BugBot: Experimentation Phase

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March 19, 2025

1 Abstract

Insects are a common nuisance, with many species appearing similar, making identification challenging without expert assistance. Many homeowners in America rely on professional pest control services, which can cost thousands of dollars. Rising costs have led homeowners to attempt pest identification themselves. To address this issue, this research focuses on developing an image classification model to identify common New England household pests using transfer learning with convolutional neural networks (CNNs). Data was collected through programmatic web scraping and supplemental sources such as Google, Reddit, and iNaturalist. The final dataset contains 11 pest classes with around 160 photos per class, and was preprocessed using manual filtering, image hashing, resizing, recoloring, and padding. The dataset was split into training, validation, and test sets, of which data augmentation was applied to the training set. For classification, a CNN was trained on 11 pest classes. We utilize three pre-trained models for transfer learning: DenseNet201, MobileNetV2, and Xception. We also incorporate batch normalization, dropout layers, L2 regularization, and Bayesian/random search for hyperparameter optimization. Performance was assessed using accuracy, precision, recall, F1 score, confusion matrices, loss and accuracy curves, AUC-ROC curves, and one-versus-rest (OVR) scores. The workflow is illustrated in Figure 1 and details the interactions between the various components of this research.

2 Introduction and Related Work

2.1 Introduction

The experimentation phase involves creating a customized classification portion layer and model tuning. Specific information related to this can be found in section 6: Training and Validation Process and in the BugBot workflow, located in Figure 1. This phase is critical to achieving our project's objectives, as we aim to develop a model that can accurately classify pest images.

2.2 Related Work

Recent studies have demonstrated the effectiveness of CNNs in pest classification across various contexts. A relevant study is the research paper "An Efficient Deep Learning Approach for Jute Pest Classification Using Transfer Learning" by Muhammad Tanvirul Islam and Md. Sadekur Rahman. The primary similarity between their work and our

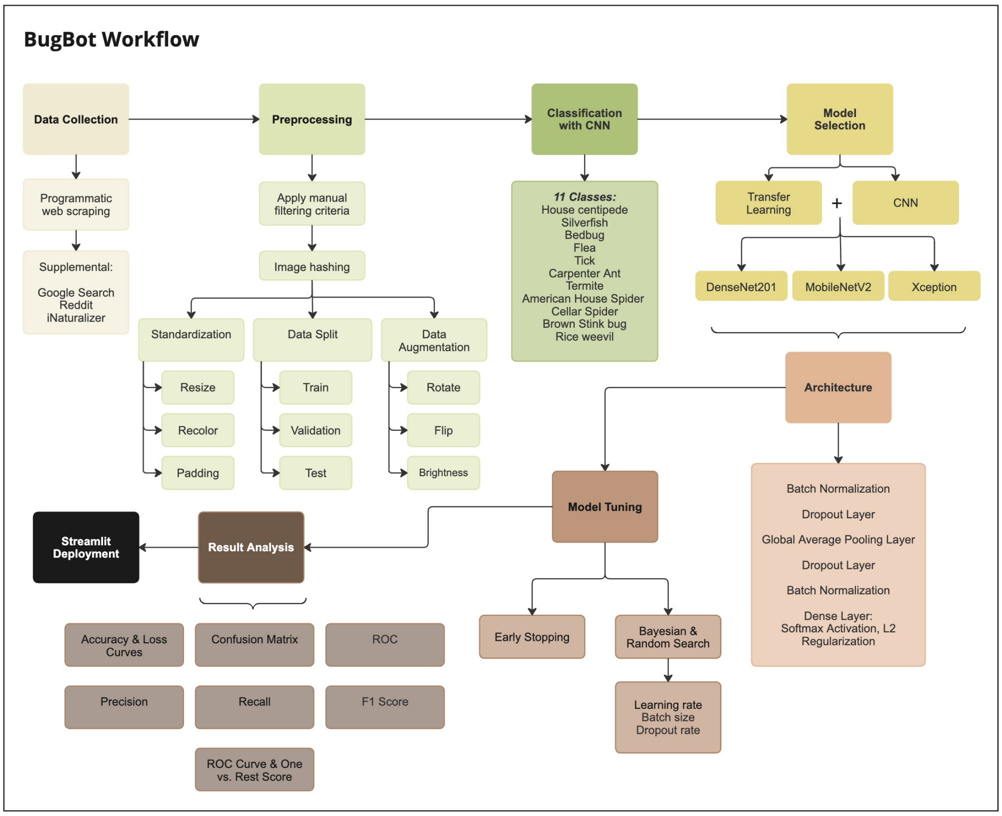


Figure 1: BugBot Workflow

proposed approach lies in the pest-classification specific image topic as well as the use of a CNN model use. However, their research specifically targets Jute pests, which pose significant challenges to Jute crop production in Bangladesh (Islam & Rahman, 2024). In contrast, our study will use a completely different dataset and will be used to classify common household pests found in New England.

In our review, we found the lack of diversity in training data to be notable factors across the literature. For example, Turkoglu et al.'s PlantDiseaseNet study in the paper "PlantDiseaseNet: Convolutional Neural Network Ensemble for Plant Disease and Pest Detection" utilized a highly controlled dataset, comprised of RGB images captured with standardized equipment and consistent resolution of 4000 x 6000 pixels. This contrasts significantly with our proposed methodology, which will incorporate web-scraped images with varying resolutions and background contexts. Furthermore, PlantDiseaseNet uses an ensemble of Support Vector Machines (SVMs) as the primary classifying component, only using a CNN as an averaging model for the final classification across multiple SVM outputs (Turkoglu et al., 2021). Meanwhile, our approach uses the CNN directly by feeding in the image data as the first layer.

The literature also reveals a consistent emphasis on data processing to improve model performance. For instance, Rehman et al.'s work on brain tumor classification in the paper "A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning", while in a different domain, provides valuable insight into image pre-processing. Their application of image flipping and rotation techniques Rehman et al. (2019) aligns with our planned approach, though our implementation must account for the greater variability in pest imagery compared to standardized medical imaging.

The research paper "Crop pest classification based on deep convolutional neural network and transfer learning" by the authors K. Thenmozhi and U. Srinivasulu Reddy also implements image processing for improved model performance, applying reflection, scaling, and rotation techniques. Thenmozhi and Reddy's research also represents one of the more comprehensive studies in the field, achieving over 95% classification accuracy across three different datasets of crop pests (Thenmozhi & Srinivasulu Reddy, 2019). They further compare custom CNN models against pre-trained architectures including AlexNet and ResNet. We intend to adapt their comparison approach and use similar augmentation techniques while acknowledging the different challenges presented by our more diverse dataset.

For contrast, Rajan et al.'s work in the research paper "Detection And Classification Of Pests From Crop Images Using Support Vector Machine" demonstrates the limitations of simpler classification approaches. Their SVM-based system, while effective for their use case of binary classification between whiteflies and aphids, highlights the need for more complex learning approaches when handling multiple pest classes. Rajan et al.'s approach relies on manually designed feature extraction to detect and recognize pests. Manual feature extraction limits the accuracy and adaptability of pest detection by failing to capture varied image characteristics (Guo et al., 2024). Furthermore, their study's reliance on controlled greenhouse imagery further underscores the importance of our more comprehensive approach using diverse image sources.

Our research aims to bridge the gap between these agricultural-focused studies and household pest identification needs by incorporating the successful methodological elements identified in the literature such as image rotation and mirroring, and by comparing our CNN model to similar projects such as Islam and Rahman (2024) jute pest study. Our planned use of web-scraped images and utilizing multiple pre-trained models represents a novel approach that addresses everyday people's needs while building upon established technical foundations.

