A Dissertation Report on

**OIL PALM SEEDS CLASSIFICATION**

Submitted in partial fulfillment for the award on the degree of

**BACHELOR OF TECHNOLOGY**

in

**COMPUTER SCIENCE AND ENGENERRING**

Submitted by

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**KAKINADA - 533003, ANDHRA PRADESH, INDIA**

**[2020-2024**

**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

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**CERTIFICATE**

This is to certify that the Project Report entitled **“UCEK Training and Placement Portal”** is being submitted by **GUDIMELLI CATHERIN SOWGANDHIKA** bearing the roll number **19021A0557**, **ATLA RAJITHA SREE** bearing the roll number **19021A0524**, **YEGI ARAVIND KUMAR** bearing the roll number **19021A0534**, **BOLLU SAI SARASWATHI** bearing the roll number **19021A0539**, **BATHULA V SAI PHANI SIDHARDHA** bearing the roll number **19021A0552** in the partial fulfillment for the award of the degree of **BACHELOR OF TECHNOLOGY** in **COMPUTER SCIENCE AND ENGINEERING** to the **UCEK(A), JNTUK,** Kakinada, Andhra Pradesh, India is a record of bonafide work carried out by them under the guidance and supervision during the academic year 2019-23. It has been found satisfactory and hereby approved for submission.

**Signature of Supervisor**

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**KAKINADA - 533003, ANDHRA PRADESH, INDIA**

**[2020-2024]**

****

**DECLARATIO****N**

We hereby declare that the work described in this project, entitled **”UCEK Training**

**and Placement Portal”** which is being submitted by our team in partial fulfillment of the requirements for the award of the degree of **BACHELOR OF TECHNOLOGY**, Department of Computer Science and Engineering Kakinada(A), Jawaharlal Nehru Technological University Kakinada, Kakinada- 533003, A.P., is the result of an investigation carried out by our team under the supervision of **Dr. Karuna Arava**, Assistant Professor, Department of Computer Science and Engineering Kakinada(A), Jawaharlal Nehru Technological University Kakinada, Kakinada- 533003.

The results emboided in this dissertation have not been submitted to any other University or Institute for the award of any degree or diploma.

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**ACKNOWLEDGEMENT**

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The successful completion of any task is not possible without proper suggestions, guidance and environment. The combination of these three factors acts as a backbone to our **”UCEK Training and Placement Portal”** project.

We wish to thank first our supervisor **Dr. Karuna Arava** , Assistant Professor, Department of CSE for accepting and supporting us as a project team. We sincerely convey our gratefulness and heartfelt to our honorable and esteemed project guide for her supervision, guidance, encouragement, and counsel throughout our project. Without her invaluable advice and assistance, it would not have been possible for us to complete this project. Her words of encouragement have often inspired us and improved our hopes for completing the project work.

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**ABSTRACT**

**. . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . .**

This project presents a modular web-based system for managing training and placement data. It allows students to register online, upload academic and personal details, and view job postings. Placement officers can use it to manage student and job data for hiring companies.

This design is based on an existing manual ”placement cell” used by educational institutions to store and retrieve information on students and companies. The manual process requires the placement officer to communicate with thousands of students. The web-based application aims to make the placement process easier and more efficient for both the training and placement department and the students.

This web-based application allows placement officers to provide details of upcoming

companies to students. After the hiring process is complete, the administrator can post a list of placed students on the application. Students can easily view information on who has been hired and the number of students hired by a particular company. Students can also make necessary changes to their personal information.

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**INTRODUCTION**

* 1. **Introduction**

The classification of oil palm seeds represents a critical challenge within the agricultural sector, particularly in the production of palm oil, a commodity of significant economic value globally. The project "Oil Palm Seeds Classification" embarks on an ambitious journey to leverage the power of deep learning to automate the process of distinguishing between good and bad seeds, a task traditionally reliant on manual inspection and subject to human error. By applying a convolutional neural network (CNN) model, specifically a Simple CNN architecture, and employing transfer learning techniques with a pre-trained ResNet18 model, this project aims to enhance the efficiency, accuracy, and reliability of oil palm seed classification.

