	accuracy	loss	val_accuracy	val_loss
1	0.6256313323974609	1.2641345262527466	0.9058823585510254	0.42930635809898376
2	0.8619528412818909	0.44874125719070435	0.9382352828979492	0.2549041211605072
3	0.9120370149612427	0.30498579144477844	0.9551470875740051	0.1979990154504776
4	0.9265572428703308	0.23819653689861298	0.9558823704719543	0.16820833086967468
5	0.9478114247322083	0.19067534804344177	0.9669117927551527	0.1382799744606018
6	0.9486532211303711	0.17341232299804688	0.9624999761581421	0.12811554968357086
7	0.9473905563354492	0.15539051592350006	0.9727941155433655	0.11250313371419907
8	0.9604377150535583	0.13197907805442081	0.9727941155433655	0.1027107685804367
9	0.9631733894348145	0.12396258115768433	0.9683823585510254	0.11364690959453583
10	0.9654881954193115	0.11370489001274109	0.9676470756530762	0.10800516605377197
11	0.9640151262283325	0.11889924854040146	0.9808823466300964	0.08710624277591705
12	0.9654881954193115	0.10811132192611694	0.9757353067398071	0.09001830965280533
13	0.9667508602142334	0.09977269172668457	0.9794117808341998	0.08148282021284103
14	0.9707491397857666	0.09966247528791428	0.9757353067398071	0.08560279756784439
15	0.9680134654045105	0.09781938046216965	0.9742646813392639	0.07973917573690414
16	0.9678030014038086	0.09409473836421967	0.9750000238418579	0.08852533251047134
17	0.9726430773735046	0.08419913798570633	0.9779411554336548	0.08499638736248016
18	0.9705387353897095	0.09282692521810532	0.9735293984413147	0.08458393067121506
19	0.9732744097709656	0.08357356488704681	0.9772058725357056	0.0758606418967247

20	0.9753788113594055	0.07606006413698196	0.9786764979362488	0.08495640009641647

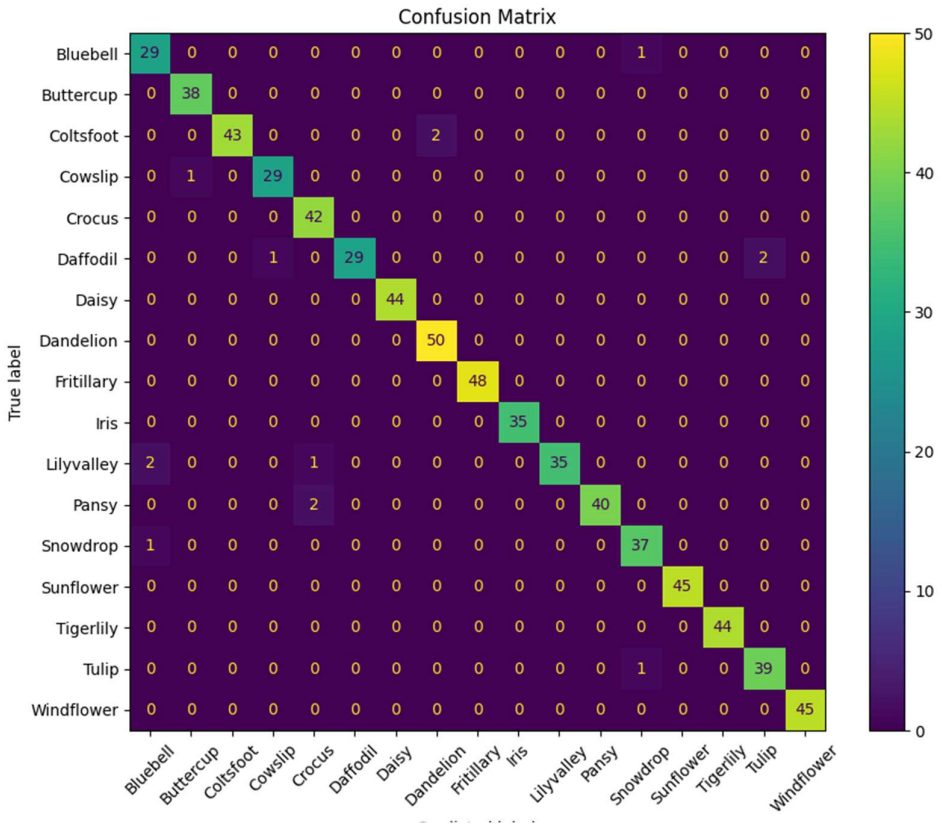
The test results achieved are also almost identical, with the exact same test accuracy of 98.1%, and a fractionally better test loss of 0.07.

Test Loss	0.07193555682897568
Test Accuracy	0.9810495376586914

The accuracy and loss plots demonstrate the success of the training stage, with the close proximity of training and validation plots suggesting that overfitting is not occurring.



The confusion matrix of 5.3 is equally as brilliant as 5.2, as they both achieved the exact same percentage of true positives, and only mislabelled 14 test images.



Now for the true purpose of 5.3: examining if the outstanding results above are reflected in the classification report. Given the brilliance of the confusion matrix, it was expected that the classification report would support the optimistic evaluation of the other metrics, and fortunately that is the case. All values within the report are north of 0.90, and the macro and weighted averages at the bottom of the report are over 0.97, meaning that the performance of the model is evidenced in the precision, recall and F1-score values. This classification report reassuringly reflects not only the confusion matrix, but also the overall success of the model development process.

In stark contrast to phase 4, all performance metrics are aligned and unified in providing an optimistic analysis of the models developed during phase 5. Given that near perfect scores have been recorded already, the room for improvement is small, however there are a couple more adjustments to test before concluding the model development process.

Class	Precision	Recall	F1-Score	Support
Bluebell	0.90625	0.9666666666666667	0.9354838709677419	30.0
Buttercup	0.9743589743589743	1.0	0.987012987012987	38.0
Coltsfoot	1.0	0.9555555555555556	0.9772727272727273	45.0
Cowslip	0.9666666666666667	0.9666666666666667	0.9666666666666667	30.0

Crocus	0.9333333333333333	1.0	0.9655172413793104	42.0
Daffodil	1.0	0.90625	0.9508196721311475	32.0
Daisy	1.0	1.0	1.0	44.0
Dandelion	0.9615384615384616	1.0	0.9803921568627451	50.0
Fritillary	1.0	1.0	1.0	48.0
Iris	1.0	1.0	1.0	35.0
Lilyvalley	1.0	0.9210526315789473	0.958904109589041	38.0
Pansy	1.0	0.9523809523809523	0.975609756097561	42.0
Snowdrop	0.9487179487179487	0.9736842105263158	0.961038961038961	38.0
Sunflower	1.0	1.0	1.0	45.0
Tigerlily	1.0	1.0	1.0	44.0
Tulip	0.9512195121951219	0.975	0.9629629629629629	40.0
Windflower	1.0	1.0	1.0	45.0
macro avg	0.9789461704006182	0.9774856872573591	0.9777459477636382	686.0
weighted avg	0.9804520796525525	0.9795918367346939	0.9795886425809673	686.0

5.4

As the model development process nears its conclusion, there are firstly a handful of adjustments to make in hopes of further increasing model performance. One such adjustment, explored in 5.4, is to reduce the degree of augmentation applied to the dataset during expansion.

LINE OR TWO ABOUT THE DIFFERENCE IN AUGMENTATION BETWEEN 5.4 AND 5.3 (5.6 AND 5.5)

SCREENSHOT OF NEW VALUES

mobilenet_LR5e-05_BS16_E20 CHANGE

The augmentation values applied during previous stages were rather substantial, meaning that the images produced may push the recognition ability of the model too far, causing confusion between classes instead of simply generating additional data for each class. By reducing the degrees of augmentation, the images produced for the enlarged dataset will be of more utility to the model, allowing it to gain a deeper understanding of each class, while hopefully avoiding the confusion caused by acute augmentation.

By examining the results table of 5.4 below, it appears as though reducing the augmentation has had the desired effect, as new high scores were obtained across all columns: 98.4%,

0.054, 99.5% and 0.036 for training accuracy, training loss, validation accuracy and validation loss respectively.

