Questions Classification of Germinated Oil Palm Seeds based on Deep Learning Models

GROUP 8:

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Abstract. This coursework focuses on the application of image classification techniques, specifically Convolutional Neural Networks (CNNs) or Vision Transformers (ViTs), to address the critical task of classifying germinated oil palm seeds into good or bad quality. The aim is to develop robust models capable of accurately distinguishing between the two categories, thereby aiding in quality assessment and decision-making processes within the agricultural domain. Through rigorous experimentation and analysis, the performance and generalizability of the trained models are evaluated. Additionally, the study explores the effectiveness of conventional image augmentation techniques and advanced generative models, such as Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Diffusion Models (DF), in enhancing the generalizability of the trained classifiers. By leveraging state-of-the-art methodologies and leveraging both conventional and advanced techniques, this research contributes to the advancement of image classification methodologies tailored for agricultural applications, with potential implications for improving crop quality assessment and yield prediction systems.

Keywords: Image classification, EfficientnetV2B1, Quality assessment.

1 Introduction

In agriculture, seed quality is an important factor influencing crop cultivation and yield success. Crops like oil palm play a significant role in the global economy, especially Malaysia. This industry contributes around 7% of the country's GDP with its export revenue [1]. To achieve quality palm oil, early and accurate assessment of the seed is essential for optimizing plantation outcomes. Traditionally, the quality of germinated oil palm seeds has been determined through manual inspection by experts. However, this method is labour-intensive, time-consuming, and vulnerable to the inconsistencies of human error. This manual method has the potential for improvement that can help Malaysia's current problem with labour shortages that cause the industry to lose billions in revenue [2].

1.1 Solution

This research project introduces an automated approach to classifying germinated oil palm seeds as "good" or "bad" quality. This approach uses advanced image classification techniques powered by deep learning, specifically exploring the implementation of Convolutional Neural Networks (CNNs) or Vision Transformers (ViT) to analyze visual characteristics extracted from seed images.

1.2 Objectives

The primary objective of this study is to develop and implement a deep learning-based system to classify germinated oil palm seeds into two categories: good and bad quality. This involves:

1. Applying image classification techniques, specifically Convolutional Neural Networks (CNNs) to distinguish between the seed qualities based on visual characteristics.
2. Analyzing the performance and generalizability of the trained models across different batches of seed images captured under varying conditions.
3. Enhancing the robustness and accuracy of the classification model by employing image augmentation techniques, using generative models such as Variational Autoencoders (VAE), Generative Adversarial Networks (GANs), and Diffusion Models (DF).

2 Methodology

2.1 Datasets

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Question 1

EfficientNetV2B1 is an excellent choice for classifying the quality of germinated oil palm seeds due to its efficiency and effectiveness in handling image classification tasks. The model is renowned for its balance between performance and computational resources, making it particularly suitable for scenarios where computational resources may be limited, such as on edge devices or in resource-constrained environments, which could be the case in agricultural settings where these seeds are typically evaluated.

Moreover, EfficientNetV2B1 is based on the efficient neural architecture search (ENAS) approach, which ensures that the model architecture is optimised for both accuracy and efficiency across various scales. This is crucial for accurately classifying the quality of germinated oil palm seeds, as the features distinguishing good and bad seeds may vary in scale and complexity. The hierarchical structure of EfficientNetV2B1 allows it to capture features at multiple levels of abstraction, enabling it to effectively learn and differentiate between subtle differences in seed quality.

Furthermore, EfficientNetV2B1 has been pre-trained on large-scale image datasets, which provides it with a strong foundation of visual features that can be fine-tuned for specific tasks, such as seed quality classification. Fine-tuning allows the model to adapt its learned representations to the specific characteristics of germinated oil palm seeds, further enhancing its performance and generalisation capabilities.

In summary, EfficientNetV2B1's balance between efficiency and accuracy, its ability to capture features at multiple scales, and its pre-trained weights make it a suitable choice for classifying the quality of germinated oil palm seeds. Its versatility and performance make it well-suited for real-world applications in agricultural settings, where accurate and efficient classification is essential for optimising crop yield and quality. [Tan, Le., 2021]

Question 2

The training process begins by splitting the dataset into training and validation sets, following the common practice of an 80% of dataset for training and 20% for testing. 80% allocation for model training is reasonable, more diverse training samples are able to avoid model from overfitting. 20% allocation of dataset is sufficient for validation set which is used to evaluate the model performance, aid the model to be more generalise to the unseen data.

Regarding the choice of hyperparameters, the number of epochs and batch size are pivotal. Epochs determine how many times the model iterates over the entire training dataset. Initially set at 50 epochs, this value may require adjustment based on the model's performance during training. Too few epochs risk underfitting, while an excessive number could lead to overfitting. Batch size, which dictates the number of samples processed before updating the model's parameters, is assumed to be defined elsewhere in the script. A larger batch size typically accelerates training but demands more memory.