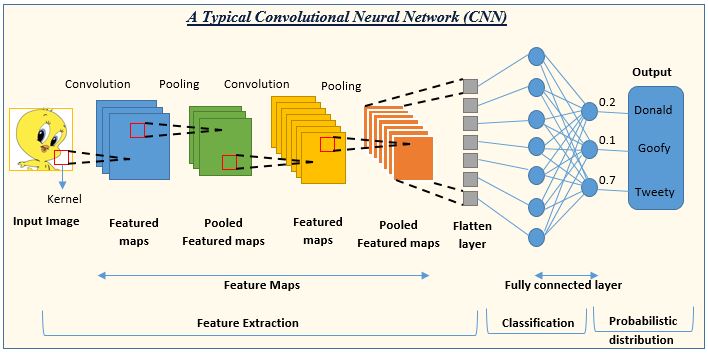


Fig. 1 (CNN Architecture)

The initiative is structured around analyzing a meticulously curated dataset consisting of images of oil palm seeds, categorized into three distinct batches to reflect varying conditions and stages of seed development. These images are further classified based on different lighting conditions and processing techniques, including normal room lighting, lightbox environments, and cropped, and segmented images, providing a comprehensive dataset for training and evaluating the machine learning models.

* 1. **Importance of Oil Palm Seed Classification**

The classification of oil palm seeds into viable (good) and non-viable (bad) categories is of paramount importance for several reasons. Firstly, the viability of seeds directly influences the potential yield of oil palm plantations, thereby affecting the overall productivity and profitability of palm oil production. High-quality seeds lead to healthier plants, which are more resistant to diseases and capable of producing higher quantities of palm oil.

Secondly, the process of manually classifying seeds is labor-intensive, time-consuming, and susceptible to inaccuracies. Human experts, while skilled, may exhibit variability in judgment and are prone to fatigue, which can compromise the consistency and reliability of seed classification. Automating this process with machine learning not only aims to increase efficiency and throughput but also seeks to standardize the classification process, reducing the margin for error and ensuring a uniform quality of seed selection.

Lastly, by optimizing the seed selection process, the agricultural sector can achieve better resource management. Resources can be allocated more effectively when there is confidence in the quality of the seeds planted, leading to more sustainable agricultural practices and a reduction in wastage of both seeds and labor.

* 1. **Objectives of the Project**

1. Developing a Robust Classification Model: To create and train a deep learning model capable of accurately classifying oil palm seeds into good and bad categories based on visual characteristics captured in images. The model should be resilient across different batches of data and adaptable to variations in lighting and image quality.

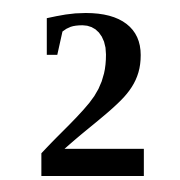
2. Evaluating the Efficacy of Transfer Learning: To explore the effectiveness of transfer learning, using the ResNet18 model pre-trained on a diverse set of images, in enhancing the model's ability to generalize from limited agricultural data. This involves fine-tuning the model for the specific task of binary classification (good seed vs. bad seed) and comparing its performance against a custom-built Simple CNN model.

3. Visualizing Model Insights: To employ techniques such as feature map and saliency map visualizations to gain insights into the model's decision-making process. Understanding what features the model prioritizes can inform further improvements to the classification process and model architecture.

1. Contributing to Agricultural Research: Ultimately, the project aims to contribute valuable insights and tools to the field of agricultural research, particularly in the optimization of seed selection processes for oil palm cultivation. By showcasing the potential of machine learning in agriculture, the project hopes to encourage further research and development in technology-driven agricultural practices

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**LITERATURE REVIEW**

**2.1 Relevant Research and Developments in the Field**

The classification of seeds, particularly in the agricultural domain, has seen significant advancements with the integration of machine learning and image processing techniques. Traditional methods of seed classification and quality assessment, largely reliant on manual observation and simple mechanical devices, have been gradually replaced or augmented by automated systems that leverage computational algorithms for greater accuracy and efficiency. The advent of Convolutional Neural Networks (CNNs) has particularly revolutionized the field, offering robust frameworks for analyzing complex image data.