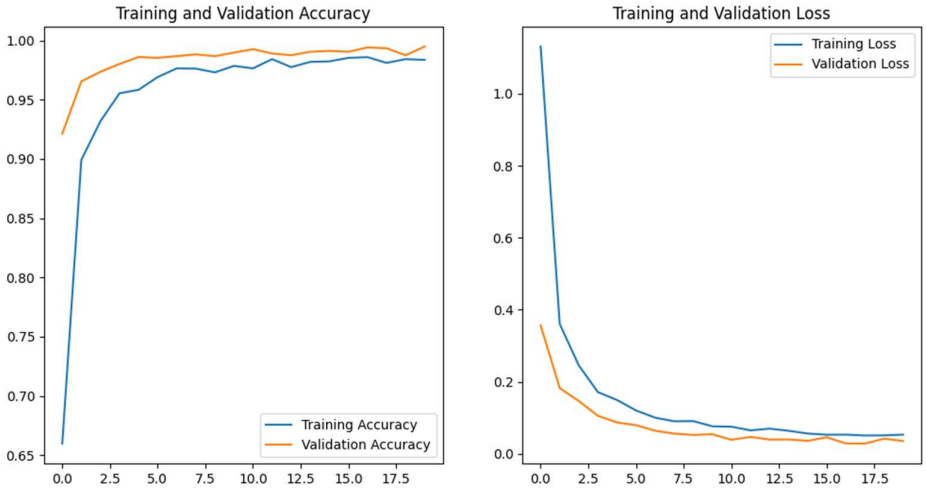
Epoch	accuracy	loss	val_accuracy	val_loss
1	0.6597222089767456	1.130545735359192	0.9213235378265381	0.35696738958358765
2	0.8992003202438354	0.36091750860214233	0.9654411673545837	0.18275301158428192
3	0.9318181872367859	0.24568496644496918	0.9735293984413147	0.14691409468650818
4	0.9553872346878052	0.17170915007591248	0.9801470637321472	0.10592234879732132
5	0.9583333134651184	0.14985704421997007	0.9860293865203857	0.08745004981756021
6	0.9690656661987305	0.12073215097188895	0.9852941036224365	0.07984044402837753
7	0.9764309525489807	0.10084906220436096	0.9867647290229797	0.06459816545248032
8	0.9762205481529236	0.09062345325946808	0.9882352948188782	0.056459397077560425
9	0.9730639457702637	0.09119988232851028	0.9867647290229797	0.05287778377532959
10	0.9785353541374207	0.07676930725574493	0.9897058606147766	0.05467388406395912
11	0.9764309525489807	0.07573401927947998	0.9926470518112183	0.03934750705957413
12	0.9842171669006348	0.06555674225091934	0.9889705777168274	0.04741937294602394
13	0.9774831533432007	0.07023613899946213	0.9875000119209229	0.03992653638124466
14	0.9819023609161377	0.06439781188964844	0.9904412031173706	0.04027123004198074
15	0.9823232293128967	0.05667911842465401	0.9911764860153198	0.03640379011631012
16	0.9852693676948547	0.05336226522922516	0.9904412031173706	0.04627865552902222
17	0.9859007000923157	0.05362839251756668	0.9941176176071167	0.029119273647665977
18	0.9810606241226196	0.051260173320770264	0.9933823347091675	0.028798824176192284
19	0.9842171669006348	0.05163523182272911	0.9875000119209229	0.04245174303650856
20	0.9835858345031738	0.053631141781806946	0.9948529601097107	0.035872623324394226

Although minutely less than the training and validation results, the test results of 5.4 still surpassed 5.3, with an improvement of around 0.01 for loss and 0.4% for accuracy. While

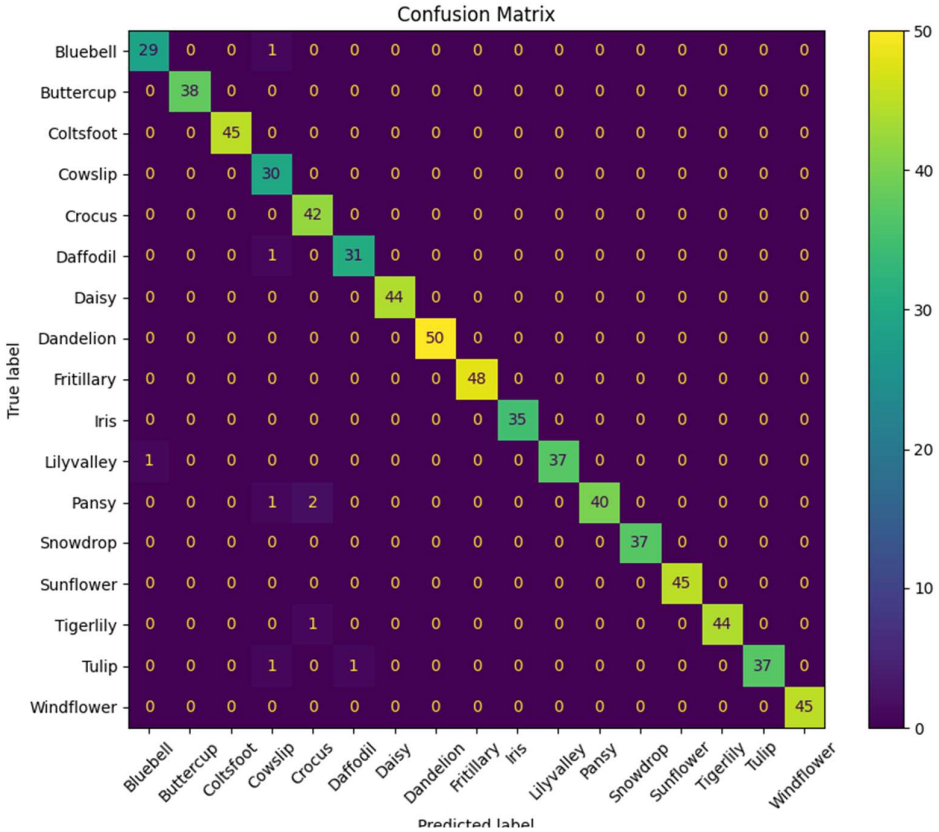
these improvements are miniscule, they are improvements nevertheless, providing confirmation that slightly reducing the augmentation is a step in the right direction.

Test Loss	0.06092633306980133
Test Accuracy	0.9854227304458618

The accuracy and loss graphs provide a visual representation of the outstanding performance of the model during the training and validation stages of 5.4:



The confusion matrix provides another visual representation of the brilliance of the model produced during 5.4, as it only mislabelled 9 images. This is 5 images less than 5.3, and another high score in terms of true positive percentage.



Additionally, the minute increase in performance is reflected in the classification report. Although it appears identical to its predecessor, the averages for precision, recall and F1-score are marginally higher than those of 5.3.

Class	Precision	Recall	F1-Score	Support
Bluebell	0.9666666666666667	0.9666666666666667	0.9666666666666667	30.0
Buttercup	1.0	1.0	1.0	38.0
Coltsfoot	1.0	1.0	1.0	45.0
Cowslip	0.8823529411764706	1.0	0.9375	30.0
Crocus	0.9333333333333333	1.0	0.9655172413793104	42.0
Daffodil	0.96875	0.96875	0.96875	32.0
Daisy	1.0	1.0	1.0	44.0
Dandelion	1.0	1.0	1.0	50.0
Fritillary	1.0	1.0	1.0	48.0
Iris	1.0	1.0	1.0	35.0
Lilyvalley	1.0	0.9736842105263158	0.9866666666666667	38.0
Pansy	1.0	0.9302325581395349	0.9638554216867473	43.0

Snowdrop	1.0	1.0	1.0	37.0
Sunflower	1.0	1.0	1.0	45.0
Tigerlily	1.0	0.9777777777777777	0.9887640449438202	45.0
Tulip	1.0	0.9487179487179487	0.9736842105263158	39.0
Windflower	1.0	1.0	1.0	45.0
macro avg	0.9853589965397923	0.9862252448134261	0.9853767206982075	686.0
weighted avg	0.9878580003429944	0.9868804664723032	0.9870027796454705	686.0

By implementing less intense augmentation in 5.4, improvements were made across all metrics, implying that the adjustment made was a success. Performance data as edged even closer to perfection, however there is still a little room for improvement.

5.5

Following the success of increasing the volume of the input dataset from 1x to 5x, stage 5.5 will take this exploration further, by increasing the factor of multiplication to 10. Since the results of 5.4 were marginally better than 5.3, and the lesser degree of augmentation was superior, the degree of augmentation in 5.5 will be the same as its predecessor, the only difference being the aforementioned increased multiplication factor. It is predicted that by providing more high-quality data for training, the model produced will achieve even better results.

mobilenet_LR1e-05_BS32_E30 – HYPERPARAMETER CHAT

In order to compensate for increasing the input dataset, the learning rate has been reduced to 0.00005, and the number of epochs has been increased to 30. This will hopefully allow for a more gradual, thorough and consistent learning process.

After analysing the training results below, it appears that the prediction made above was correct: by providing twice the volume in comparison to the previous stage, the model was able to achieve better results. In the 2nd epoch, a training accuracy of 92.0% was achieved, while from the 4th epoch onwards, the validation accuracy remained north of 99%. The loss data is equally as impressive: from the 6th epoch onwards, the training loss remains below 0.1, while from the 13th epoch onwards, the validation loss was less than 0.02. Remarkably, in the final 6 epochs, the validation loss actually remained below 0.01. Once again, with a new stage, new high scores have been achieved.