3 Objectives and Hypotheses

3.1 Objectives

The objective of our experimentation is to improve our key evaluation metrics by customizing the classification portion layer and fine-tuning the models. Our goal is to develop a model with a relatively high performance, requiring evaluation of multiple models to assess trade-offs in diverse metrics including accuracy, one-versus-rest score, and other performance metrics. By comparing these models, we gain insight into which model achieves best performance for pest classification, accounting for model speed, comparative model results, and effects of more complex architectures.

3.2 Hypotheses

In this study, we investigate the effectiveness of convolutional neural networks (CNNs) for household pest classification and propose the following hypotheses.

First, we hypothesize that CNN-based models can classify household pests accurately. Transfer learning using pre-trained architectures such as DenseNet201, MobileNetV2, and Xception is expected to improve classification performance by leveraging feature representations from large-scale datasets. Additionally, training models on a diverse dataset of real-world pest images should enhance generalization, making the models more applicable for real-world scenarios.

Second, hyperparameter tuning is critical for optimizing model performance. Adjusting learning rate, dropout rate, and batch size using Bayesian Optimization and Random Search is expected to yield better accuracy and efficiency. Regularization techniques such as early stopping, batch normalization, and L2 regularization can further help mitigate overfitting. Moreover, the architectural design of the classification head, including the number of dense layers, activation functions, and neuron distributions, is likely to significantly impact the final performance.

Lastly, we hypothesize that DenseNet201 will outperform other models. Due to its deeper architecture and densely connected layers, DenseNet201 is expected to capture intricate image features more effectively than MobileNetV2 and Xception. The incorporation of regularization techniques, optimized data augmentation, and mixed-precision training should further improve generalization and computational efficiency.

4 Experimental Setup

4.1 Hardware and Software

The experiments were conducted on a high-performance laptop powered by an Intel Core i9-12900H processor from Intel's 12th Generation Alder Lake series. This processor features 14 cores, including 6 performance cores (P-cores) and 8 efficiency cores (E-cores), with a total of 20 threads enabled via Hyper-Threading Technology. The base clock speed of 2.50 GHz can turbo boost up to 5.0 GHz, providing high computational power for deep learning tasks. The system is equipped with 32GB of DDR4 RAM, ensuring smooth execution of computationally intensive tasks such as training neural networks and hyperparameter tuning.

For model training, we used a NVIDIA GeForce RTX 3080 Ti GPU with 12GB of GDDR6 VRAM. This GPU offers high-speed parallel computing with dedicated CUDA cores and Tensor cores optimized for deep learning acceleration. While ray tracing and AI-enhanced processing capabilities are present, they were not directly utilized in this study. The experiments were conducted on a 1TB NVMe SSD, ensuring fast data access and reducing storage bottlenecks.

The software stack included TensorFlow-GPU 2.x, configured to leverage CUDA and cuDNN for GPU acceleration. CUDA 11.x was installed to enable efficient parallel computing, while cuDNN 8.x was used to accelerate convolutional operations and deep learning computations. Hyperparameter tuning was performed using Keras Tuner, utilizing Bayesian Optimization and Random Search to find optimal model parameters. Data preprocessing and augmentation were implemented using TensorFlow's tf.data API, while TensorFlow's ImageDataGenerator was used for image augmentation. Model evaluation and visualization were done using Matplotlib, Sklearn, and Tensorflow to track training metrics and assess performance.

4.2 Model Selection

To evaluate model effectiveness, we initially ran seven different models: CNN without transfer learning, EfficientNet, ResNet50, VGG16, MobileNetV2, DenseNet201, and Xception. Based on the validation metrics, we decided to use the following three CNN architectures: DenseNet201, MobileNetV2, and Xception. DenseNet201 had the best performance regarding evaluation metrics and, with its ability to strengthen feature propagation and reduce redundant parameters, it makes it highly effective for classification tasks with limited data. MobileNetV2 had the second-best performance and was selected for its lightweight architecture, which balances accuracy and efficiency, making it ideal for real-time applications. Lastly, Xception had the third-best performance in accuracy.

5 Dataset and Preprocessing

The majority of the BugBot dataset was scraped using a publicly available API for scraping images from Bing search queries. A manual review and filtering process was then applied to the Bing-based dataset and was subject to the following standards:

1. The insect must be present in the image
2. The image must show at least 75% of the insect's body
3. The photo is not a drawing, cartoon, or an AI generated image
4. The image depicts the adult/matured insect

For all collected images, it is also essential to eliminate duplicates or near-duplicates to prevent data leakage. Visual inspection in addition to image hashing are implemented. Since no temporal or spatial dependencies exist in the dataset, random splitting for training, validation, and test subsets is appropriate. The validation set will guide hyperparameter tuning, while the test set will provide an unbiased assessment of the model's performance.

Furthermore, it is important to note the unique nature of many pests that usually infest home environments in groups or colonies, including ants, termites, and bed bugs. Therefore, a direct effort was made to collect additional group images of insect infestations to be included in the dataset. After filtering, a range of approximately 16%-76%, depending on the insect class, was kept from the original scraped data based on the above criteria.

After web scraping, additional data was collected by performing manual Google searches for image results using insect keywords, and by taking advantage of community postings on websites such as Reddit to collect home-environment-specific images. After combining the scraped images and manual supplement, the resulting dataset includes 160 raw images across each of the 11 insect classes.

Since our dataset consists of RGB images with x and y coordinates, the only features are the image pixels themselves. However, additional hidden features will be extracted through preprocessing and modeling the data and includes visual characteristics, such as texture, RBG value, and pixel sequence. Furthermore, when the complete image matrix is flattened into a 1-dimensional feature vector, each pixel element becomes a feature of the overall image.

The target variable in this supervised learning project is the insect class, representing one of the 11 common household pests. It is a well-defined categorical variable with clear labels derived from the dataset. Since the dataset is designed with a balanced distribution of 160 images per class (100 for training, 40 for validation, and 20 for testing), there is no inherent class imbalance, and resampling techniques are not necessary. This ensures that the model will not favor any single class during training or evaluation.

Due to the dataset design and manual filtering criteria, we have curated a dataset that adequately represents every insect class to ensure equal distribution of training, validation, and test data to reduce bias. We are also aware of potential bias in web scraping data due to the prevalence of scientific images which may not reflect the targeted end user – an everyday homeowner classifying an insect in their home. To mitigate this we have further supplemented the dataset with manually selected images with diverse backgrounds and contexts including images from Reddit and iNaturalist.

In terms of resources required, the dataset, consisting of 1,760 images, is relatively small and is manageable to process with standard resources. The dataset size even after augmentation does not exceed the limits of local storage or memory. Therefore, the dataset does not require advanced techniques such as distributed processing (e.g., using Apache Spark or Dask) since the computational and storage demands are minimal. Although no distributed processing will be required, the data will require multiple pre-processing steps which include:

1. Image hashing to remove duplicates
2. Standardizing the data to a fixed image size (e.g., 224x224)
3. Normalizing the pixel values
4. Color standardization (i.e., RGBA $\rightarrow$ RGB)
5. Adding padding to the images
6. Applying data augmentation techniques including rotation, height and width shift, and brightness adjustments to expand the training dataset

It is important to acknowledge the limitations of this dataset which could include a lack of sufficient data, potentially leading to over-fitting during training and data imbalance. When this case occurs, it could skew model predictions and affect the model's accuracy. This will be addressed and mitigated through data augmentation, mentioned above, through techniques including image rotation, horizontal and vertical flips, and cropping of images. By ensuring that each insect class contains 160 unique images and by expanding the dataset to include varied versions of all images, we effectively diversify the data set to mitigate over-fitting and enhance the model performance.

6 Training and Validation Process

This section discusses the architecture, training process, and hyperparameter-tuning methodology for BugBot. As discussed in the previous section (Section 4: Model Selection), the three aforementioned pre-trained models were employed to accomplish the transfer learning portion of our modeling. By using these models for transfer learning, we leverage the generalized knowledge pre-trained on ImageNet's diverse 1.4 million images for each model. This approach reduces computational resources and training time and is accomplished by freezing the base model's 20 million parameters and training our custom classification head. By employing transfer learning, we are able to focus further resources on hyperparameter optimization rather than designing complex networks from scratch.