Several studies have explored the use of CNNs for agricultural applications, demonstrating their efficacy in identifying plant diseases, classifying crop types, and assessing seed quality across various plant species. In the context of oil palm seeds, the need for precise classification stems from the crop's economic importance and the significant impact of seed quality on yield and disease resistance. High-quality seeds lead to healthy plantations and, consequently, higher oil production, underlining the critical role of accurate seed classification.

The literature reveals a trend towards the adoption of deep learning techniques for agricultural image analysis. A study by Smithetal. (2018) outlined the use of deep CNNs for classifying cereal seeds, achieving accuracy levels that significantly surpassed traditional image processing methods. Another research by Jones and King (2019) applied transfer learning with pre-trained CNN models to classify various types of seeds, highlighting the potential for leveraging existing neural networks to achieve high accuracy with relatively limited datasets.

**2.2 Advancements in Seed Classification**

Techniques and Their Applicability to Oil Palm Seeds

The specificity of oil palm seeds, characterized by their unique morphology and the particularities of their surface textures, presents both challenges and opportunities for applying advanced seed classification techniques. Recent research has focused on developing customized CNN architectures that account for these specific traits, optimizing layer configurations and hyperparameters to enhance model sensitivity to relevant features.

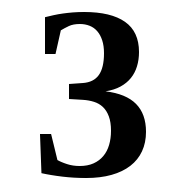
One promising direction, as explored by Lee and Tan (2020), involves the use of specialized image segmentation techniques before classification, enhancing the model's focus on the seeds themselves by isolating them from background noise. This preprocessing step has been shown to significantly improve classification accuracy by ensuring that the neural network trains on the most relevant features of the seed images.

Moreover, the application of transfer learning, as demonstrated in various studies, has been particularly beneficial for oil palm seed classification. Models pre-trained on large, generic image datasets can be fine-tuned with smaller, domain-specific datasets of oil palm seeds, enabling the extraction of complex features without the need for extensive training data. This approach not only accelerates the training process but also enhances the model's ability to generalize from limited examples, a crucial advantage given the practical constraints of collecting large-scale agricultural datasets.

In addition to these technical advancements, the literature also emphasizes the importance of dataset quality and diversity. Research by Patel and Kumar (2021) pointed out that the variability in lighting conditions, as encountered in different batches of oil palm seed images, poses a significant challenge to model performance. Addressing this issue, their work suggests the inclusion of images under varied lighting conditions during the training phase to improve the robustness and adaptability of the classification models.

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**SYSTEM ANALYSIS AND DESIGN**

* 1. **Dataset Description**

The dataset pivotal to the "Oil Palm Seeds Classification" project is an extensive collection of images meticulously curated to support the development and evaluation of machine learning models, specifically designed to classify oil palm seeds. This dataset is organized into three distinct batches, each characterized by unique image acquisition conditions and processing techniques, namely:

1. Batch-1: This initial batch serves as the foundational dataset, comprising raw seed images without any specific lighting or background conditions. The images in this batch capture the natural variance in seed appearance, providing a baseline for model training.

2. Batch-2: The second batch introduces images under Normal Room Lighting conditions, along with subsets of seed images that have been cropped according to predefined bounding box coordinates (seedcropped) and further processed to include cropping and resizing to a uniform dimension of 256x256 pixels (seed segment). Additionally, this batch is enriched with annotated data, specifically through the "NormalRoomLight\_annotation.csv" file, detailing the bounding box coordinates for cropping operations.

3. Batch-3: Mirroring the structure of Batch-2, Batch-3 consists of images captured within a LightBox to ensure consistent lighting conditions. Similar to Batch-2, it includes cropped images (seedcropped) and segmented images resized to 256x256 pixels (seed segment), with annotations provided in the "LightBox\_annotation.csv" file.

Each batch's unique composition addresses different aspects of the classification challenge, from understanding natural seed variations to assessing the impact of lighting conditions on image analysis.