Epoch	accuracy	loss	val_accuracy	val_loss
1	0.7202230691909790	0.9252597689628601	0.9499999880790710	0.24670648574829102
2	0.9189814925193787	0.2839754223823547	0.9786764979362488	0.12890176475048065
3	0.9481270909309387	0.1927310228347783	0.9856617450714111	0.08291604369878769

4	0.962226450443 2678	0.13700279593467 712	0.992647051811 2183	0.059462714940309 525
5	0.968013465404 5105	0.11401835083961 487	0.993749976158 1421	0.048569709062576 294
6	0.975378811359 4055	0.09390944242477 417	0.995588243007 6599	0.039764150977134 705
7	0.976957082748 4131	0.08915504068136 215	0.995588243007 6599	0.034693248569965 36
8	0.978219687938 6902	0.07676397264003 754	0.995955884456 6345	0.028020149096846 58
9	0.982218027114 8682	0.06924855709075 928	0.996323525905 6091	0.025619052350521 088
10	0.979692757129 6692	0.06791752576828 003	0.997058808803 5583	0.022172439843416 214
11	0.981902360916 1377	0.06351611018180 847	0.997058808803 5583	0.022720884531736 374
12	0.982954561710 3577	0.06131436303257 942	0.995955884456 6345	0.020107423886656 76
13	0.980534493923 1873	0.06210521608591 08	0.997794091701 5076	0.019726401194930 077
14	0.982744097709 6558	0.05631340295076 37	0.997426450252 533	0.016212290152907 37
15	0.982638895511 6272	0.05621267110109 329	0.997426450252 533	0.014518540352582 932
16	0.983691096305 8472	0.05271307751536 369	0.997794091701 5076	0.012878702953457 832
17	0.981797158718 1091	0.05311378464102 745	0.997426450252 533	0.014269452542066 574
18	0.986005902290 3442	0.04794914647936 821	0.996323525905 6091	0.016370059922337 532
19	0.986216306686 4014	0.04570940509438 515	0.998529434204 1016	0.010918369516730 309
20	0.985900700092 3157	0.04356583580374 718	0.998161792755 127	0.012143265455961 227
21	0.986531972885 1318	0.04298747330904 007	0.998897075653 0762	0.008486246690154 076
22	0.986637234687 8052	0.04276638478040 695	0.997426450252 533	0.011019202880561 352
23	0.984322369098 6633	0.04735783115029 335	0.998529434204 1016	0.011176807805895 805
24	0.985164165496 8262	0.04437693953514 099	0.998161792755 127	0.009232908487319 946
25	0.985900700092 3157	0.04302025586366 6534	0.998897075653 0762	0.007596189621835 947
26	0.987268507480 6213	0.04164636507630 348	0.998897075653 0762	0.006834399886429 31
27	0.989372909069 0613	0.03487109392881 3934	0.999264717102 0508	0.008016808889806 27

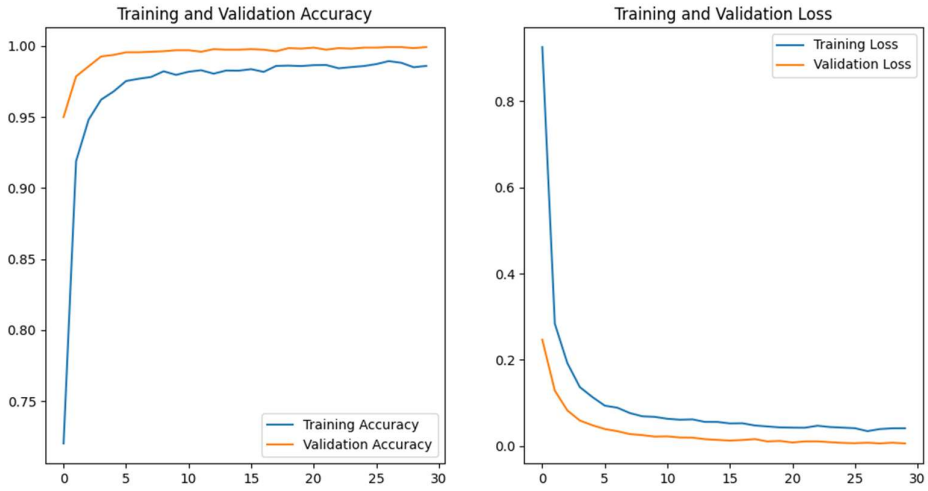
28	0.9882155060768127	0.03970054164528847	0.9992647171020508	0.0062927426770329475
29	0.9850589036941528	0.04143829643726349	0.9985294342041016	0.0080679133534431 46
30	0.9860059022903442	0.04153968393802643	0.9992647171020508	0.0063509736210107 8

New high scores were also obtained during testing, as can be seen in the table below: 0.01 is the lowest loss score ever achieved, and the accuracy of 99.85% means that room for improvement has become even smaller.

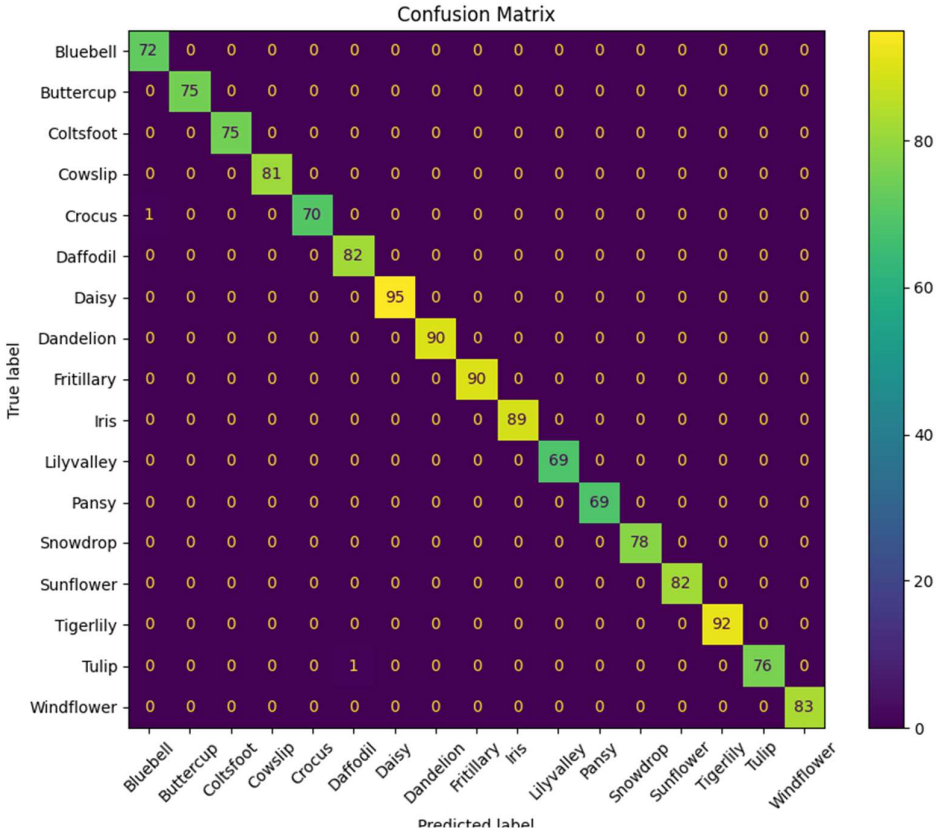
Test Loss	0.010740709491074085
Test Accuracy	0.9985401630401611

Although the training and validation plots of the accuracy and loss graphs appear to have a slight gap between them, this is not being classed as overfitting, as statistically the distance between the plots is miniscule, and is exaggerated by the scale of the graphs. The visible plateaus are also a welcome sight, as they confirm that the model has been trained thoroughly, while its performance remains consistent.

One note worth making from both the table above and the graph below is that peak values are reached within the first 10 epochs. While it is good that they remained at their peaks for the remainder of the training period, 30 epochs may be excessively high, as no benefit is gained during the latter epochs.



Impact of the increased dataset is brilliantly reflected in the confusion matrix. Even though the input data was increased 10x compared to the original, and 5x compared to the previous stage, this confusion matrix contains only 2 incorrect predictions. Clearly, the additional input data allowed the model to gain even deeper understanding of the differentiating details of each class, enabling it to achieve near-perfect results.



Once again, even though the difference is minute, the classification report for 5.5 reflects yet another improvement in model performance. 1.0 is the most populous value within the table, reiterating the almost perfect analysis of the confusion matrix, while the remaining values such as the averages at the bottom of the table edge even closer to total accuracy.

Class	Precision	Recall	F1-Score	Support
Bluebell	0.9863013698630136	1.0	0.993103448275862	72.0
Buttercup	1.0	1.0	1.0	75.0
Coltsfoot	1.0	1.0	1.0	75.0
Cowslip	1.0	1.0	1.0	81.0
Crocus	1.0	0.9859154929577465	0.9929078014184397	71.0
Daffodil	0.9879518072289156	1.0	0.9939393939393939	82.0
Daisy	1.0	1.0	1.0	95.0
Dandelion	1.0	1.0	1.0	90.0
Fritillary	1.0	1.0	1.0	90.0
Iris	1.0	1.0	1.0	89.0
Lilyvalley	1.0	1.0	1.0	69.0
Pansy	1.0	1.0	1.0	69.0
Snowdrop	1.0	1.0	1.0	78.0

Sunflower	1.0	1.0	1.0	82.0
Tigerlily	1.0	1.0	1.0	92.0
Tulip	1.0	0.987012987012987	0.9934640522875817	77.0
Windflower	1.0	1.0	1.0	83.0
macro avg	0.9984854810054077	0.9984075576453373	0.9984361585836046	1370.0
weighted avg	0.9985589392867943	0.9985401459854014	0.9985399010990842	1370.0

5.6

Although the results of 5.5 were close to perfection, there is still a small amount of room for improvement. Stage 5.6 will hopefully conclude the model development process, as the final point of interest is explored, that being the fine-tuning of the base model. Throughout all previous stages of phase 5, the pre-trained *MobileNetV2* architecture had been frozen, meaning that the values within its layers were not manipulated, it was only the additional layers of the network whose values could be adjusted to improve performance. 5.6 is different, as the final 20 layers of the *MobileNetV2*'s architecture have been unfrozen, allowing them to be fine-tuned and optimized to produce a model with even better performance overall.