The training process is monitored using Keras' fit method, which logs training and validation loss and accuracy for each epoch. Training and validation loss indicates the error between true labels and the predicted values while accuracy measures the samples are correctly classified. Ideally, we want the training and validation loss to decrease gradually and accuracy increase, which indicates that the model is learning the features from the samples and improving the ability to classify the training samples correctly. Besides, monitoring the gradients during the training process, we are able to detect overfitting from the performance result. For instance, if the model achieve high accuracy from training dataset but fails to perform well in validation dataset, we could know that the model is overfitting since it fails to generalise to new data.

When it comes to the choice between pretraining and training from scratch, the provided code employs the EfficientNetV2B1 model with pretrained weights from ImageNet. Leveraging pretrained weights allows the model to capitalise on features learned from a vast and diverse dataset, potentially enhancing performance on the seed image dataset. Freezing the pretrained weights (model.trainable = False) ensures they remain unchanged during training, a common practice in transfer learning with limited data. By freezing the pretrained weights and only training the added layers, the aim is to adapt the model to the seed image dataset's specific characteristics while retaining general features from ImageNet.

In summary, the training process encompasses dataset splitting, hyperparameter selection, monitoring using built-in Keras functionalities, leveraging pretrained weights for transfer learning, and adapting the model to the seed image dataset. While gradient monitoring is not explicitly implemented in the provided code, it can be facilitated using TensorBoard for deeper insights into the training process.

3 Experimental Results

Question 3

a)

We decided to test my model on both good and bad seeds which are essential for comprehensive evaluation. By testing on both good and bad seeds, we can figure out where any biases occur on our model’s predictions. If the model is misclassified on either class than the other, it could indicate the model is biassed towards the specific class and the model is not robust enough to learn from the relevant features of the specific class. Besides testing both seeds' quality, we can gain insight into how the model behaves under different light conditions, and whether the model performance differs between good and bad seeds under different scenarios. Furthermore, testing only good or bad seeds might skew the evaluation metric if the training data is imbalanced. Evaluation metrics like precision, recall and F1-score may not accurately reflect the complete model performance.

These metrics provide valuable insights into the performance of the deep learning model in classifying germinated oil palm seeds into good and bad categories. The accuracy of 0.788 indicates that approximately 78.8% of the seeds were classified correctly overall. The precision of 0.841 suggests that 84.1% of the seeds predicted as good were indeed good, minimising false positives. The recall of 0.711 indicates that 71.1% of the actual good seeds were correctly identified by the model, minimising false negatives.

The F1-score of 0.771, which is the harmonic mean of precision and recall, provides a balanced measure of the model's performance in terms of both precision and recall. Moreover, the AUC of 0.788 signifies the model's ability to discriminate between good and bad seeds across various decision thresholds, with a higher AUC indicating better discrimination ability.

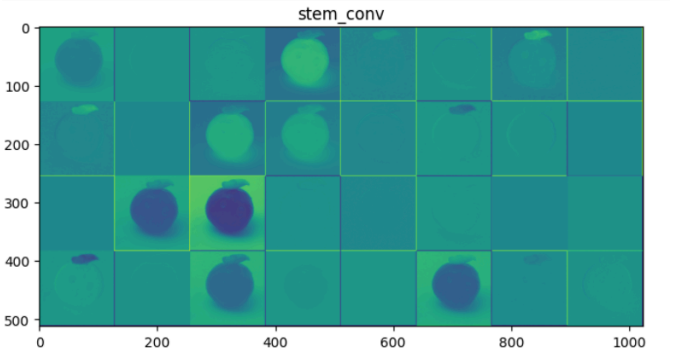
Overall, these metrics demonstrate promising performance in the quality classification of germinated oil palm seeds using deep learning models trained on the Batch-1 dataset. However, further analysis and refinement may be necessary to enhance the model's accuracy, precision, recall, F1-score, and AUC for practical applications in agricultural settings.

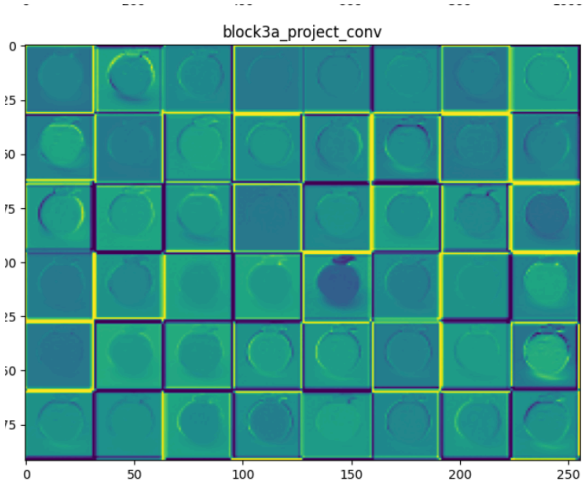
```
Accuracy: 0.7880299251870324
Precision: 0.8411764705882353
Recall: 0.7114427860696517
F1-score: 0.7708894878706201
Auc: 0.7882213930348259
```