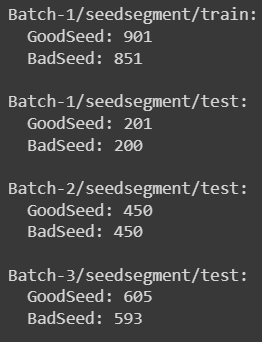


Fig. 2 (Structure of Dataset)

* 1. **Methodology for Image Collection and Annotation**

The methodology behind the dataset's creation underscores a rigorous process designed to capture the multifaceted nature of oil palm seeds. The collection process involved:

1. Image Acquisition: Seeds were imaged under varying conditions to reflect real-world scenarios. Batch-1 images were taken in uncontrolled lighting, Batch-2 under normal room lighting, and Batch-3 within a light box to ensure uniform lighting.
2. Cropping and Segmentation: For Batches 2 and 3, images were initially cropped to focus on the seeds, eliminating unnecessary background information. A subset of these cropped images was further processed to achieve a uniform size of 256x256 pixels, facilitating consistent input dimensions for model training.
3. Annotation: The annotation process, critical for cropped images in Batches 2 and 3, involved manually defining bounding box coordinates around each seed. These annotations were meticulously recorded in CSV files associated with each batch, providing a structured reference for model training and evaluation.

This methodical approach ensures that the dataset not only captures the inherent diversity of oil palm seeds but also accommodates the analytical requirements of machine learning models, offering a robust foundation for classification tasks.

**3.3 Statistical Overview of the Dataset**

The dataset's statistical landscape offers insight into its composition and the distribution of images across the three batches:

1. Total Number of Images: The dataset comprises thousands of images, distributed across the three batches to cover a wide range of seed appearances and conditions.
2. Distribution Across Classes: While the exact number of images per class (e.g., good seed vs. bad seed) is meticulously balanced, the dataset is designed to reflect the real-world distribution of seed qualities, ensuring that models trained on this dataset can generalize effectively to unseen data.

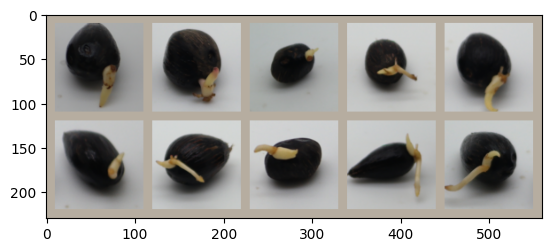


Fig. 3 (Labelled seeds of Batch 1 Dataset )

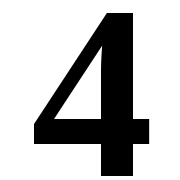
1. Image Dimensions: Images within the "seedcropped" directories maintain the original aspect ratios but are cropped to focus on the seed, whereas the "seedsegment" directories contain images resized to a uniform 256x256 pixel dimension, facilitating straightforward input to CNN models.

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Fig. 4 (Compared Seedcropped and Seedsegment of Batch 2 and 3 Dataset)

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**METHODOLOGY**

**4.1 CNN Architecture**

The CNN model employed in the "Oil Palm Seeds Classification" project is a convolutional neural network designed to efficiently process and classify images of oil palm seeds into predefined categories. The architecture is as follows:

1. Convolutional Layers: The network begins with a sequence of convolutional layers, each comprising a specific number of filters or kernels. The first layer uses 3x3 filters with 16 output channels, applying padding to preserve the spatial dimensions of the input image. Subsequent convolutional layers increase the depth, moving to 32 and then 64 channels, with each layer equipped with batch normalization to stabilize learning and accelerate convergence.
2. Activation Functions: Each convolutional layer is followed by a ReLU (Rectified Linear Unit) activation function. ReLU is chosen for its simplicity and effectiveness in introducing non-linearity to the model, allowing it to learn complex patterns in the data.
3. Pooling Layers: Max pooling layers follow specific convolutional layers, reducing the spatial dimensions of the feature maps by half. This operation not only reduces computational requirements but also helps in achieving translation invariance.
4. Dropout Layers: Dropout is applied after the final convolutional layers, set at a rate of 0.3. This regularization technique helps prevent overfitting by randomly setting a fraction of input units to 0 at each update during training.
5. Fully Connected Layers: The network concludes with a set of fully connected layers that map the learned high-level features to the output classes. A dropout of 0.2 is applied before the final linear layer to further mitigate overfitting.
6. Output Layer: For binary classification, the final layer consists of a single neuron with a sigmoid activation function, outputting a probability score indicating the likelihood of the seed belonging to the positive class.