Due to the excessively long training process in 5.5, the number of epochs has been reduced to 15 for 5.6. To balance this and ensure efficient convergence, the learning rate has been increased to 0.00005.

mobilenet_finetune_LR5e-05_BS32_E15

The table below contains the performance results of the training process of 5.6. It appears that implementing the fine-tuning was a success, as from around the 3rd and 4th epochs onwards, both the training and validation accuracy is effectively 100%. Additionally, from around a similar point onwards, the training and validation loss values are negligibly minute, with the final training accuracy being 0.002 and the final validation accuracy being 0.0009. This training process has clearly produced the best results of any stage or test throughout the entire project.

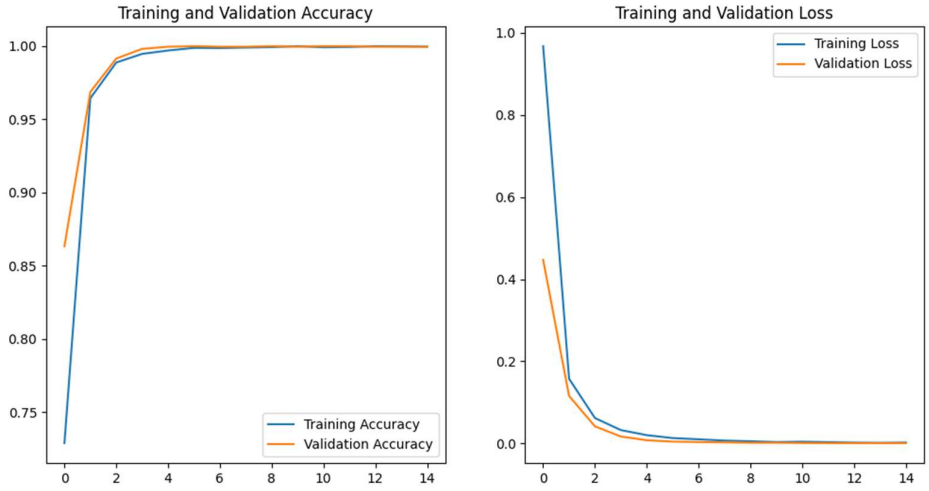
Epoch	accuracy	loss	val_accuracy	val_loss
1	0.7287458181381226	0.9673189520835876	0.8632352948188782	0.4471583068370819
2	0.9644360542297363	0.15753474831581116	0.96875	0.11574357002973557
3	0.9888467788696289	0.06195348873734474	0.9915441274642944	0.04180223494768143
4	0.9947390556335449	0.032655052840709686	0.9981617927551270	0.016980042681097984
5	0.9970538616180420	0.020272744819521904	0.9996323585510254	0.007962165400385857

6	0.998842597007 7515	0.013228721916675 568	1.0	0.004651791416108 608
7	0.998737394809 7229	0.010243386961519 718	0.999632358551 0254	0.003601826261729 002
8	0.999053001403 8086	0.007150378543883 562	0.999632358551 0254	0.002622971078380 9423
9	0.999368667602 5391	0.005513632670044 899	1.0	0.001840853481553 495
10	1.0	0.003525648964568 9726	0.999632358551 0254	0.001993079902604 2223
11	0.999263465404 5105	0.004370170179754 496	1.0	0.001312418025918 305
12	0.999473929405 2124	0.003353137988597 1546	1.0	0.001091118552722 0368
13	1.0	0.002178705530241 1318	0.999632358551 0254	0.001015680958516 8958
14	0.999894797801 9714	0.001653369748964 9057	0.999632358551 0254	0.000921065860893 5773
15	0.999684333801 2695	0.002337891142815 3515	0.999632358551 0254	0.000955387949943 5425

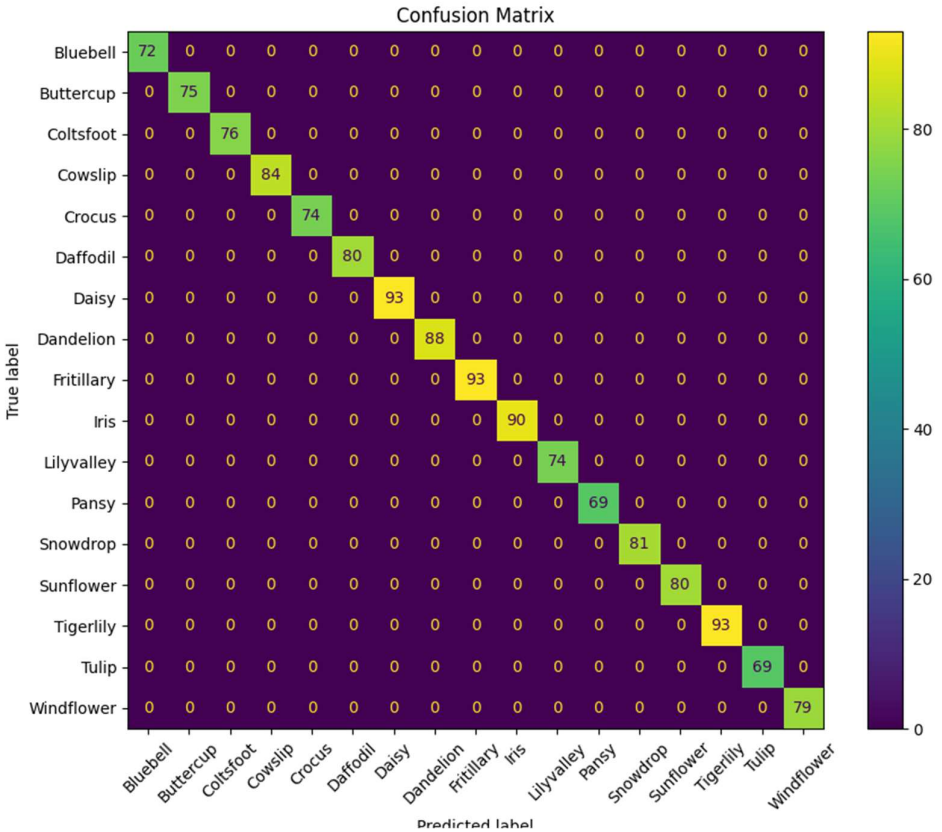
The outstanding training process is reflected in equally outstanding test results, as the test accuracy is 100%, while the test loss is 0.0003.

Test Loss	0.0003348965838085 86
Test Accuracy	1.0

The graphs accompanying the training process display the perfect outcome of the training process, with rapid convergence and negligible fluctuation.



Further confirmation of the success of this training stage comes in the form of the perfect confusion matrix below, which contains not a single incorrect prediction.



As expected, the accompanying classification report echoes the rest of the performance metrics, with the precision, recall and F1-Score of every single class achieving a score of 1.0, or perfection.

Class	Precision	Recall	F1-Score	Support
Bluebell	1.0	1.0	1.0	72.0
Buttercup	1.0	1.0	1.0	75.0
Coltsfoot	1.0	1.0	1.0	76.0
Cowslip	1.0	1.0	1.0	84.0
Crocus	1.0	1.0	1.0	74.0
Daffodil	1.0	1.0	1.0	80.0
Daisy	1.0	1.0	1.0	93.0
Dandelion	1.0	1.0	1.0	88.0
Fritillary	1.0	1.0	1.0	93.0
Iris	1.0	1.0	1.0	90.0
Lilyvalley	1.0	1.0	1.0	74.0
Pansy	1.0	1.0	1.0	69.0
Snowdrop	1.0	1.0	1.0	81.0
Sunflower	1.0	1.0	1.0	80.0
Tigerlily	1.0	1.0	1.0	93.0
Tulip	1.0	1.0	1.0	69.0
Windflower	1.0	1.0	1.0	79.0
macro avg	1.0	1.0	1.0	1370.0

weighted avg	1.0	1.0	1.0	1370.0

In conclusion, based upon all the data gathered during the training and testing stages, the model created in 5.6 has mastered the input dataset, and has become highly confident and accurate in predicting the 17 species of flowers contained within. Of course, this perfect accuracy is unlikely to remain intact once the model is given new images from external sources such as user photographs, however it has clearly understood the nuances which differentiate the various classes of the dataset, and should retain a solid capability to classify the species it knows with confidence.

Now that perfect results have been achieved by the model of 5.6, the model development stage can be relievingly concluded. The next stage of the project will be to create some kind of application to house the model, so that users will be able to interact with it, providing it with images of flowers and receiving predictions on their species. Once the app is created, both the app and model can be tested in real-world scenarios.