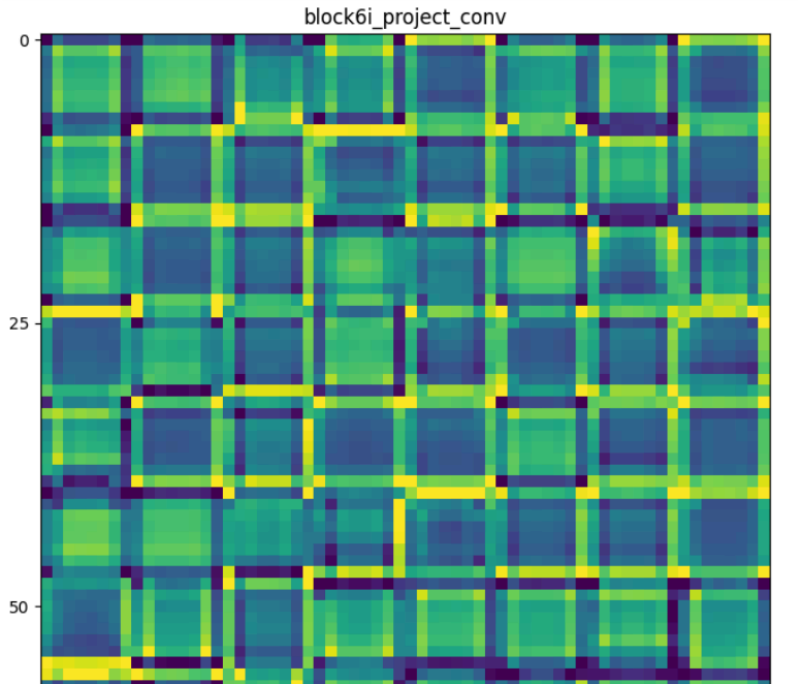
Performance Metric for Batch 1

b)

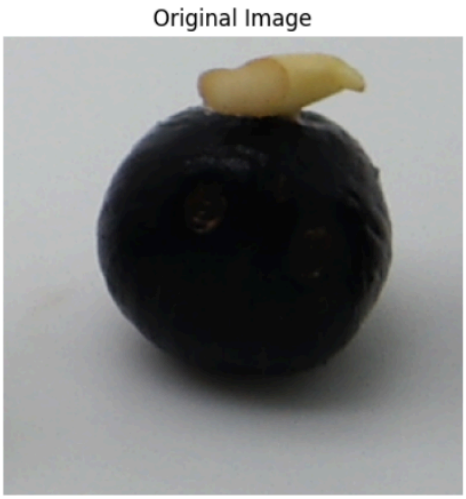
Features Map:

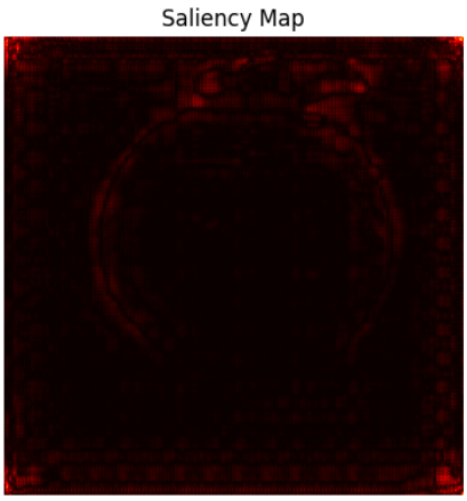






Saliency Map:





Analysis:

The initial feature maps from the "stem_conv" layer show clear and varied responses, indicating that this early layer of the CNN is detecting basic features such as edges, colors, and textures. The distinct colors and shapes within these feature maps suggest that the model is identifying various elements of the seeds. At this intermediate stage, the feature maps have variety of responses suggests that the network is successfully combining the low-level features into more complex patterns. The deepest layer featured in these images demonstrates very abstract patterns. he distinct blocks of color and texture patterns indicate that different filters are activating for different features, which is a good sign of a well-functioning feature hierarchy within the CNN.

The saliency map provides insight into which areas of the original image are most impactful for the CNN's predictions. The bright areas indicate regions of high importance. In this case, the saliency map highlights the perimeter of the seed, which suggests that the network is focusing on the boundaries and perhaps the textures that differentiate the seed from its background.

Question 4

a)

We decided to test my model on both good and bad seeds which are essential for comprehensive evaluation. By testing on both good and bad seeds, we can figure out where any biases occur on our model's predictions. If the model is misclassified on either class than the other, it could indicate the model is biassed towards the specific class and the model is not robust enough to learn from the relevant features of the specific class. Besides testing both seeds' quality, we can gain insight into how the model behaves under different light conditions, and whether the model performance differs between good and bad seeds under different scenarios. Furthermore, testing only good or bad seeds might skew the evaluation metric if the training data is imbalanced. Evaluation metrics like precision, recall and F1-score may not accurately reflect the complete model performance.