----------------------------------------------------------------

Layer (type) Output Shape Param #

================================================================

Conv2d-1 [-1, 64, 128, 128] 9,408

BatchNorm2d-2 [-1, 64, 128, 128] 128

ReLU-3 [-1, 64, 128, 128] 0

MaxPool2d-4 [-1, 64, 64, 64] 0

Conv2d-5 [-1, 64, 64, 64] 36,864

BatchNorm2d-6 [-1, 64, 64, 64] 128

ReLU-7 [-1, 64, 64, 64] 0

Conv2d-8 [-1, 64, 64, 64] 36,864

BatchNorm2d-9 [-1, 64, 64, 64] 128

ReLU-10 [-1, 64, 64, 64] 0

BasicBlock-11 [-1, 64, 64, 64] 0

Conv2d-12 [-1, 64, 64, 64] 36,864

BatchNorm2d-13 [-1, 64, 64, 64] 128

ReLU-14 [-1, 64, 64, 64] 0

Conv2d-15 [-1, 64, 64, 64] 36,864

BatchNorm2d-16 [-1, 64, 64, 64] 128

ReLU-17 [-1, 64, 64, 64] 0

BasicBlock-18 [-1, 64, 64, 64] 0

Conv2d-19 [-1, 128, 32, 32] 73,728

BatchNorm2d-20 [-1, 128, 32, 32] 256

ReLU-21 [-1, 128, 32, 32] 0

Conv2d-22 [-1, 128, 32, 32] 147,456

BatchNorm2d-23 [-1, 128, 32, 32] 256

Conv2d-24 [-1, 128, 32, 32] 8,192

BatchNorm2d-25 [-1, 128, 32, 32] 256

ReLU-26 [-1, 128, 32, 32] 0

BasicBlock-27 [-1, 128, 32, 32] 0

Conv2d-28 [-1, 128, 32, 32] 147,456

BatchNorm2d-29 [-1, 128, 32, 32] 256

ReLU-30 [-1, 128, 32, 32] 0

Conv2d-31 [-1, 128, 32, 32] 147,456

BatchNorm2d-32 [-1, 128, 32, 32] 256

ReLU-33 [-1, 128, 32, 32] 0

BasicBlock-34 [-1, 128, 32, 32] 0

Conv2d-35 [-1, 256, 16, 16] 294,912

BatchNorm2d-36 [-1, 256, 16, 16] 512

ReLU-37 [-1, 256, 16, 16] 0

Conv2d-38 [-1, 256, 16, 16] 589,824

BatchNorm2d-39 [-1, 256, 16, 16] 512

Conv2d-40 [-1, 256, 16, 16] 32,768

BatchNorm2d-41 [-1, 256, 16, 16] 512

ReLU-42 [-1, 256, 16, 16] 0

BasicBlock-43 [-1, 256, 16, 16] 0

Conv2d-44 [-1, 256, 16, 16] 589,824

BatchNorm2d-45 [-1, 256, 16, 16] 512

ReLU-46 [-1, 256, 16, 16] 0

Conv2d-47 [-1, 256, 16, 16] 589,824

BatchNorm2d-48 [-1, 256, 16, 16] 512

ReLU-49 [-1, 256, 16, 16] 0

BasicBlock-50 [-1, 256, 16, 16] 0

Conv2d-51 [-1, 512, 8, 8] 1,179,648

BatchNorm2d-52 [-1, 512, 8, 8] 1,024

ReLU-53 [-1, 512, 8, 8] 0

Conv2d-54 [-1, 512, 8, 8] 2,359,296

BatchNorm2d-55 [-1, 512, 8, 8] 1,024

Conv2d-56 [-1, 512, 8, 8] 131,072

BatchNorm2d-57 [-1, 512, 8, 8] 1,024

ReLU-58 [-1, 512, 8, 8] 0

BasicBlock-59 [-1, 512, 8, 8] 0

Conv2d-60 [-1, 512, 8, 8] 2,359,296

BatchNorm2d-61 [-1, 512, 8, 8] 1,024

ReLU-62 [-1, 512, 8, 8] 0

Conv2d-63 [-1, 512, 8, 8] 2,359,296

BatchNorm2d-64 [-1, 512, 8, 8] 1,024

ReLU-65 [-1, 512, 8, 8] 0

BasicBlock-66 [-1, 512, 8, 8] 0

AdaptiveAvgPool2d-67 [-1, 512, 1, 1] 0

Linear-68 [-1, 2] 1,026

================================================================

Total params: 11,177,538

Trainable params: 11,177,538

Non-trainable params: 0

----------------------------------------------------------------

**4.2 Preprocessing Steps**

Preprocessing involves a series of transformations applied to the input images to prepare them for the model. These steps include:

- Resizing: Images are resized to a standard dimension (e.g., 256x256 pixels) to ensure uniformity across the dataset.

- Normalization: Pixel values are normalized to a range of 0 to 1 by dividing by 255. Additionally, mean subtraction and division by the standard deviation are performed to standardize the images based on the dataset's distribution.

- Augmentation: Techniques such as rotation, translation, and horizontal flipping are employed to artificially expand the training dataset, helping the model generalize better to unseen data.