Implementation & Testing – App Development Phase

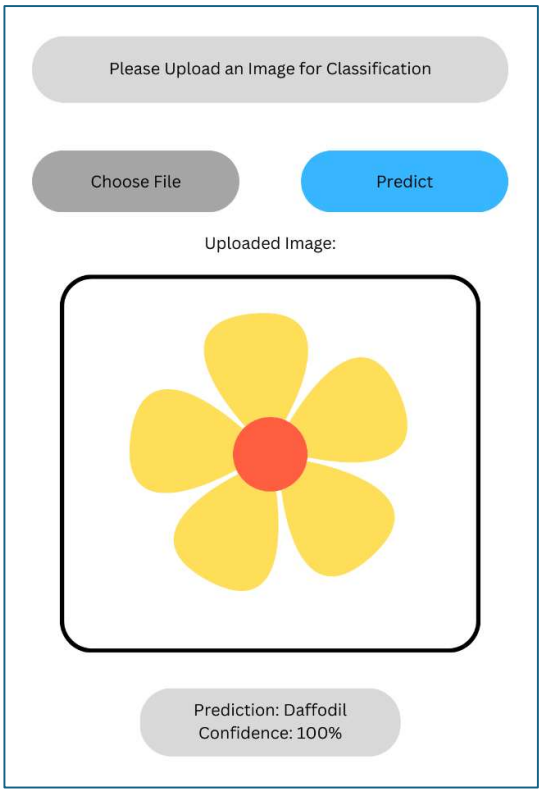
Now that the substantial model development process has been completed, the next task is to create an app which can house the model and allow it to be deployed and used in real-world scenarios. Various approaches could be taken to create this. For one, a full mobile application could be created, using either native technologies such as Swift or Kotlin, or cross-platform frameworks such as Flutter or React Native. Alternatively, a desktop application could be created, like a Windows *WinForm* application using C# and *.NET*, or a MacOS application using Swift. Or finally, a web-based application could be created using any of the many available technologies, such as HTML and CSS for a simple front-end design, or React.js or Vue.js for more dynamism, and then for the back-end, Node.js, Django or Flask would be suitable tools.

Initial experimentation was performed with Kotlin and Android studio to create a native mobile application, as well as with Dart and Flutter to explore the possibility of creating a cross-platform application, with TensorFlow integrated seeming highly plausible due to both these frameworks being supported by Google, just like TensorFlow itself. Various tutorials were completed, primarily from the Google and Android Developer services, however the complexity and learning process were daunting, and deemed excessive for a simple application such as this. Therefore, the decision was made to explore the creation of a web-based application, as this approach would be relatively simple and efficient yet completely appropriate for the task at hand. The technologies targeted for use are HTML and CSS for the front-end due to their simplicity and familiarity, as well as Flask for the back-end due to its light weight, flexibility, and ease of TensorFlow integration.

Additional important technologies will be a hosting service such as Google Cloud Run, as well as a containerisation service such as Docker. The former will facilitate a smooth deployment process and provide scalability and reliability, while the latter will package the entire application into a light-weight container, including the front-end, back-end, model and all required tools and libraries, ensuring consistency between devices.

Wireframe

The figure below is a wireframe depicting the desired design of the web application. It features a text box containing an appropriate title; two buttons, one for uploading an image and another for requesting a prediction; a section to display the most recently uploaded image; and a text box at the bottom containing the model's predicted label alongside its confidence percentage.



Although rather basic in its design, this wireframe contains all essential components, while maintaining a clean and elegant aesthetic.

Front-End

As previously stated, the front-end design is intentionally kept minimal and clean while ensuring all necessary functionality is incorporated, using HTML and CSS. The purpose of the front-end code is to provide the user with an interactive, comprehensible interface through which they can obtain predictions on uploaded flower imagery.

During operation, the front-end accepts the user's image input and sends it to the back-end, where it is classified by the trained TensorFlow model. Once processed, the model's prediction and confidence percentage are returned and displayed via the front-end. Additionally, the uploaded image is shown to allow the user to verify that the correct image has been classified.

The first key section of the front-end code is the snippet shown in the figure below, which specifies the document type and language used. The `<title>` tag at the bottom of this section sets the text that appears on the browser tab when the web application is running.

```html
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Species Classifier</title>
```

Following this, the next important section is the CSS styling block, responsible for the visual appearance of all UI elements. The upper body styling area defines the background colour, font, text alignment, and padding, ensuring consistency across the application. The .container section specifies details of the central content box, which houses all core UI features, including the header (h2), the upload form, buttons, and the image container. This section is primarily responsible for the clean and user-friendly appearance of the interface.

```css
<style>
    body {
        font-family: 'Arial', sans-serif;
        background-color: #f4f4f9;
        text-align: center;
        padding: 20px;
    }
    .container {
        background: white;
        max-width: 500px;
        margin: auto;
        padding: 20px;
        border-radius: 10px;
        box-shadow: 0 4px 8px rgba(0, 0, 0, 0.2);
    }
    h2 {
        color: #333;
    }
    form {
        margin: 20px 0;
    }
    input[type="file"] {
        margin: 10px 0;
    }
    button {
        background-color: #007BFF;
        color: white;
        border: none;
        padding: 10px 15px;
        font-size: 16px;
        border-radius: 5px;
        cursor: pointer;
    }
    button:hover {
        background-color: #0056b3;
    }
    .image-container {
        margin-top: 20px;
    }
    img {
        max-width: 100%;
        border-radius: 10px;
        border: 2px solid #ddd;
    }
    .result {
        margin-top: 15px;
        font-size: 18px;
        font-weight: bold;
        color: #2c3e50;
    }
    .confidence {
        color: #555;
        font-size: 16px;
    }
</style>
```

Next is the header section, containing the visible title displayed at the top of the web application. This header provides clear instructions, ensuring that users understand the purpose of the application at first glance.

```html
<div class="container">
    <h2>Upload an Image for Classification</h2>
```

The following section of vital importance is the image upload form, which handles the receipt of the user's uploaded image. In the opening `<form>` tag, the `action="/"` attribute sends the data to the back-end's root route, the `method="post"` attribute specifies that the form will use the HTTP POST method to transmit the file securely, and `enctype="multipart/form-data"` ensures that the binary file data is properly encoded. The next line contains `<input type="file" name="file" required>`, where `type="file"` creates a file picker button in the UI, allowing the user to select an image from their device. The `name="file"` attribute is essential because it sets the key name used by the back-end to retrieve the uploaded file. Including the `required` attribute prevents form submission without a file, thereby improving usability by enforcing correct input. The final line within the form is the `<button type="submit">Predict</button>` element, which creates the Predict button. When pressed, this button triggers the submission of the form and the selected image, sending a POST request to the back-end as defined earlier. The back-end processes this request, passing the image to the TensorFlow model to generate a classification result.

```
<form action="/" method="post" enctype="multipart/form-data">
    <input type="file" name="file" required>
    <button type="submit">Predict</button>
</form>
```

The penultimate section of significance is responsible for displaying the classification result once the model has processed the uploaded image. This block is conditionally displayed only after a prediction has been made by the back-end. It dynamically shows the uploaded image, the predicted class label, and the confidence percentage. These features ensure that the user not only sees the classification result but can also verify the image they uploaded and view the model's confidence in its prediction.

```
{% if filename %}
    <div class="image-container">
        <h3>Uploaded Image:</h3>
        <img src="{{ url_for('static', filename='uploads/' + filename) }}" alt="Uploaded Image">
        <p class="result">Prediction: <strong>{{ prediction }}</strong></p>
        <p class="confidence">Confidence: <strong>{{ "%.2f"|format(confidence) }}%</strong></p>
    </div>
{% endif %}
```

Lastly, the final section, shown in the figure below, handles the display of any errors encountered throughout the process, such as the submission of an invalid file type. This section plays an important role in enhancing the user experience by clearly informing users of any issues that may arise during operation, allowing them to correct errors promptly.

```
{% if message %}
    <p style="color: red;">{{ message }}</p>
{% endif %}
```

Back-End

The back-end of the application is implemented using Flask, a lightweight Python-based web framework, and is responsible for handling the core functionality of the system. Specifically, it manages image uploads from the user, processes the uploaded image using the trained

TensorFlow model, and returns the resultant prediction and confidence score to the front-end. The back-end ensures smooth interaction between the user interface and the machine learning model, allowing the system to provide accurate, real-time classifications.