These metrics provide additional insights into the performance of the deep learning model when tested on a different dataset. The accuracy of 0.712 indicates that approximately 71.2% of the seeds were classified correctly overall. The precision of 0.671 suggests that 67.1% of the seeds predicted as good were indeed good, minimising false positives. The recall of 0.831 indicates that 83.1% of the actual good seeds were correctly identified by the model, minimising

false negatives.

The F1-score of 0.743, which is the harmonic mean of precision and recall, provides a balanced measure of the model's performance in terms of both precision and recall. Moreover, the AUC of 0.712 signifies the model's ability to discriminate between good and bad seeds across various decision thresholds for the Batch-2 dataset.

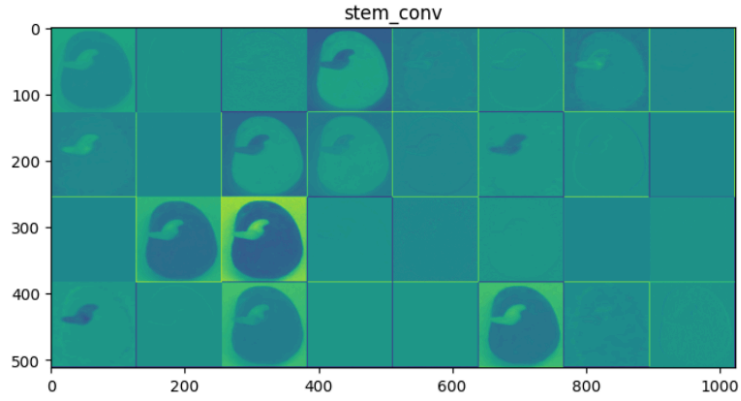
Comparing the results between the Batch-1 and Batch-2 datasets, it is evident that there are differences in the model's performance. While the accuracy and precision are slightly lower for the Batch-2 dataset, the recall and AUC are higher, indicating a trade-off between precision and recall.

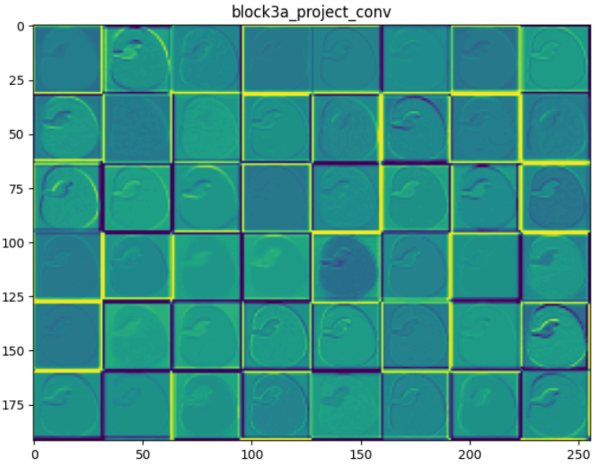
```
Accuracy: 0.7122222222222222
Precision: 0.6714542190305206
Recall: 0.8311111111111111
F1-score: 0.7428003972194637
Auc: 0.7122222222222222
```

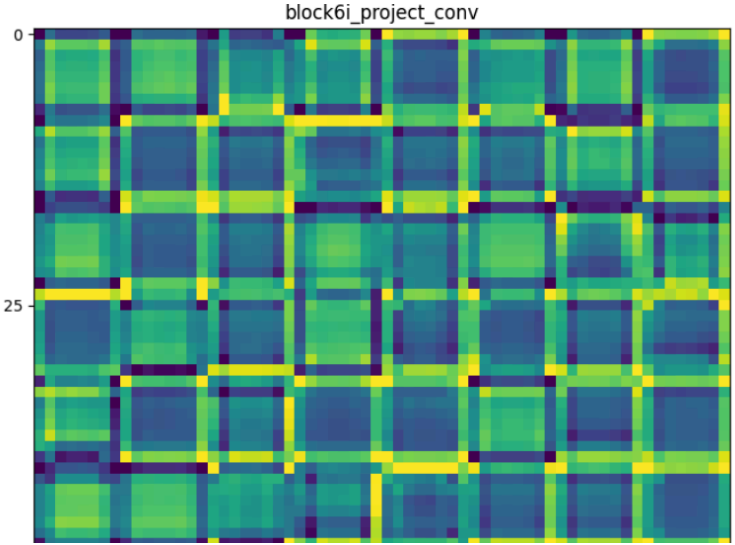
Performance Metric for Batch 2

b)