6.1 Model Architecture and Configuration

To configure each transfer learning model with a custom classification head, the following structure was used:

For each baseline model (DenseNet201, MobileNetV2, Xception):

- Use preprocessed training data as input (see Figure 1: BugBot Workflow)
- Set baseline model as an initial base, freezing ImageNet weights
- Append customized classification head to the base model consisting of:
  - First batch normalization layer
  - First dropout layer with tunable rate for regularization
  - Global Average Pooling layer to reduce spatial dimensions while preserving channel information
  - Second dropout layer with tunable rate for regularization
  - Second batch normalization layer
  - Dense output layer with softmax activation, output neuron count matching the number of pest classes (11), and uses L2 regression as a kernel regularizer

6.2 Data Preprocessing and Data Split

Before training, the data is preprocessed using the preprocessing steps in Figure 1 and importantly includes standardization measures of resizing, scaling, recoloring, and removing duplicates via image hashing with the Undouble library (see Section 3: Data Collection and Preparation). The data is then divided into three separate directories: training, validation, and testing sets following the split of 100 training images, 40 validation images, and 20 test images for each class. The training set then undergoes data augmentation, including image mirroring, brightness adjustment, and rotation using PIL Image, ImageEnhance, and Numpy libraries. Notably, for each dataset directory, Keras ImageDataGenerator library is used to create custom data generators for efficiency throughout the model training and evaluation process:

- `TRAIN_GENERATOR`: Provides shuffled batches for model training

- `VAL_GENERATOR`: Provides validation data during training and hyperparameter tuning
- `TEST_GENERATOR`: Provides unshuffled data for final model evaluation
- `EVAL_VAL_GENERATOR`: Provides unshuffled validation data for metric calculation

6.3 Mitigating Overfitting

AS previously mentioned, when training a CNN on a small dataset like ours, the risk of overfitting can be high since the model can memorize the training data instead of generalizing it to unseen data. Therefore, mitigating overfitting and performing hyperparameter tuning for better model performance and efficiency was essential in our model experiments. To do this, the models are configured with batch normalization, dropout, L2 regularization, and early stopping. Batch normalization helps by keeping the activations of each layer stable during training. Dropout helps by randomly dropping neurons during training, preventing reliance on specific features. We employed two layers of dropout, each of which is tuned using Keras Tuner, described in section 5.4. L2 Regularization (ridge regression) helps by penalizing large weights without zeroing out features as L1 regularization does. Early stopping, unlike the other methods mentioned, is not a layer application and instead contributes to mitigating overfitting by preemptively stopping the training process when the validation loss stops improving. Besides specifying validation loss as the metric to keep an eye on, there are two parameters we also set: patience (set to 3) and min_delta (set to 0.001). Patience is the number of epochs with no improvement allowed before stopping training, and min_delta is the minimum change in the monitored metric required to consider it an improvement.

6.4 Hyperparameter Tuning and Optimization Algorithms

Two hyperparameter tuning methodologies were implemented for each model using Keras Tuner: Bayesian Optimization and RandomSearch. Notably, grid search was initially implemented for our models. However, we found the implementation to be inefficient for our limited resources. The inefficiency of grid search is due to its exhaustive approach to exploring all possible hyperparameter combinations, resulting in high computational costs. In contrast, Bayesian optimization and random search explore the hyperparameter search space more efficiently by focusing on probable combinations. Essentially, these algorithms make smarter and more efficient decisions than grid search, requiring fewer trials and less computational resources to identify optimal hyperparameters.

In BugBot, Bayesian optimization is used as the main optimization algorithm and is specifically set to optimize combinations for validation accuracy. Random search is used to help verify the robustness of hyperparameters and to provide other potential hyperparameter combinations to explore if results differ from the Bayesian optimization result. Since neither algorithm explores the entire search space, setting the max_trials parameter, which defines the maximum number of combinations the algorithm will attempt, is important. For each model, the learning rate, dropout rate, and batch size are tuned, resulting in the following hyperparameter space:

- Learning rate: [0.01, 0.001, 0.0001]

- Dropout rate: [0.2, 0.3, 0.4, 0.5]
- Batch size: [16, 32, 64]

Given three choices for learning rate, four for dropout, and three for batch size, the maximum number of trials is 36 (3 * 4 * 3). Therefore, we set max_trials to 20, representing 20/36. This means the algorithms will, at most, search about 55% of the original search space compared to grid search, which would explore all 36.

6.5 Hyperparameter Optimization Workflow

The hyperparameter tuning is implemented as the following process for each model:

For each algorithm (Bayesian and Random Search):

1. Multiple trials are conducted with different hyperparameter combinations
2. Each model is evaluated on validation data from `VAL_GENERATOR`
3. Early stopping halts training as needed with the last epoch being saved
4. The best-performing hyperparameter combination is identified and saved to a dedicated dictionary for the current model and current optimization algorithm
5. A final model is constructed with the best parameters identified in step 4
6. The model is trained for the optimal number of epochs identified in step 3
7. Evaluation metrics (described in section 6) are calculated on both validation and test sets and saved to CSV for comparison with other models

Multiple independent tuning runs were conducted to ensure the robustness of the model, particularly concerning early stopping parameters. The model pipelines were tested using the argparse library for efficient parameter modification through the command line, allowing for adjustments of patience values to [3, 5, 10] and min_delta values to [0.0001, 0.001, 0.01].

The systematic methodology we use for BugBot combines transfer learning, custom classification heads, and dual hyperparameter optimization algorithms for robust pest identification that employs different overfitting mitigation techniques.

6.6 Final Testing

After DenseNet201, Xception, and MobileNetV2 completed their respective hyperparameter tuning, the final models were built using the hyperparameter tuning results for best learning rate, best batch size, and best dropout rate which are uniquely defined for each model. Additionally, random seeds are defined as constants for reproducibility. The final models are trained on the training dataset, and the history is of training and learning is saved for both training data and validation data. This history is important because it is used to gain important insight into the model's learning patterns by tracking changes in accuracy and loss over time.

After the model is trained, the test data is passed through the model for classification. The results are then used to evaluate the model performance. The metrics and diagrams reported include the following: macro-averaged one-vs-rest ROC AUC score, accuracy, precision, recall, F1 Score, classification report, confusion matrices and ROC curve. These metrics are defined and analyzed in the following Results section.

7 Results

The loss and accuracy curves of our three pre-trained models are depicted in Figures 2 and 3. Based on these curves, there is a gap between training and validation accuracy, which suggests overfitting. As shown in Figure 3, the models show a steady increase in training accuracy from epochs 0 to 15, reaching over 85%. However, the validation accuracy stays relatively low for MobileNetV2 and Xception, fluctuating between 65% to 70% throughout the training. The overall trend for validation accuracy for those two models is inconsistent and does not match the increase in training accuracy. In contrast, DenseNet201 shows slightly better validation accuracy performance with fewer variations. Although there is still a noticeable gap between training and validation accuracy, DenseNet201 appears to generalize better than MobileNetV2 and Xception, with fewer strong fluctuations in its validation accuracy curve. The loss curves further support overfitting. In Figure 2, the training loss for all the models decreases steadily throughout the epochs, indicating effective learning on the training data. However, the validation loss remains higher than the training loss and shows inconsistent fluctuations across the epochs. This is evident in MobileNetV2 and Xception, where the training loss rapidly declines and stabilizes at a low value, while the validation loss remains considerably higher without a consistent downward trend. The results of these curves indicate that the models quickly learn patterns in the data, reaching saturation early in training. DenseNet201 follows similar patterns as the two other models, except it has a smaller gap between training and validation loss. This indicates that DenseNet201, despite achieving high training accuracy, is also overfitting to the training data. However, compared to MobileNetV2 and Xception, the validation loss for DenseNet201 shows slightly less fluctuation, which indicates better generalization. Based on the curves displayed in Figures 2 and 3, DenseNet201 appears to be the most effective model during training.