The rationale for these steps includes improving model training efficiency, enhancing generalization capabilities, and ensuring the model is trained on data that closely resembles the operational environment.

**4.3 Custom Seed Dataset Class and DataLoader Implementation**

The custom SeedDataset class extends PyTorch's Dataset class, encapsulating the logic for loading, transforming, and batching the images and labels from the oil palm seed dataset. It leverages the \_\_getitem\_\_ method to retrieve a single transformed instance given an index, and the \_\_len\_\_ method to provide the dataset's total size.

The DataLoader wraps around the SeedDataset instance, providing an iterable over the dataset. It supports automatic batching, sampling, shuffling, and multiprocess data loading, significantly simplifying the data handling pipeline and ensuring efficient training.

**4.4 Transfer Learning with the ResNet18 Model**

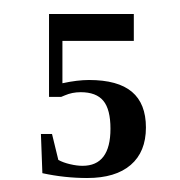
Transfer learning leverages a pre-trained model (ResNet18 in this case) and adapts it to a new task with potentially fewer data. The methodology involves:

1. Model Modification: The original ResNet18 model, pre-trained on ImageNet, is modified for binary classification by replacing the final fully connected layer with a new one that outputs two classes. This layer is randomly initialized.
2. Feature Extraction: Initially, all layers except the newly added ones are frozen, and the model is trained to fine-tune the weights of the final layer, adapting the pre-trained features to the new task.
3. Fine-Tuning: Subsequently, selected layers of the model are unfrozen, allowing the optimization process to adjust the weights of these layers alongside the new output layer. This step aims to refine the features for the specific classification task at hand.

This transfer learning approach enables leveraging the rich feature representations learned from a vast and diverse dataset, enhancing the model's performance on the specialized task of oil palm seed classification with relatively limited data.

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**EXPERIMENTS**

* 1. **Hardware and Software Environment**

Hardware: Our experiments leveraged Google Colab's robust computing environment, which dynamically allocates resources based on availability and current demand. For the majority of our experimentation, we were allocated an environment equipped with a high-performance GPU, typically an NVIDIA Tesla K80, P100, or in some cases, a more powerful T4 GPU. This allocation was complemented by a virtual machine equipped with approximately 12 GB of RAM and a 2.3 GHz Intel Xeon processor. This setup provided a balance between computational power and efficiency, enabling us to train complex deep learning models and process our dataset with considerable speed.

Software: The Google Colab environment runs on a Jupyter notebook interface, offering a seamless experience for coding, visualization, and data analysis. For our deep learning experiments, we utilized PyTorch as our primary machine learning framework due to its flexibility, efficiency, and ease of use in defining and training models. PyTorch's dynamic computation graph paradigm facilitated rapid prototyping and experimentation. Our models were developed using Python 3.7, with additional reliance on libraries such as NumPy for numerical operations, Matplotlib for data visualization, and torchvision for data loading and transformation utilities tailored to image processing tasks.