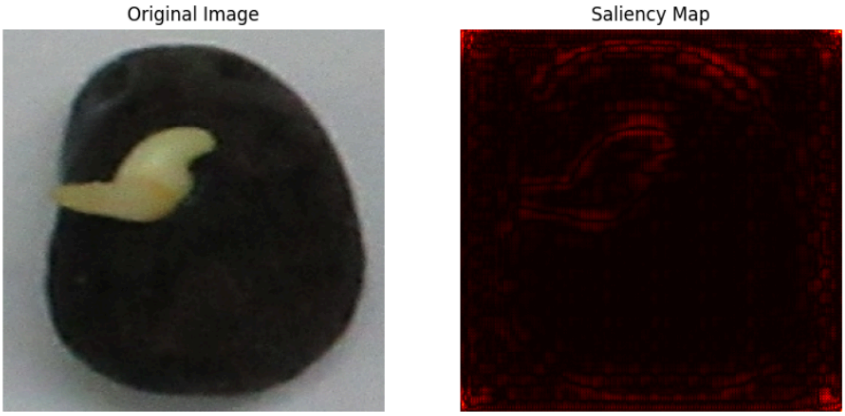
Features Map:







Saliency Map:



Analysis:

In the beginning layer, the feature maps are still clear and distinct, indicating that the model's initial layer is sensitive to various aspects of the seed. There's a consistent focus on certain shapes within the seeds, which suggests that the filters are doing their job of edge and texture detection. The next layer show that the model is able to abstract the initial features into more complex patterns. The variety in the feature maps suggests that the model is detecting different characteristics from the seeds. The deepest layer continues to show a wide range of activations. The different patterns indicate that the network is processing the information and, likely, focusing on different high-level features that will be used in the final decision-making process.

The saliency map in this second dataset also shows a clear focus on the edges and the contrast between the seed and its background, which is similar to the first dataset. The bright regions around the contour of the seed imply that the model considers those areas as important for whatever task it is designed to perform (e.g., classification, detection).

Question 5

a)

We decided to test my model on both good and bad seeds which are essential for comprehensive evaluation. By testing on both good and bad seeds, we can figure out where any biases occur on our model's predictions. If the model is misclassified on either class than the other, it could indicate the model is biassed towards the specific class and the model is not robust enough to learn from the relevant features of the specific class. Besides testing both seeds' quality, we can gain insight into how the model behaves under different light conditions, and whether the model performance differs between good and bad seeds under different scenarios. Furthermore, testing only good or bad seeds might skew the evaluation metric if the training data is imbalanced. Evaluation metrics like precision, recall and F1-score may not accurately reflect the complete model performance.

These metrics provide additional insights into the performance of the deep learning model when tested on a different dataset. The accuracy of 0.619 indicates that approximately 61.9% of the seeds were classified correctly overall. The precision of 0.590 suggests that 59.0% of the seeds predicted as good were indeed good, minimising false positives. The recall of 0.805 indicates that 80.5% of the actual good seeds were correctly identified by the model, minimising false negatives.

The F1-score of 0.681, which is the harmonic mean of precision and recall, provides a balanced measure of the model's performance in terms of both precision and recall. Moreover, the AUC of 0.617 signifies the model's ability to discriminate between good and bad seeds across various decision thresholds for the Batch-3 dataset.

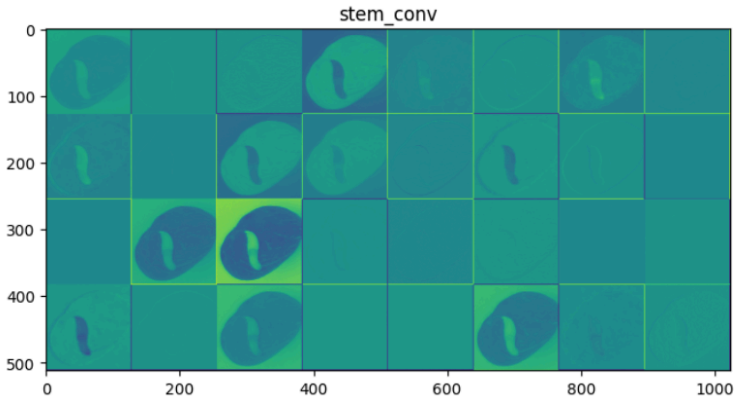
Comparing the results among the Batch-1, Batch-2, and Batch-3 datasets, it is evident that there are variations in the model's performance across different datasets. While the accuracy and precision are relatively consistent, there are fluctuations in recall and AUC values.