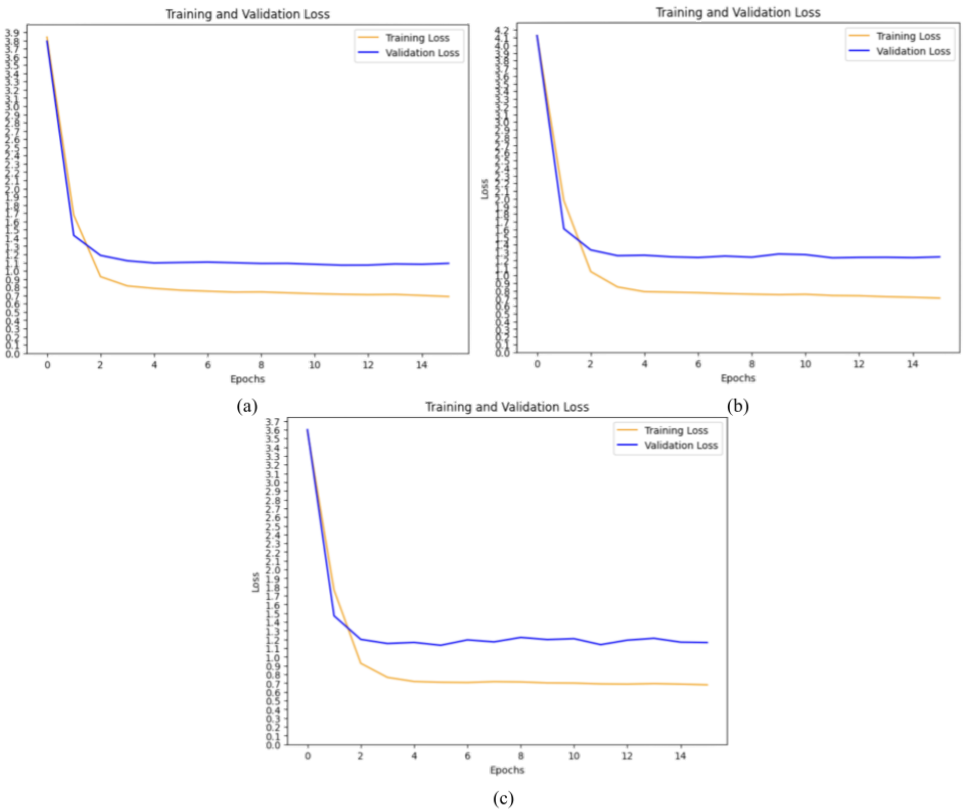


Figure 2. Loss curve (a) DenseNet201; (b) MobileNetV2; (c) Xception.

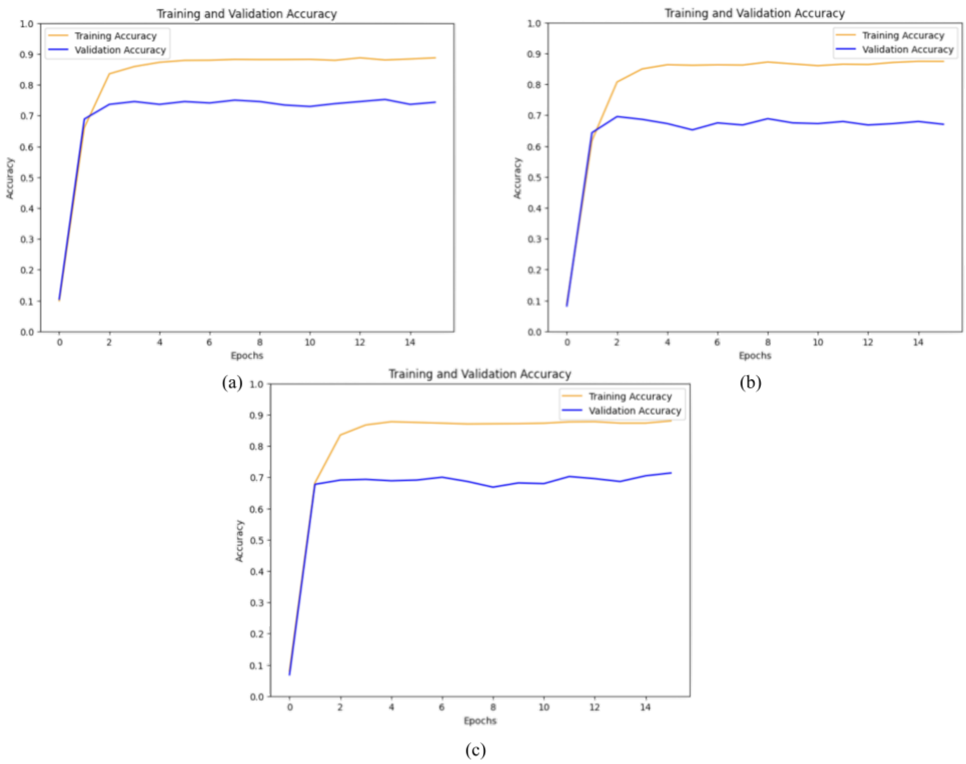
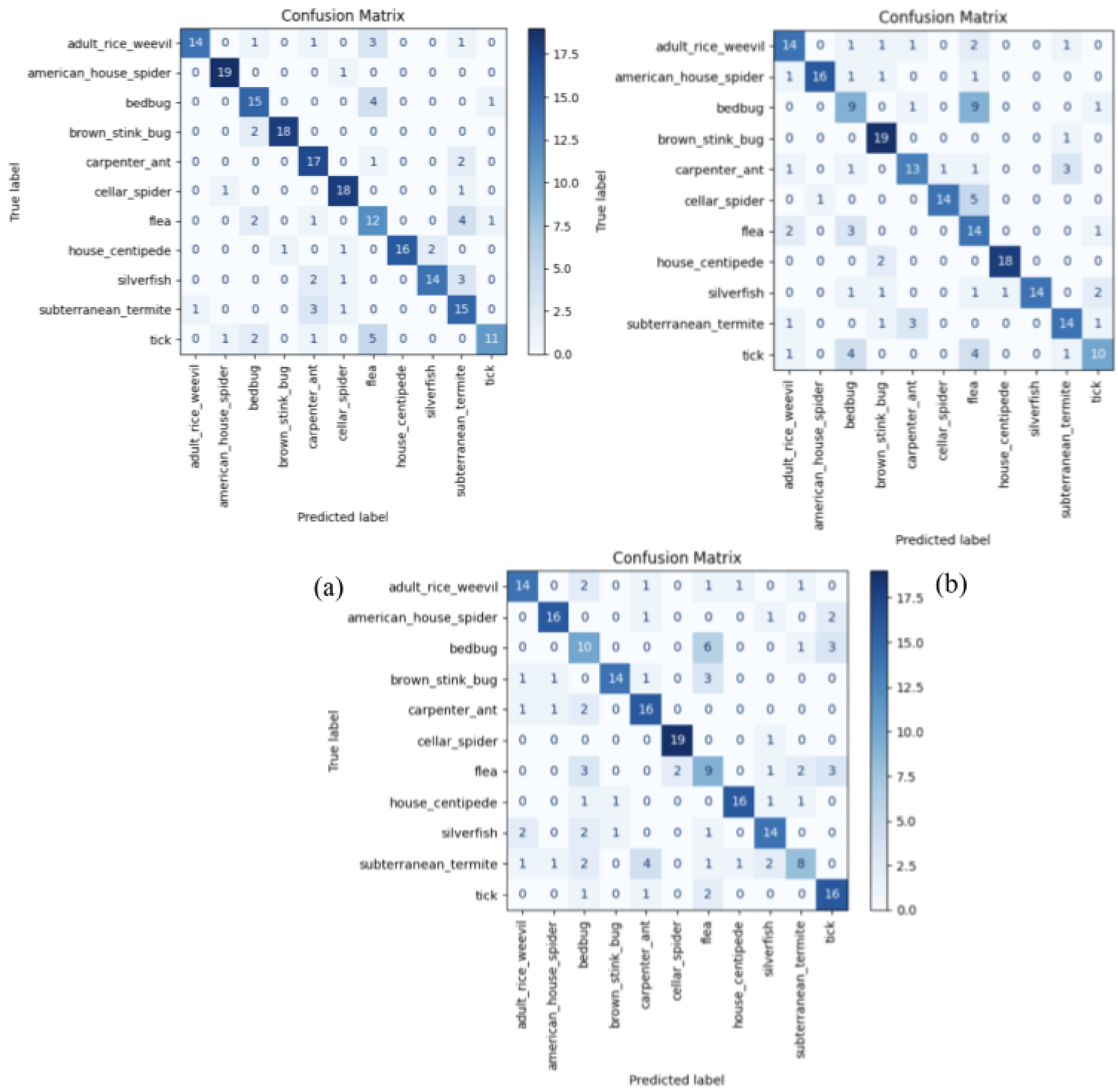