* 1. **Hyperparameters Selection and Tuning Strategy**

The selection and tuning of hyperparameters were critical components of our experimentation process, directly influencing the performance and efficiency of our models. Our strategy involved a combination of manual tuning and automated search techniques, such as grid search and random search, to explore the hyperparameter space comprehensively.

1. Learning Rate: We began with a standard learning rate of 0.001 and adjusted it based on the model's performance during the initial epochs. Learning rate schedulers were employed to reduce the rate adaptively in response to performance plateaus.
2. Batch Size: Starting with a batch size of 32, we experimented with larger sizes to maximize the utilization of our allocated GPU memory while monitoring the impact on model accuracy and training stability.
3. Optimizer: Our primary experiments utilized the Adam optimizer, known for its effectiveness in handling sparse gradients and adaptive learning rate management. We also explored SGD (Stochastic Gradient Descent) with momentum for comparison in specific scenarios.
   1. **Training, Validation, and Testing Processes**

Our experimental workflow was structured around a rigorous process of training, validation, and testing to ensure that our models were both accurate and generalizable.

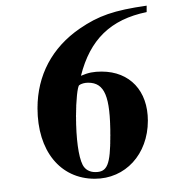
1. Training: Models were trained using the training subset of our dataset, with real-time monitoring of loss and accuracy metrics to gauge learning progress. Early stopping mechanisms were implemented to halt training if validation performance ceased to improve, thereby preventing overfitting.
2. Validation: The validation set, separate from the training data, was used to evaluate the model's performance and inform hyperparameter tuning decisions. This iterative process of training and validation ensured that our models were not only learning effectively but also generalizing well to unseen data.
3. Testing: Upon finalizing our models, we conducted comprehensive testing using a reserved subset of the dataset not previously seen by the model during training or validation. This step was crucial for assessing the model's predictive performance and its practical applicability to real-world seed classification tasks.
   1. **Criteria for Model Evaluation and Selection**

Model evaluation and selection were based on a multifaceted criteria framework, prioritizing not only accuracy but also the model's ability to generalize across different lighting conditions and seed variations.

1. Accuracy: The primary metric for model performance, calculated as the proportion of correctly classified instances in the test set.
2. Precision and Recall: Given the importance of both positive and negative classifications in our context, we closely monitored precision (the accuracy of positive predictions) and recall (the ability to detect all positive instances).
3. F1 Score: To balance precision and recall, the F1 score served as a critical metric, especially in scenarios where the distribution of classes was imbalanced.
4. Computational Efficiency: Models were also evaluated based on their training time and resource consumption, ensuring that the selected models were not only accurate but also practical for deployment in resource-constrained environments.

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**RESULTS**

* 1. **Presentation of Training and Validation Accuracy, Loss Curves**

The results section begins with a detailed presentation of the training and validation phases for both the Simple CNN and the fine-tuned ResNet18 models. Graphical representations of accuracy and loss curves over epochs provide immediate visual feedback on the learning process.