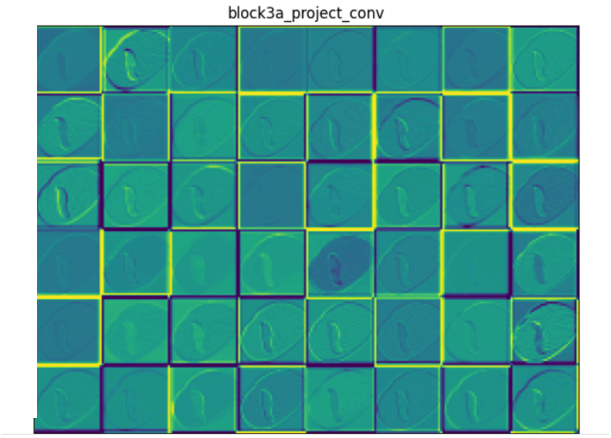
```
Accuracy: 0.6185308848080133
Precision: 0.589588377723971
Recall: 0.8049586776859504
F1-score: 0.6806429070580015
Auc: 0.6166446002257746
```

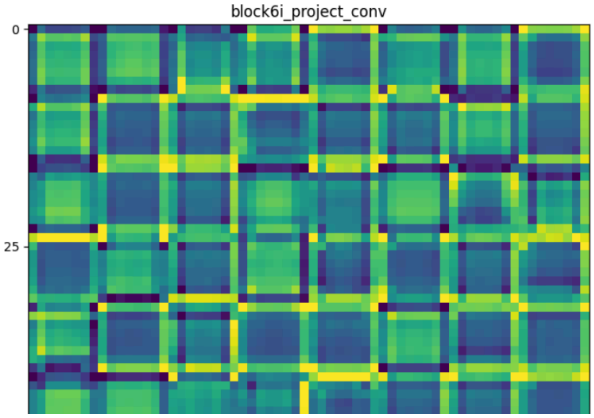
Performance Metric for Batch 3

b)

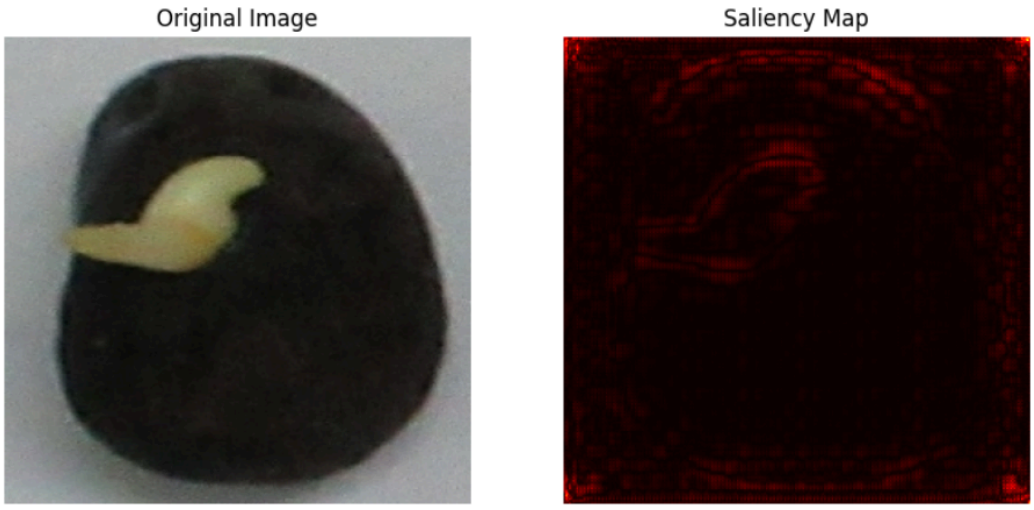
Feature Map:







Saliency Map:



Analysis:

The early CNN layers are learning basic visual features like edges and textures from the seed images, which is expected behaviour. Having a variety of these low-level features being captured is a good sign. As we move deeper into the CNN, the layers should combine the basic features into more complex and abstract representations. The feature maps in the middle layers should show structured patterns rather than just noise, indicating that higher-level features are being learned successfully. In the deepest layers shown, the feature maps become highly abstract and challenging to interpret individually. However, seeing diverse activation patterns across these feature maps, rather than repetitive or uniform maps, suggests the network is still effectively learning distinct high-level representations without overfitting.

The seed is highlighted with a brighter red color in the saliency map, indicating that the model relied heavily on this region to make its classification.

Question 6

The performance of the EfficientNetV2B1 classification model on the three different batches provides insights into its strengths and weaknesses, particularly in handling variations in lighting conditions and camera types. Let's discuss:

Strengths:

Robustness to Variations in Lighting Conditions: Despite being trained on images from the first batch with specific lighting conditions, the model demonstrates decent performance on batches 2 and 3, which have different lighting conditions. This suggests that the model has learned to generalise well to some extent and is not overly sensitive to

changes in illumination.

Overall Good Performance: The model achieves respectable metrics across all batches, with accuracy ranging from 0.619 to 0.788. This indicates that the model is capable of making accurate predictions on unseen data, even when faced with variations in lighting and camera types.

Weaknesses:

Decreased Performance on Batches 2 and 3: While the model performs reasonably well on all batches, there is a noticeable drop in performance on batches 2 and 3 compared to batch 1. This suggests that the model is less effective at generalising to images with different lighting conditions and captured using different cameras.

Lower Precision and Accuracy on Batches 2 and 3: The precision and accuracy metrics are lower for batches 2 and 3 compared to batch 1. This indicates that the model is more prone to making false positive predictions and overall less accurate on images with varying lighting conditions and camera types.