Figure 3. Accuracy curve (a) DenseNet201; (b) MobileNetV2; (c) Xception.

After training, all models were evaluated using the testing dataset. The evaluation process used multiple approaches to assess model performance. The confusion matrix provided insights into the number of correct and incorrect classifications. The confusion matrix for each model is presented in Figure 4, displaying the counts of true positives, true negatives, false positives, and false negatives, for the predicted values. After analyzing the confusion matrices, it was observed that Xception and MobileNetV2 produced similar classification results. DenseNet201 had the best performance in classifying pests, with fewer misclassifications compared to MobileNetV2 and Xception. A notable result from the confusion matrix is that bed bugs were often misclassified as fleas, highlighting that all three models had trouble distinguishing between these two classes, which is evident in Tables 1, 2, and 3. As shown in Figure 4, the models can be ranked based on their classification ability in the following order: DenseNet201, MobileNetV2, and Xception.



(a) (b) (c)

Figure 4. Confusion matrix (a) DenseNet201; (b) MobileNetV2; (c) Xception.

Following the analysis of the models using the confusion matrix, we evaluated their performance by calculating precision, recall, F1 score, and accuracy. Tables 1, 2, and 3 present these metrics for each model across different pest categories, while Table 4 summarizes the overall accuracy, including one-versus-rest score. In Tables 1-3, Xception and MobileNetV2 displayed moderate performance, with some inconsistencies across certain pest classes, such as fleas and bed bugs. DenseNet201 consistently outperformed both models, delivering higher values for all three metrics across most pest classes. Viewing the macro-average measures in Tables 4, Xception and MobileNetV2 achieved competitive scores, but DenseNet201 demonstrated the highest scores for all the metrics. The ROC curves (located in the Appendix) further reinforce these findings, as DenseNet201 achieved the highest true positive rates. Based on these results, this research concludes that DenseNet201 is the most effective and reliable model for accurately identifying common household pests.

Class Name	Precision (%)	Recall (%)	F1 Score (%)
Rice weevil	74	70	72
American house spider	84	80	82
Bed bug	43	50	46
Brown stink bug	87	70	78
Carpenter ant	67	80	72
Cellar spider	90	95	93
Flea	39	45	42
House centipede	89	80	85
Silverfish	70	70	70
Subterranean termite	61	40	49
Tick	67	80	73

Table 1. Performance of the customized Xception model on individual classes.

Class Name	Precision (%)	Recall (%)	F1 Score (%)
Rice weevil	70	70	70
American house spider	94	80	87
Bed bug	45	45	45
Brown stink bug	76	95	84
Carpenter ant	72	65	68
Cellar spider	93	70	80
Flea	38	70	49
House centipede	95	90	92
Silverfish	100	70	82
Subterranean termite	70	70	70
Tick	67	50	57

Table 2. Performance of the customized MobileNetV2 model on individual classes.

Class Name	Precision (%)	Recall (%)	F1 Score (%)
Rice weevil	93	70	80
American house spider	90	95	92
Bed bug	68	75	71
Brown stink bug	95	90	92
Carpenter ant	68	85	75
Cellar spider	81	90	85
Flea	48	60	53
House centipede	100	80	89
Silverfish	87	70	78
Subterranean termite	58	75	65
Tick	85	55	67

Table 3. Performance of the customized DenseNet201 model on individual classes.

Model Name	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)	OVR Score (%)
Xception	70	69	69	69	94
MobileNetV2	74	70	71	70	95
DenseNet201	79	77	77	77	97

Table 4. Overall performance (Macro Avg.) of the customized pre-trained model in our dataset.

7.1 Interpretation

Through experimentation and a comparative analysis of various deep learning architectures, the proposed model was able to successfully identify multiple pest classes. With a high OVR score, the classifier can distinguish each class from all others with high confidence. The combination of web scraping and data augmentation allowed us to generate more training data, thus enhancing the model performance. Among the tested models, DenseNet201 demonstrated the highest accuracy over the other techniques, achieving 77% classification performance, and a high 97% OVR score. The effectiveness of the approach was validated using precision, recall, F1 score, confusion matrices, loss curves, and accuracy curves, confirming the potential of deep learning for automated household pest detection.

Given our available resources, our team focused on developing a household pest identification model that balances efficiency, accessibility, and accuracy. To ensure the models could run smoothly on local devices, we prioritized using computationally efficient architectures, making the system more practical and easier for users to replicate without requiring advanced hardware. The limitations of this study are as follows:

- The dataset size was relatively small, therefore it does not cover the full diversity of household pests, as certain species might not have sufficient images available for training, leading to an incomplete representation.

- The system might not perform equally well in all lighting conditions as pest images from smartphones can vary in terms of quality.
- Despite efforts to prevent overfitting, the model may still perform suboptimally when applied to unseen pest images and would benefit from more training images.
- While the goal is to create an accessible system, achieving high accuracy often requires computationally intensive models and, therefore, could cause computational constraints.

To address the current limitations, future work could focus on expanding the dataset by collecting more diverse and high-quality images of household pests. Implementing additional data augmentation techniques could further enhance model robustness. Additionally, exploring more advanced deep learning architectures that balance performance and computational efficiency could improve classification accuracy without sacrificing accessibility.

Key successes in our project include collecting enough data to achieve 77% accuracy and an OVR score of 97, building and training multiple models, and implementing hyperparameter tuning and overfitting mitigation strategies. However, we encountered some limitations and unexpected findings that were quickly identified and resolved. During image preprocessing, standardizing the images to a fixed size (224x224) led to distortion in image quality. To address this, we applied padding to preserve the original image quality. Furthermore, we identified data leakage, which was fixed by implementing image hashing to detect and remove duplicate images. We then reran the image preprocessing pipelines, which are automated and modularized, therefore, this process was efficient and did not impact project deadlines. Lastly, there were computational constraints, as model training times were initially long. To overcome this, we utilized a GPU to reduce training time from 15 hours to 4-6 hours (depending on the pre-trained model).

The results align with our original objectives in that we were able to use deep learning (e.g., CNNs with transfer learning) to classify household pests, bridge the gap between agricultural and household pest research by building a dataset with images taken and uploaded by users, optimizing the model performance by applying different techniques, and creating an interface via Streamlit for users to upload their images and classify them.