The first important section of the back-end code is the list of imported dependencies, as shown in Figure 4.1 below. This section imports several essential libraries, including Flask and its *render_template* function, which allows the application to render dynamic HTML pages. TensorFlow and NumPy are imported to load the pre-trained model and process numerical data, while PIL (Python Imaging Library) is imported for image processing tasks. Additionally, *secure_filename* from the `werkzeug.utils` library is imported to safely handle file names when saving uploaded images.

```
import os
import tensorflow as tf
import numpy as np
from flask import Flask, request, render_template
from werkzeug.utils import secure_filename
from PIL import Image
```

Insert Figure 4.1 – Imported Dependencies and Libraries

The next key section of the back-end, shown in Figure 4.2, involves the initialization and configuration of the Flask application. Here, the Flask app is initialized, and the UPLOAD_FOLDER variable is defined to specify the directory where uploaded images will be stored. The folder is created if it does not already exist, ensuring the application can store incoming files. The ALLOWED_EXTENSIONS set is also defined, listing the supported image formats (PNG, JPG, JPEG) that the system will accept for classification.

```
# Initialize Flask app
app = Flask(__name__)

# Configure upload folder
UPLOAD_FOLDER = r"static/uploads/"
os.makedirs(UPLOAD_FOLDER, exist_ok=True)  # Ensure directory exists
app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER
ALLOWED_EXTENSIONS = {'png', 'jpg', 'jpeg'}
```

Insert Figure 4.2 – Flask Initialization and Upload Configuration

Following this, the TensorFlow model is loaded, as illustrated in Figure 4.3. The trained model is loaded from the specified file path using TensorFlow's `load_model` function. Alongside this, a list of class names is defined, corresponding to the output indices of the model. This allows the system to map the model's numeric output to a human-readable class label, which will later be displayed to the user.

```
# Load TensorFlow model
MODEL_PATH = r"model/model2.h5"
MODEL = tf.keras.models.load_model(MODEL_PATH)

# Define class names (match your training dataset's class names)
class_names = ["Bluebell","Buttercup","Coltsfoot","Cowslip","Crocus",
               "Daffodil","Daisy","Dandelion","Fritillary","Iris",
               "Lilyvalley","Pansy","Snowdrop","Sunflower","Tigerlily","Tulip","Windflower"]
```

Insert Figure 4.3 – Model Loading and Class Name Definitions

The next section of significance is the file validation function, shown in Figure 4.4. The `allowed_file()` function checks the uploaded file's extension to ensure it matches one of the supported image formats defined earlier. This step is crucial in preventing invalid files from being processed and improves system reliability and security.

```
# Function to check allowed file extensions
def allowed_file(filename):
    return '.' in filename and filename.rsplit('.', 1)[1].lower() in ALLOWED_EXTENSIONS
```

Insert Figure 4.4 – Allowed File Type Check Function

The image preprocessing function, presented in Figure 4.5, is responsible for preparing the uploaded image to match the input requirements of the TensorFlow model. This function converts the image to RGB format, resizes it to 224x224 pixels, normalizes the pixel values, and adds a batch dimension. Proper preprocessing ensures that the model receives input in the same format as it was trained on, which is essential for achieving accurate predictions.

```
# Image preprocessing function (matches training pipeline)
def preprocess_image(image_path):
    img = Image.open(image_path).convert("RGB")  # Convert to RGB
    img = img.resize((224, 224))  # Resize to match model input size
    img_array = np.array(img) / 255.0  # Normalize pixels to [0, 1]
    return np.expand_dims(img_array, axis=0)  # Add batch dimension
```

Insert Figure 4.5 – Image Preprocessing Function

A simple health check route is also included in the back-end, as seen in Figure 4.6. This route returns an HTTP 200 response when accessed, indicating that the server is running correctly. While not directly related to user-facing features, it plays an important role in deployment, particularly on platforms like Google Cloud, where health monitoring is essential.

```
@app.route("/health")
def health_check():
    return "OK", 200
```

Insert Figure 4.6 – Health Check Endpoint

The main route definition of the application is shown in Figure 4.7. This route handles both GET and POST requests sent to the root URL. When the user accesses the application initially, a GET request is made, prompting the back-end to render the front-end interface. When the user submits an image, a POST request is sent, triggering the subsequent processing steps.

```
@app.route("/", methods=["GET", "POST"])
```

Insert Figure 4.7 – Main Route Definition

The next section, displayed in Figure 4.8, handles the file upload process. The system first checks if a file has been submitted and validates its format using the previously defined `allowed_file()` function. If the file is valid, it is safely saved to the designated upload folder using a secure filename. If no file is submitted, or if the file is invalid, an appropriate error message is rendered back to the front-end.

```
def upload_predict():
    if request.method == "POST":
        if "file" not in request.files:
            return render_template("index.html", message="No file uploaded")

        file = request.files["file"]
        if file and allowed_file(file.filename):
            filename = secure_filename(file.filename)
            file_path = os.path.join(app.config["UPLOAD_FOLDER"], filename)
            file.save(file_path)
```

Insert Figure 4.8 – File Upload Handling and Validation

Following this, the model prediction process is conducted, as demonstrated in Figure 4.9. The uploaded image is preprocessed, passed through the TensorFlow model, and the resulting prediction is obtained. The model's output is processed to extract the predicted class index and the associated confidence score, which is converted into a percentage for display purposes. The class index is then mapped to the corresponding species name from the predefined list.

```
# Preprocess image and make prediction
img = preprocess_image(file_path)
predictions = MODEL.predict(img)
predicted_class = np.argmax(predictions, axis=1)[0]  # Get class index
confidence = float(np.max(predictions)) * 100  # Convert to percentage

# Map index to class name
species_name = class_names[predicted_class] if predicted_class < len(class_names) else "Unknown"
```

Insert Figure 4.9 – Model Prediction and Result Extraction

Once the prediction has been completed, the system dynamically renders the front-end HTML page, passing the prediction result, confidence score, and filename of the uploaded image back to the user interface. This is achieved through Flask's `render_template`

function, as shown in Figure 4.10. This step ensures that the front-end can display the results to the user clearly and accurately.

```
return render_template("index.html", filename=filename, prediction=species_name, confidence=confidence)
```

Insert Figure 4.10 – Rendering Prediction Results to Front-End

In the case of a GET request, or if no valid image has been uploaded, the system simply renders the front-end page without any prediction data, as illustrated in Figure 4.11. This allows the user to view the interface and upload an image when desired.

```
return render_template("index.html")
```

Insert Figure 4.11 – Rendering Initial Front-End Page

The final section of the back-end, shown in Figure 4.12, involves starting the Flask web server. The application is configured to listen on a dynamic port, which is particularly useful for cloud-based deployments, and runs on all available IP addresses to ensure accessibility.

```
# Run the Flask app
if __name__ == "__main__":
    port = int(os.environ.get("PORT", 8080))  # Cloud Run will set the port
    app.run(host="0.0.0.0", port=port, debug=False)
```

Insert Figure 4.12 – Starting the Flask Web Server

In summary, the back-end handles all essential functionality behind the scenes, including validating user input, preprocessing images, executing the TensorFlow model, and returning dynamic results to the front-end interface. Its clean and efficient design allows for seamless interaction between the user and the classification model, ensuring a smooth user experience throughout the application.

Containerisation

To ensure the application can be deployed and run consistently across different environments, containerisation is utilised through Docker. Docker allows the entire application, including its dependencies and runtime environment, to be packaged into a single, lightweight container image. This eliminates potential issues arising from differing system configurations and simplifies deployment.

The container is built based on the configuration defined in the `Dockerfile`, shown in *Figure Y.1*. The Dockerfile begins by specifying an official lightweight Python 3.9 base image. It then sets the working directory within the container to `/app` and copies all necessary files from the current directory into this directory. Following this, it installs the application's dependencies using `pip` and the `requirements.txt` file. Port 8080 is exposed to allow communication with the Flask web server. Finally, the application is configured to run using Gunicorn, a production-ready WSGI HTTP server, which serves the Flask app on all available network interfaces at port 8080.

```
# Use an official lightweight Python image
FROM python:3.9

# Set the working directory inside the container
WORKDIR /app

# Copy all files from the current directory into the container
COPY . /app

# Install dependencies listed in requirements.txt
RUN pip install --no-cache-dir -r requirements.txt

# Expose port 8080 for the Flask app
EXPOSE 8080

# Start the Flask app using Gunicorn
CMD ["gunicorn", "-b", "0.0.0.0:8080", "app:app"]
```

Insert Figure Y.1 – Dockerfile Configuration

To further optimise the containerisation process, a `.dockerignore` file is included, shown in *Figure Y.2*. This file specifies files and directories that should be excluded from the Docker image, such as Python cache files, virtual environments, environment files, and version control metadata. By excluding unnecessary files, the build context is kept lightweight, resulting in a smaller, more efficient container image.

```
__pycache__/
*.pyc
*.pyo
venv/
.env
.git
```

Insert Figure Y.2 – .dockerignore Configuration

Through the use of Docker, the application can be reliably built, tested, and deployed in a reproducible manner, ensuring consistency across different environments.

Hosting

For hosting the containerised application, Google Cloud Run is employed. Google Cloud Run is a fully managed serverless platform that enables the deployment of containerised applications without the need to manage infrastructure.

The container image, built locally using Docker, is pushed to Google Container Registry or Artifact Registry. From there, Google Cloud Run is used to deploy the container, allowing the application to scale automatically in response to incoming traffic. The platform handles

all aspects of provisioning, managing, and scaling the infrastructure, ensuring high availability and minimal operational overhead.

Additionally, Cloud Run supports dynamic port assignment, which is accommodated within the Flask back-end code by retrieving the port from the environment variable PORT, defaulting to 8080 if not specified. This seamless integration ensures that the application runs correctly within the Cloud Run environment.