Lower AUC Score on Batches 2 and 3: The area under the ROC curve (AUC) provides a measure of the model's ability to distinguish between classes. The lower AUC scores for batches 2 and 3 suggest that the model's performance in correctly classifying images may suffer when faced with changes in lighting conditions and camera types.

In summary, while the EfficientNetV2B1 classification model demonstrates robustness to some degree against variations in lighting conditions, it still exhibits limitations in generalising to images captured under different conditions. Improving the model's performance on such diverse datasets may require additional techniques such as data augmentation, transfer learning, or fine-tuning on images with varying lighting and camera characteristics.

5 Model Enhancement Using Generative Models

Question 7

In this section, we discuss the implementation of Generative Adversarial Networks (GANs) to enhance the quality of training data by generating synthetic images of germinated oil palm seeds.

5.1 Model Selection

The model architecture for the enhancement includes a Generator and a Discriminator, designed using the principles of Generative Adversarial Networks (GANs). The Generator model is responsible for creating new, synthetic images of germinated oil palm seeds, while the Discriminator evaluates their authenticity.

The Generator starts with a latent vector z which is transformed through a series of deconvolutional layers, each followed by batch normalization and ReLU activation. The final output is a 64x64 image which matches the size of real seed images used in training. This architecture is capable of capturing and reproducing the complex textures and features of germinated oil palm seeds, which are essential for the training of the classification models.

The Discriminator model assesses the authenticity of both real and generated images. It is a convolutional neural network that downsamples its input through a series of convolutions, each followed by batch normalization (except the first layer) and LeakyReLU activation. The final layer outputs a single scalar through a sigmoid function, representing the probability that the input image is real.

5.2 Implementation

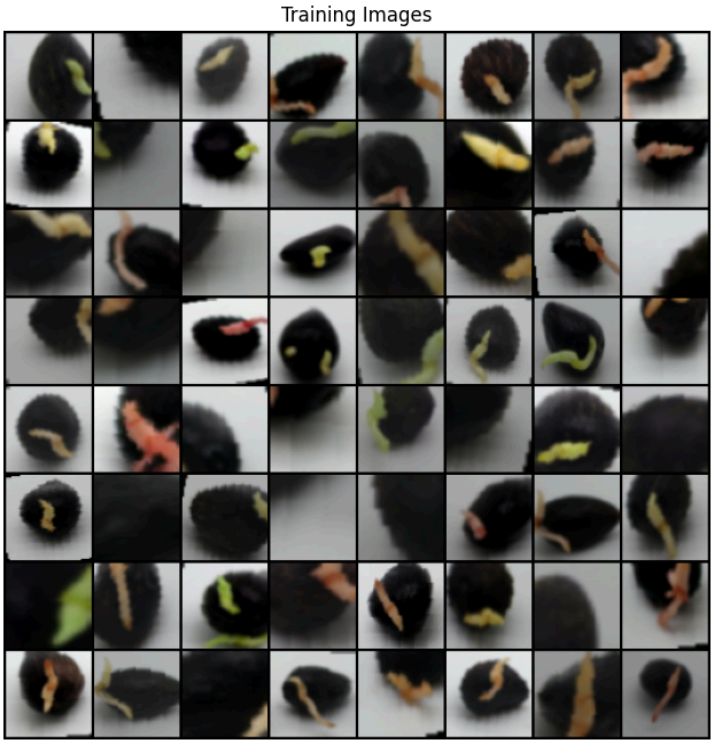
The implementation process involves setting up the data loaders, training the GAN models, and integrating the synthetic images into the training dataset for the main classification model.

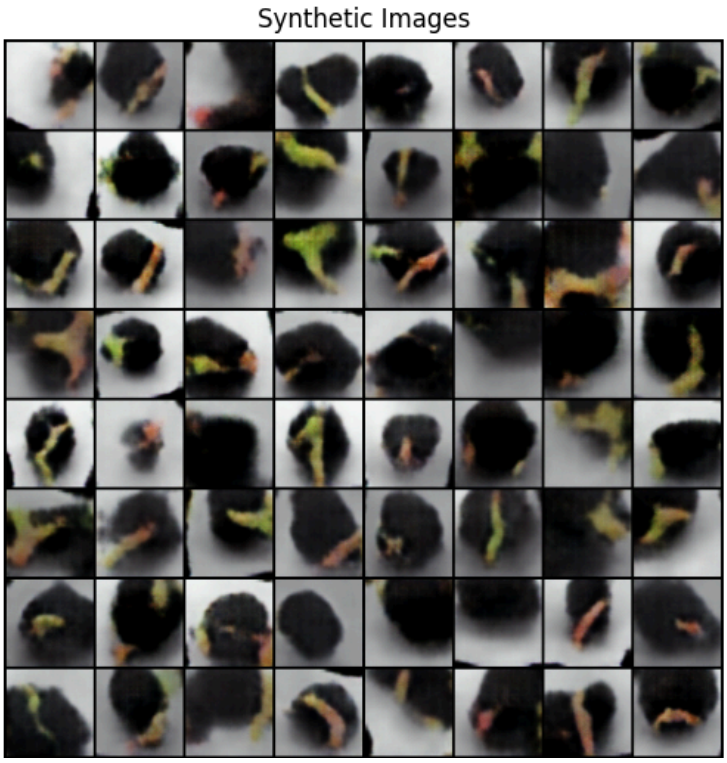
The images undergo several transformations to ensure uniformity in size and to enhance model training through data augmentation and normalization. These transformations include resizing, center cropping, random horizontal flipping, rotation, cropping, color adjustments, Gaussian blurring, and tensor conversion, followed by normalization. Such preprocessing not only standardizes the input data but also introduces variability, aiding the model in handling different orientations, sizes, and visual appearances.