8 Evaluation Metrics and Validation

8.1 Performance Metrics

To ensure a thorough assessment of model performance and guide the selection of the final model, we used a comprehensive set of key metrics: accuracy, loss curve, confusion matrix, precision, recall, and F1 score. These are standard metrics used for classification tasks that will allow us to show performance, tracking model history, and see the model's ability to accurately identify pests. The final model decision was further supported by supplemental metrics, comprising of receiving operating curves (ROC) and one versus rest scores (OVR), which provided additional insights into the model's discrimination ability across different threshold settings for multi-class classification. The ROC curve helps visualize the trade-off between true positive and false positive rates, while the OVR scores measure performance for each class independently, ensuring fair assessment across all pest categories. By using a diverse set of metrics, we can have a full evaluation of our models, capturing overall performance and class-specific behavior, ultimately leading to the final model selection.

- **Accuracy**: A metric to correctly detect pests. It is given by:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision**: A metric to determine the number of successful positive predictions the model has created. It is given by:

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall**: A metric that counts the number of accurate positive predictions made out of all possible positive predictions. It is given by:

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1 Score**: A metric that is the harmonic mean of the recall and precision scores, used to compare two classifiers. A score of 1 indicates a flawless classifier. It is given by:

$$F1\ Score = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \times 100$$

- **ROC AUC**: A plot of the false positive rate versus the true positive rate. The area under the curve (AUC) is used to compare different models.

- **One-versus-rest score**: A classification strategy that trains one binary classifier per class. For each classifier, the target class is treated as positive, while all other classes are treated as negative. This approach is commonly used for multiclass classification problems.

- **Macro Average**: The arithmetic mean of each class related to precision, recall, and F1 score. This evaluation is used for the overall performance of multiclass classification. It is given by:

$$\text{Macro Average} = \frac{1}{N} \sum_{i=1}^{N} \text{measure in class}_i$$

8.2 Validation Techniques

We reinforced the validation strategies from previous iterations, maintaining consistency in our approach and ensuring that the methods used were appropriate for evaluating the model's performance.

9 Discussion and Iterative Improvements

9.1 Model Adjustments

To optimize the performance of the DenseNet201 model, we conducted three tuning runs with different hyperparameter settings and evaluated their impact on classification accuracy and generalization. The goal was to determine the most effective combination of parameters while avoiding overfitting.

We tested three different configurations. In Run 1, we set the hyperparameters to epochs=30, patience=5, min_delta=0.001, executions_per_trial=1, and max_trials=20, aiming to improve generalization with a moderate patience level and limited trials. In Run 2, we increased the number of executions per trial to 3 and max trials to 60 while keeping other parameters the same to explore whether a more exhaustive search would yield better results. Finally, in Run 4, we reduced epochs to 20 and patience to 3 to observe whether a faster, less aggressive tuning approach could achieve similar or better performance. Table 5 presents the key evaluation metrics from each run.

Metric	**Run 4 (Selected)**	**Run 1**	**Run 2**
Test Accuracy	0.764	0.75	0.74
Validation Accuracy	0.723	0.72	0.698
Best Learning Rate	0.001	0.001	0.001
Best Dropout	0.3	0.3	0.3
Best Batch Size	16	16	16
Best Epochs	1	1	1
Test Precision	0.78	0.779	0.76
Test Recall	0.764	0.75	0.741
Test F1 Score	0.766	0.754	0.744

Table 5. Comparison of different hyperparameter tuning runs.

Run 4 was executed first, followed by Run 1 and Run 2 for comparison. Despite the increased max trials and executions per trial in Runs 1 and 2, no improvement in validation accuracy or test performance was observed. Consequently, Run 4 was selected as the final model configuration due to its faster training time and comparable performance. The results suggest that increasing trials and executions per trial did not yield any gains, possibly due to the model already converging within fewer trials. Based on these findings, we proceed with Run 4's hyperparameter settings for deployment.

Furthermore, we experimented with the model architecture to attempt to improve its performance. In the first approach, we applied an activation function (e.g., ReLU) after batch normalization, while in the second, we applied it before batch normalization. The results of these approaches can be found in Table 6.

Metric	**Current Architecture (%)**	**Approach 1 (%)**	**Approach 2 (%)**
OVR Score	97	96	96
Accuracy	77	75	74
Precision	80	77	77
Recall	77	75	74
F1 Score	77	75	75

Table 6. Performance for the current and modified architectures.

As shown in Table 6, the current architecture achieved the highest performance across all evaluation metrics despite being simpler than the alternative approaches. Specifically, it attained the highest macro-average OVR score (97%), accuracy (77%), precision (80%), recall (77%), and F1 score (77%). In comparison, approach 1 and 2 had slightly lower results for all of the metrics. We decided to continue to use the original architecture as our final model given the reduced complexity of the model and slightly higher metrics.

9.2 Data Adjustments

During the validation of our dataset, we found that duplicate images appeared in the training, validation, and testing sets, therefore we had a data leakage issue. To address this, we implemented image hashing using the Undouble library to detect and eliminate duplicate images. After removing the duplicate images, we reran the preprocessing pipelines to ensure data integrity. Additionally, we consolidated all image preprocessing and augmentation steps into a single script, streamlining the workflow and improving the reproducibility of our data processing.

9.3 Future Work

Future research directions could explore incorporating alternative formats, such as videos. Moreover, including geospatial data to create pest population maps and potentially provide recommendations for insect control. Our team would ideally want to expand to incorporating more insect species and potentially handling rare insect scenarios, not just common pests.

10 Conclusion

10.1 Key Takeaways

The key takeaways from the experimentation phase are that a simpler architecture can achieve better results, and increasing the number of maximum trials and executions per trial did not lead to any significant improvements in model performance. These findings highlight the importance of balancing model complexity and computational resources, reinforcing that our chosen architecture is able to perform well with less complexity and resources.

10.2 Broader Project Objectives

Currently, there is a strong emphasis on image classification for agricultural pests, therefore, our research aims to expand this focus to pests commonly found in homes. By developing an accessible and efficient pest identification model, BugBot aligns with the broader objective of providing residents with a tool for identifying household pests using smartphone images. Our results contribute to this goal in several ways:

- Improved Classification for Real-World Images: Unlike many existing datasets that rely on professionally captured insect images, BugBot's model is trained on a dataset curated from user-uploaded images. This ensures that our classifier is robust to variations in lighting, angle, and image quality, making it more applicable for everyday users.

- Insights for Pest Management: Accurate pest identification is important for informed decision-making in pest control. BugBot quickly fixes this issue by providing instant feedback on potential infestations.

- Expansion of Pest Classification Research: By shifting the focus from agricultural to household pests, our work broadens the application of artificial intelligence based in pest identification. This could encourage further research into urban pest classification, crowd sourced data collection, and pest control solutions.

The next steps in refining our approach would be to expand the dataset by collecting more diverse and high-quality images of household pests. Implementing additional data augmentation techniques could further enhance model robustness. Additionally, exploring more advanced deep learning architectures that balance performance and computational efficiency could improve classification accuracy without sacrificing accessibility.

11 Reproducibility

11.1 GitHub

The Github repository for this project can be reached here: https://github.com/keeganveazey/BugBot

11.2 Repository Structure

Figure 2 notes the repository and directory structure of BugBot.