By leveraging Google Cloud Run, the application benefits from scalability, security, and reliability, while minimising the complexity involved in managing servers or infrastructure manually.

Minor Adjustments

Include project title – Flower Power – at top of application

Include name and student number at bottom of application

Implement webp format acceptance

Improved error handling

https://chatgpt.com/c/67d8581f-9a00-8009-b6bf-7072d2c3efdb - brave - roms11497

https://chatgpt.com/c/67d6cd69-b544-8000-be0f-fd46f871a3fd - chrome - rms11497

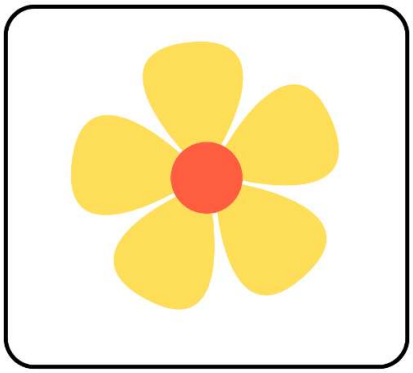
FLOWER POWER

Please Upload an Image for Classification

Choose File

Predict

Uploaded Image:



Prediction: Daffodil
Confidence: 100%

Rhodri Morris-Stiff - 30031906

Testing

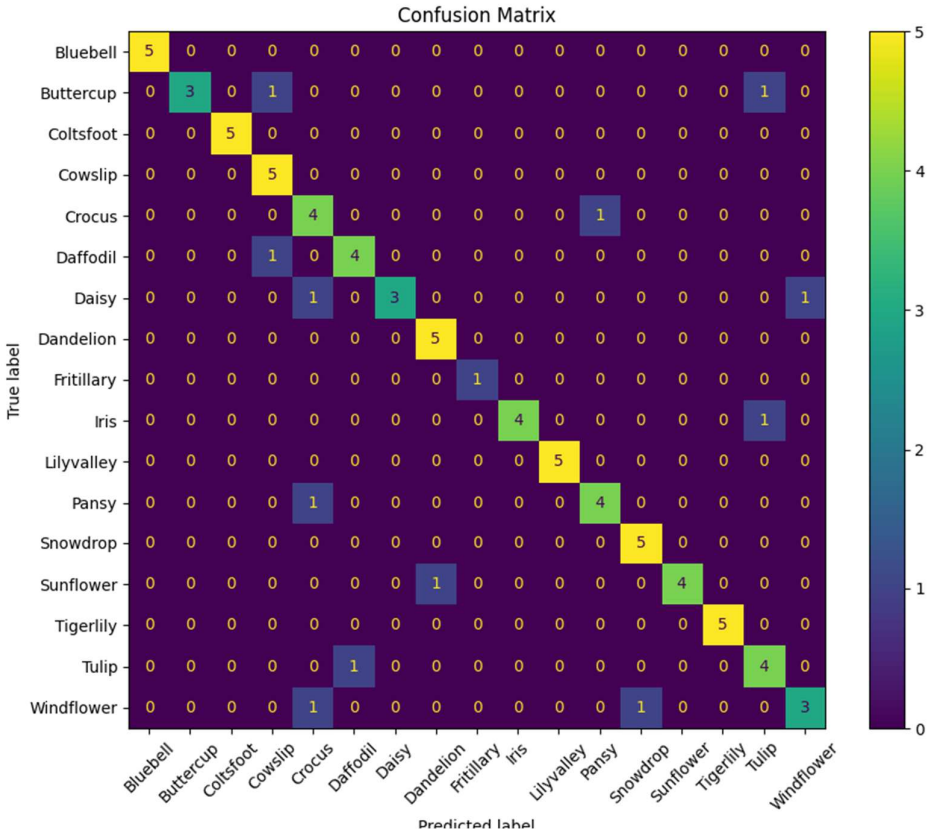
Model Testing 1

Online images – 5 per class, formed into 17-class dataset

Created code to accept test dataset + model paths, produce accuracy, loss, confusion matrix, classification report, board of 9 random images

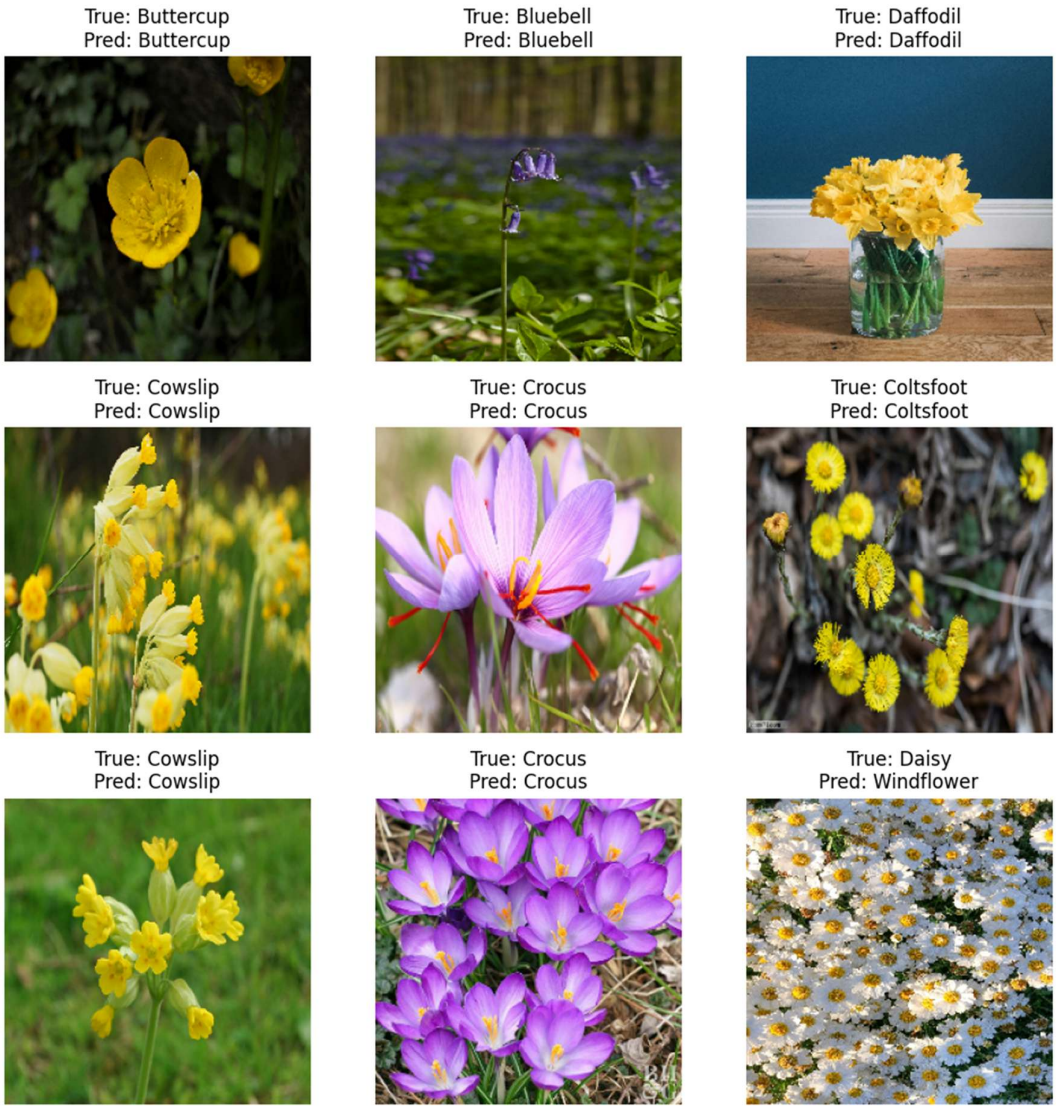
Link to code

Test Loss	0.4064536392688751
Test Accuracy	0.8518518805503845



Class	Precision	Recall	F1-Score	Support
Bluebell	1.0	1.0	1.0	5.0
Buttercup	1.0	0.6	0.75	5.0
Coltsfoot	1.0	1.0	1.0	5.0
Cowslip	0.7142857142857143	1.0	0.8333333333333334	5.0
Crocus	0.5714285714285714	0.8	0.6666666666666666	5.0

Daffodil	0.8	0.8	0.8	5.0
Daisy	1.0	0.6	0.75	5.0
Dandelion	0.8333333333333334	1.0	0.9090909090909091	5.0
Fritillary	1.0	1.0	1.0	1.0
Iris	1.0	0.8	0.8888888888888888	5.0
Lilyvalley	1.0	1.0	1.0	5.0
Pansy	0.8	0.8	0.8	5.0
Snowdrop	0.8333333333333334	1.0	0.9090909090909091	5.0
Sunflower	1.0	0.8	0.8888888888888888	5.0
Tigerlily	1.0	1.0	1.0	5.0
Tulip	0.6666666666666666	0.8	0.7272727272727273	5.0
Windflower	0.75	0.6	0.6666666666666666	5.0
macro avg	0.880532212885154	0.8582352941176447	0.8582293523469994	81.0
weighted avg	0.8746325690770136	0.8518518518518519	0.8512283327098141	81.0



Model Testing 2

Go garden centre, take a bunch of images, create a dataset and analyse

Application Testing

Field testing – go to garden centre and attempt to classify targeted species. Overlaps with app testing but is model-focused

Try uploading different file types + other tests

Evaluation

Project Summary

Key Findings

Areas of Improvement

Conclusion

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Appendix

Ethics Form

SECTION A: Project Definition

FOR UNDERGRADUATE & TAUGHT POSTGRADUATE ONLY

Complete the following table with full and relevant information relating to your research.