Training involves alternating between updating the Discriminator and the Generator. The Discriminator learns to distinguish real images from those generated by the Generator. Simultaneously, the Generator is trained to produce increasingly authentic-looking images to fool the Discriminator. The training uses the Adam optimizer with a learning rate of 0.0002 and a beta1 value of 0.5. The models are trained for 200 epochs, reflecting a balance between sufficient training time and resource efficiency. The effectiveness of the GAN is monitored by examining the losses of both the Generator and Discriminator and by visual inspections of the generated images.

Synthetic images produced by the Generator are added to the training dataset for the main classification model. This helps to increase the variability and volume of the training data, which is crucial for improving the model's generalization capabilities. The integration of synthetic images is managed to ensure a balanced representation of seed qualities, enhancing the robustness of the classification models against overfitting and underrepresented features in the training data.

5.3 Results





The synthetic images visually resemble the training images, not just in terms of content but also in color, texture, and overall style. In both sets, there appears to be a good variety of shapes and color patterns that match well. This indicates that the GAN has learned the distribution of the training data reasonably well.

The images are understandably a bit blurrier than the real training images, which is common for GANs, especially in areas of fine detail. However, for the purpose of data augmentation, it's more important that the generated images follow the correct overall structure and color patterns, which they seem to.

In the synthetic images, there may be some signs of artifacts or inconsistencies that don't appear in the training set (for example, overly smooth regions or color bleeding).

The images also show various combinations of features, suggesting good diversity.

5.4 Question 8: Evaluation of model with augmented Batch-1 dataset

The results of the evaluation are as follows:

```
Accuracy: 0.6676176890156919
Precision: 0.6629834254143646
Recall: 0.6837606837606838
F1-score: 0.6732117812061712
```

Performance Metric for Augemented Dataset.

The dataset used in this evaluation process is an augmented dataset that contains Batch-1 dataset and the 300 synthetic images produced in 5.2. The synthetic images, GOOD and BAD, are appended to each class of the original Batch-1 dataset respectively.

The results of the model evaluation are as follows: The model correctly classified approximately 66.76% of the samples. A precision of 0.6630 indicates that approximately 66.30% of the samples predicted as "GOOD" were actually "GOOD". A recall of 0.6838 indicates that approximately 68.38% of the actual "GOOD" samples were correctly classified as "GOOD" by the model. The F1-score is approximately 0.6732 which indicates better performance

Overall, the model demonstrates moderate performance. The results suggest that the model achieves a good balance between precision and recall, indicating that it effectively identifies positive instances while minimizing false positives. there may be room for improvement in terms of accuracy and overall performance

5.5 Question 9: Comparison of results with Batch-2 and Batch-3

The results for the augmented batch does not exceed the results of Batch-2 and Batch-3, only better than Batch-3 in terms of accuracy. This is due to the extra complexity of the augmented batch. The augmented batch has extra 300 synthetic images added to the dataset, furthermore, these images that are produced has a different initial size (64x64) compared to the original Batch-1 images (256x256). Although this is rectified by resizing the images to 256x256, it was not processed by extra steps such as normalisation.

6 Conclusion

In this coursework, we classified germinated oil palm seeds into good or bad quality using deep learning-based image classification techniques. Our primary objective was to develop robust models capable of accurately distinguishing between the two categories to aid in quality assessment within the agricultural domain.

We employed Convolutional Neural Networks (CNNs)as our primary models for image classification. Through rigorous experimentation and analysis, we evaluated the performance and generalizability of these models across different batches of seed images captured under varying conditions. Our results demonstrated promising performance, with the models achieving high accuracy in distinguishing between good and bad quality seeds.

Furthermore, we also employed Generative Adversarial Networks (GANs) models as our image augmentation technique enhancing the generalizability of the trained classifiers. These techniques proved valuable in providing us valuable insights into augmentation as well as improving the robustness and accuracy of the classification model, particularly in scenarios with limited labeled data or varying image conditions.

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