- DATA folder houses the raw data
- Best Models folder contains the notebooks which build the final DenseNet201, Xception, and MobileNetV2 models with the tuned hyper parameters
- Model Tuning folder contains the scripts to run hyperparameter tuning for each model
- BugBot Architecture Diagrams folder contains diagrams relevant to ButBot
- webapp folder contains resources for Streamlit deployment
- Files in orange are lone files and are described as follows:
  - global_bug_bot_functions.py contains evaluation functions and data splitting functions used in multiple files across the repository
  - Iteration_3_report is a methodology report for BugBot and includes technical information about the project's methods
  - README.md is a file used to detail information about the repository and provides a project overview

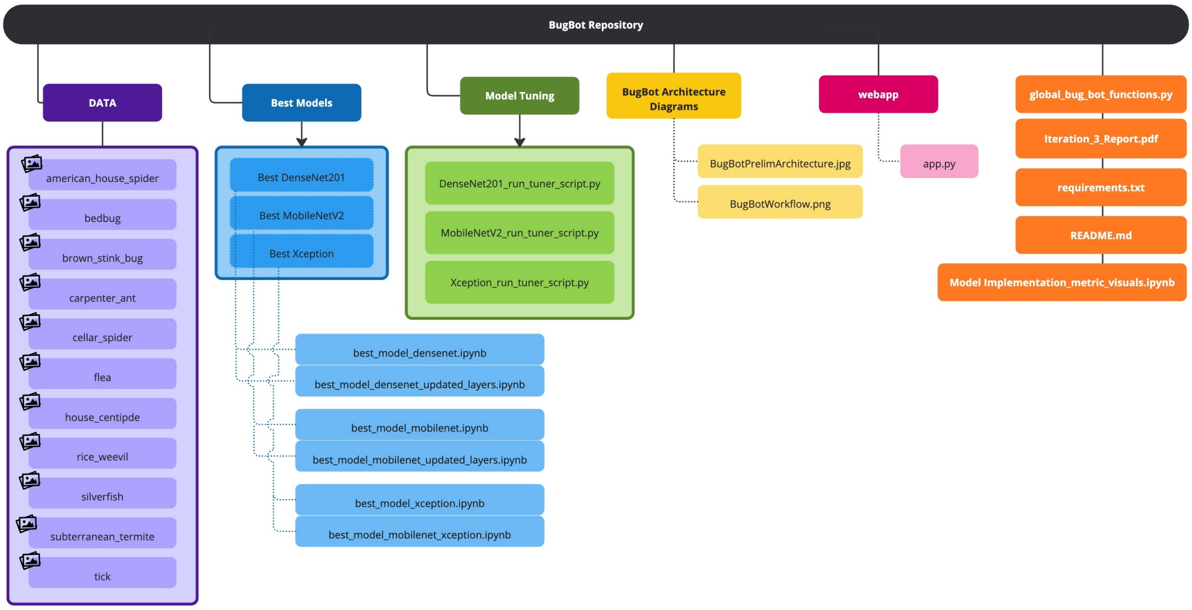


Figure 2: GitHub Repository Structure

- Model Implementation_metric_visuals.ipynb is a notebook containing code used to run and measure performance of seven originally considered models from which DenseNet201, Xception, and MobileNetV2 were chosen as top performers.

11.3 Data Access

The raw dataset is available in the repository in the folder "DATA". Inside the DATA folder, there are 11 subfolders, each consisting of 1 of the 11 insect classes as shown in Figure 2, GitHub Repository Structure. To reproduce our data preprocessing and training, validation and test set splitting, the user can follow the instruction in the "Set Up" section of README.md:

1. Pip install requirements.txt to a virtual environment (Python 3.12)
2. cd to repo location (change directory)

Complete the following if you do not already have an environment set up the repository's requirements.txt:
Type: pip install virtualenv, press enter.

1. Update pip if needed (type: pip install –upgrade pip, press enter).
2. Type: python -m venv bugbot_env, press enter
3. Type: source bugbot_env/bin/activate, press enter
4. You should now see something that looks like (bugbot_env)(base) in front of your curser in the terminal

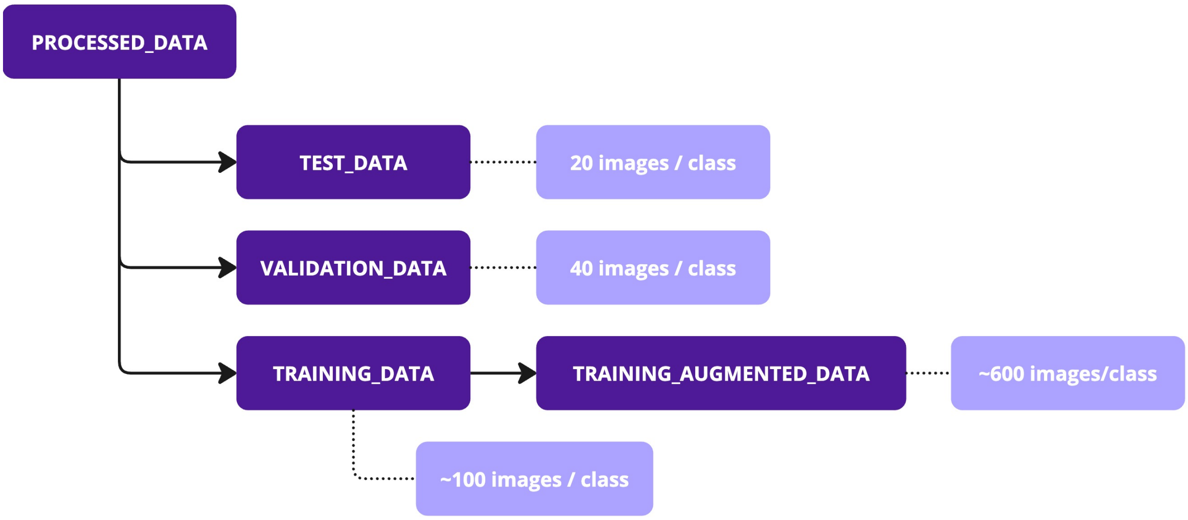


Figure 3: Data Preprocessing Pipeline Output Structure

5. Type: pip install -r requirements.txt, press enter

Use the preprocessing pipeline script to reproduce the model-ready dataset:

1. To run the notebook you are interested in, type jupyter notebook in the terminal of your now activated environment. After the browser opens, click the notebook of interest.

2. To run the preprocessing script, download the raw data in DATA provided in the repository. Type: python data_processing_pipeline.py

After following the above steps, the raw data will have undergone standardization and augmentation as discussed in Section 5. The final, model-ready preprocessed data will be in the user's directory as shown in Figure 3: Data Preprocessing Pipeline Output Structure. The data split is done using a defined random seed so the user's script run will result in same split as our team.

11.4 Dependecy Management

Notably, it is extremely important to install requirements.txt and use Python 3.12 to ensure that dependencies and versioning are taken care of before running any code. Figure 4 provides the explicitly called libraries and their versions. Please refer to the requirements.txt file in the GitHub repository for a comprehensive list.

Resource	Version
python	3.12
beautifulsoup	4.12.3
keras	3.8.0
keras-tuner	1.4.7
matplotlib	3.10.0
numpy	1.26.4
pandas	2.2.3
pipeline	0.1.0
scikit-learn	1.6.1
scipy	1.15.1
seaborn	0.13.2
tensorflow	2.18.0
tqdm	4.67.1
undouble	1.4.6