Student Name	Rhodri Owain Morris-Stiff
Student Number	30031906
Student E-mail Address (please use University e-mail)	30031906@students.southwales.ac.uk
Name of Principal Project Supervisor	Janusz Kulon
Project Title	Deep Learning in Object Detection and Recognition

Briefly describe the project, being sure to identify any aspects that are relevant to the Ethical Evaluation in Section B. NOTE: A project determined to be High Risk will need to include additional information in Section B to fully-specify the risks and mitigations.	This project aims to develop a deep learning-based system for classifying tree species using images of their leaves. By leveraging Convolutional Neural Networks (CNNs), the project seeks to automate the identification process, providing an accurate and efficient solution for tasks such as ecological research, biodiversity monitoring, and educational purposes. The project will involve collecting a diverse dataset of leaf images, applying data augmentation techniques to enhance the model's generalization, and using transfer learning with pre-trained CNN models to improve classification accuracy. The final model will be evaluated based on key metrics such as accuracy, precision, and recall, and will be deployed as a user-friendly application capable of real-time leaf classification.
Please add an explanation of your study in plain English, with particular focus on any parts of your study which involve human participants. No more than 100 words. This is to help the Faculty Research Ethics Committee (FREC) to understand the project.	This project will use deep learning to create an app that can identify tree species just by analysing photos of their leaves. It will involve training a computer model to recognize different types of leaves and provide accurate results, making it useful for nature enthusiasts, researchers, and anyone interested in identifying trees quickly and easily.

SECTION B: Ethical Evaluation

FOR UNDERGRADUATE & TAUGHT POSTGRADUATE ONLY

Consider the following points to determine the level of ethical risk your research presents:

1. Involves those who are considered vulnerable such as:
   - Children under 16.
   - Adults with learning difficulties.

   Unless in an accredited setting, accompanied by a carer or professional with a duty of care.
2. Involves those who are considered highly vulnerable such as:
   - Adults or children with diagnosed mental illness/terminal illness/dementia/in a residential care home.
   - Adults or children in emergency situations.
   - Adults or children with limited capacity to consent
3. Involves those who are "dependent" on others (such as teacher or lecturer to student). Unless in an accredited setting associated with normal working conditions or routines and within normal operating hours, such as a cultural institution, pre-school, school, or youth club where the research is carried out as part of professional practice such as curriculum development.
4. Requires full NHS ethical approval via the Integrated Research Application System.
5. Requires a Human Tissue Act license.
6. Involves "covert" procedures as in covert observation studies.
7. Involves anything considered "sensitive". For example, does not carry a risk of those involved disclosing information which compromises the research (e.g., illegal activities; activities where moral opinion may differ, potential professional misconduct – work errors).
8. Induces significant psychological stress or anxiety, or produce humiliation or cause more than fleeting harm / negative consequences beyond the risks encountered in the normal life of the participants (and where the potential for fleeting "harm" is clearly detailed in the participant information sheet). If in doubt regarding definition of the above terminology please contact the research governance office.
9. Involves administration of drugs, placebos or other substances (such as food substances or vitamins) as part of this study.
10. Involves invasive procedures (not limited to blood sampling, collection of biological samples, or passing current through a participant's body, etc.).
11. Offers any financial inducements to participate in the study.
12. Intends to recruit serving prisoners or serving young offenders via Her Majesty's Prison & Probation Service.

For your course, there may be specific requirements in **addition** to these, depending on the nature of the subject and how your project is assessed. You must also complete those requirements.

If **none** of the 12 points above apply, then the research can be considered **Low Risk**, *unless your course identifies additional criteria relevant to your subject that*

would render it High Risk. This Section is then signed off by yourself and your supervisor, and held on file for review by FREC.

If **<u>any</u>** of the 12 points applies, then the research is considered **High Risk** and students must bring the matter to the attention of their research supervisor immediately. **Research cannot then commence until mitigations for the risk are agreed by FREC**. Seek advice from your Supervisor, who can help you identify mitigations of the risk or redesign as a Low Risk project.

All students must complete the section below, in collaboration with their supervisor.

Please strike through the statement that **does not** apply.

1. An ethics review has been completed, and the project has been identified as Low Risk.
2. An ethics review has been completed, and a High Risk was identified. I agree to explain how they may be mitigated below, and agree to abide by any conditions identified at this stage, by my Project Supervisor, the School or the Faculty. I understand that High Risk projects can only proceed with approval from the Faculty Research Ethics Committee.

Issues: (Include as much information as possible to help FREC members to understand the issues. Extend onto additional pages as necessary.)
Data Privacy and Ownership - If using publicly sourced images or data gathered by third parties, issues may arise around the legality and ethics of data usage. Unauthorized use could infringe on the original creator's rights.
Accuracy and Misclassification Risks - Misclassifying leaves could lead to incorrect species identification, potentially impacting environmental studies, conservation efforts, or educational uses. Over-reliance on an imperfect model may also encourage users to bypass expert verification.
Bias in Dataset and Model Performance - If the dataset is not representative of all leaf species or includes only specific conditions (e.g., particular lighting, angles), the model may perform poorly on underrepresented categories or environments.
Environmental Impact of Training Models - Training deep learning models can be computationally intensive, consuming significant energy and resources, which may contribute to environmental harm.
Responsibility and User Education - Users might rely on the tool without understanding its limitations, leading to potential misapplication in contexts where high accuracy is critical (e.g., professional ecological studies).

Proposed mitigations: (Include as much information as possible to help FREC members to understand the mitigations. Extend onto additional pages as necessary.)
Data Privacy and Ownership - Ensure all datasets are publicly available, properly licensed, or collected with explicit permissions. Consider using open-source datasets or creating your own to avoid data ownership conflicts. Always cite data sources and follow any associated usage restrictions.
Accuracy and Misclassification Risks - Clearly communicate the model's limitations and accuracy, suggesting that users verify classifications with expert resources or other means, especially in professional contexts. Conduct thorough testing and validation to improve the model's accuracy, ideally involving domain experts in testing phases.
Bias in Dataset and Model Performance - Ensure diverse data collection to cover various species, angles, and environmental conditions. Use data augmentation techniques to simulate this diversity and regularly evaluate the model across different data subsets to identify and address any biases.
Environmental Impact of Training Models - Optimize the model's training process to minimize computational waste, such as by using efficient architectures (e.g., EfficientNet), smaller datasets, or pretrained models. Consider cloud platforms with energy-efficient infrastructure or select green data centers to reduce environmental impact.
Responsibility and User Education - Include disclaimers explaining the model's intended use and limitations. Provide a user guide outlining scenarios where the model is best used and where expert consultation is advisable, promoting informed and responsible use.

Student's Signature: Rhodri Owain Morris-Stiff
Date: 28/10/2024

Supervisor's statement: I have ensured due diligence and accountable decision making by the student. I have sought appropriate advice where required to support my judgment in this.

Supervisor's Signature:
Date:

Any false or mis-represented information contributing to this Ethical Evaluation, including attempting to pass off a High Risk project as a Low Risk project, is subject to the Student Misconduct Regulations and may also have legal repercussions.

Both signatures are **required** for all projects, both Low Risk and High Risk.

Exported Gantt Chart

Name	Assign	Date	Status
Define aims and objectives	Rhodri M-S	@October 1, 2024 → October 5, 2024	Done
Research fundamental ML/DL terms	Rhodri M-S	@October 6, 2024 → October 12, 2024	Done
Learn about DL models/architectures	Rhodri M-S	@October 10, 2024 → October 16, 2024	Done
Perform Literature Review	Rhodri M-S	@October 11, 2024 → October 25, 2024	Done
Research existing datasets	Rhodri M-S	@October 13, 2024 → October 17, 2024	Done
Research frameworks/Libraries	Rhodri M-S	@October 13, 2024 → October 18, 2024	Done
Research related products	Rhodri M-S	@October 15, 2024 → October 19, 2024	Done
Compose Milestone 1	Rhodri M-S	@October 19, 2024 → October 31, 2024	In progress
Perform Risk Assessment	Rhodri M-S	@October 25, 2024 → October 29, 2024	Done
Complete Ethics Form	Rhodri M-S	@October 28, 2024 → November 1, 2024	Done
Submit Milestone 1	Rhodri M-S	@November 1, 2024 → November 4, 2024	In progress
Establish project plan	Rhodri M-S	@November 4, 2024 → November 8, 2024	Not started
Determine required technologies	Rhodri M-S	@November 6, 2024 → November 12, 2024	Not started
Choose data approach	Rhodri M-S	@November 9, 2024 → November 13, 2024	Not started
Begin initial experimentation	Rhodri M-S	@November 11, 2024 → November 15, 2024	Not started

Figure 75 - Exported Gantt Chart