Figure 4: Libraries and Versioning

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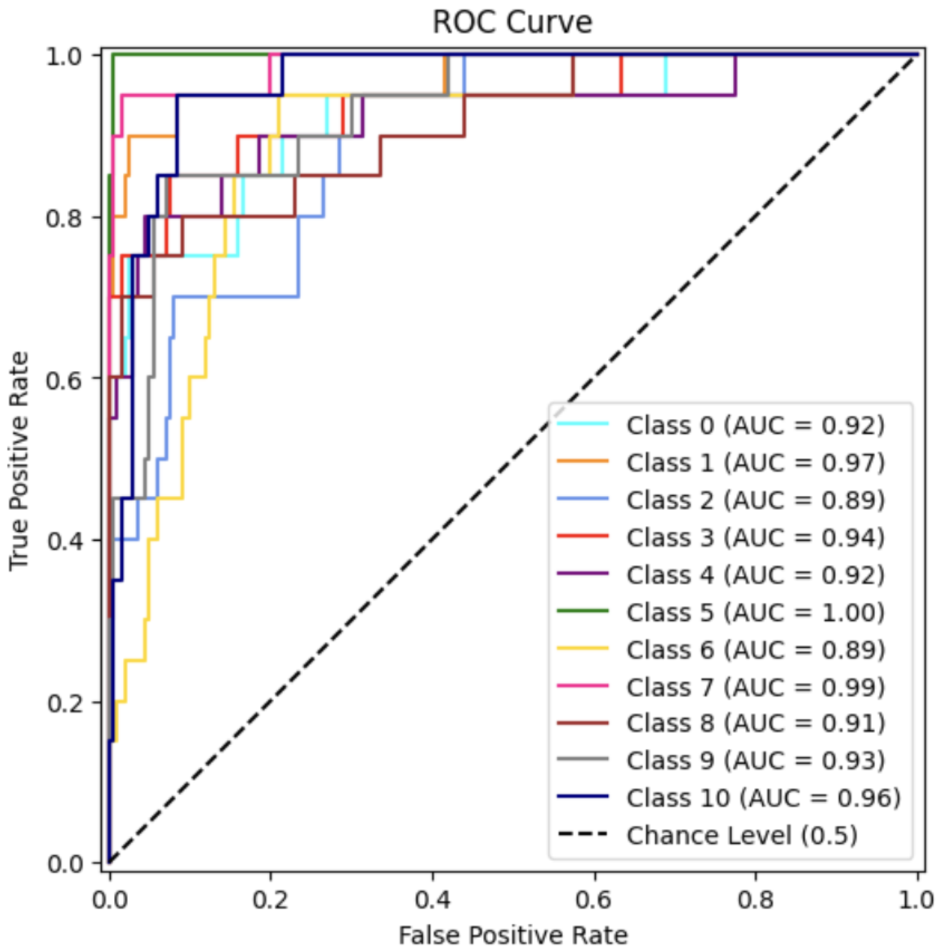
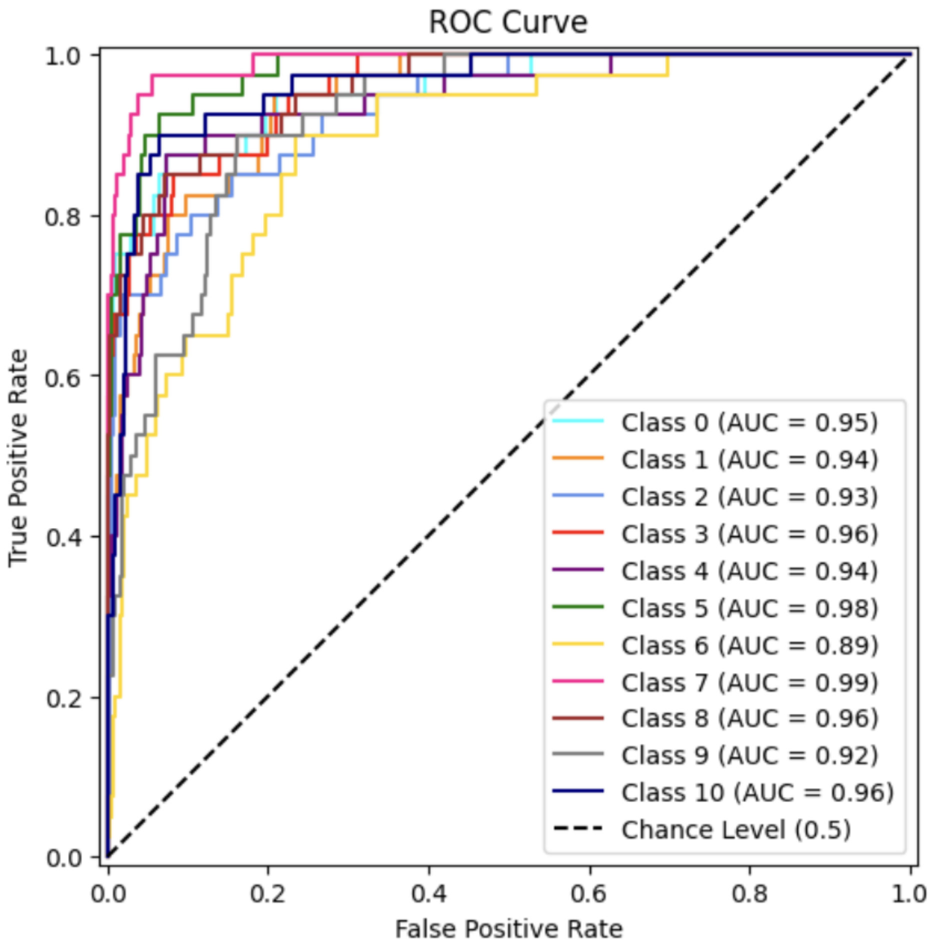
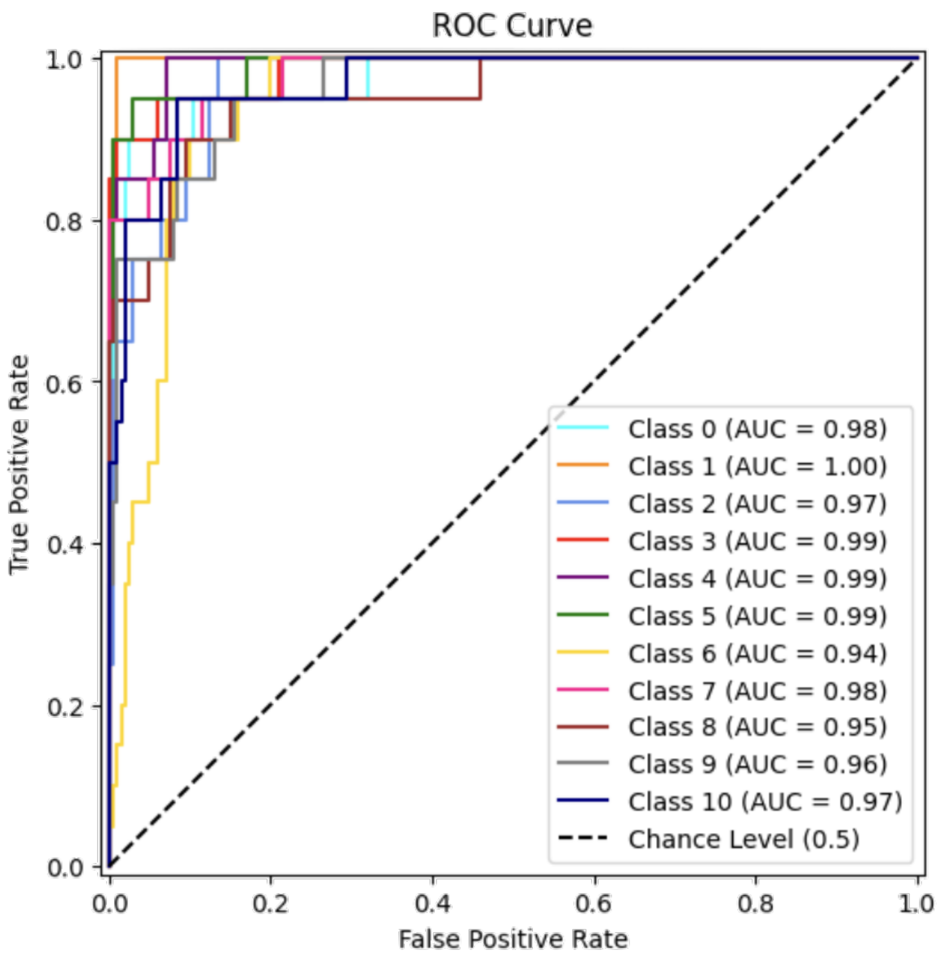
Appendix



Appendix-1: ROC curve of Xception



Appendix-2: ROC curve of MobileNetV2



Appendix-3: ROC curve of DenseNet201