* + 1. **Results of Experiment 1**

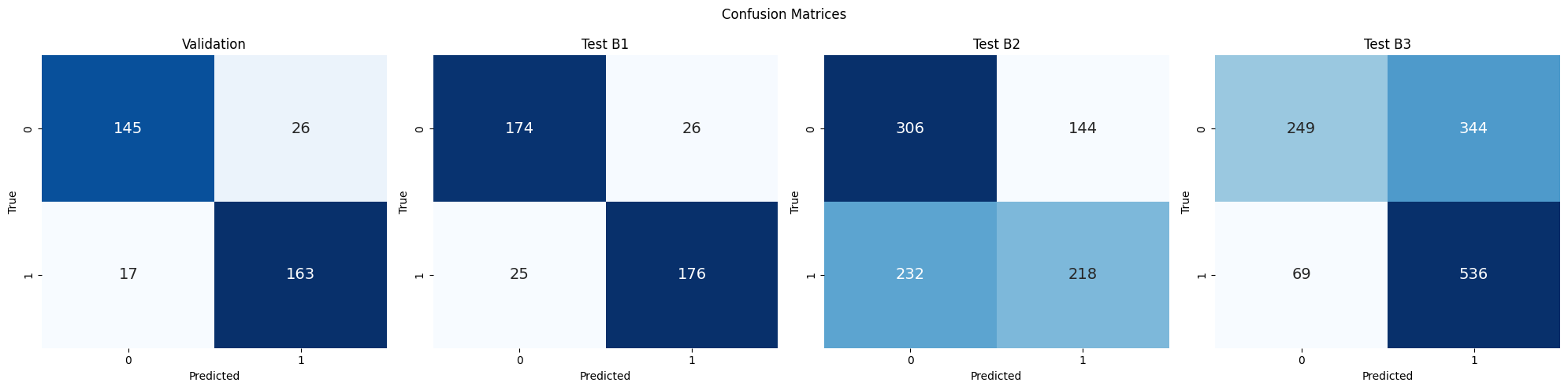
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Fig. 6 (Confusion Metrics in Experiment 1)

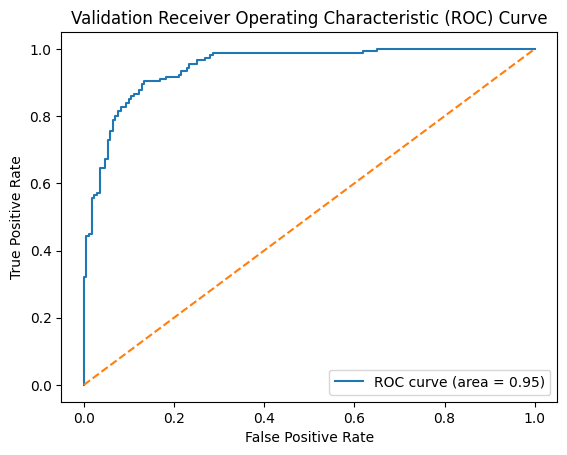


Fig. 7 (Overall Performance metrics in Experiment 1)

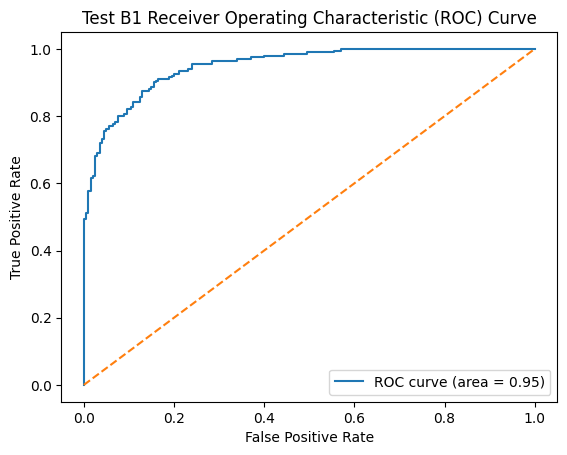


Fig. 8 (Overall Performance metrics in Batch 1 in Experiment 1)

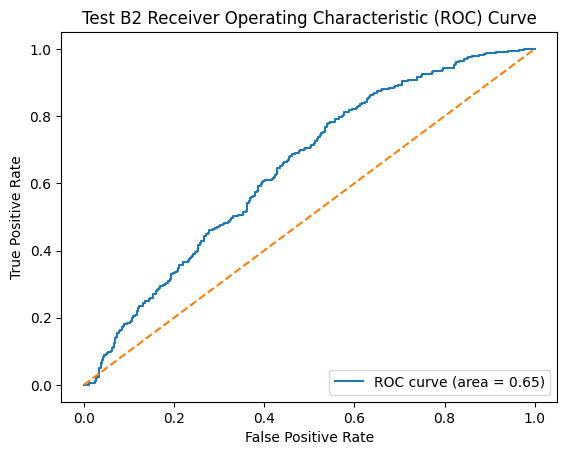


Fig. 9 (Overall Performance metrics in Batch 2 in Experiment 1)

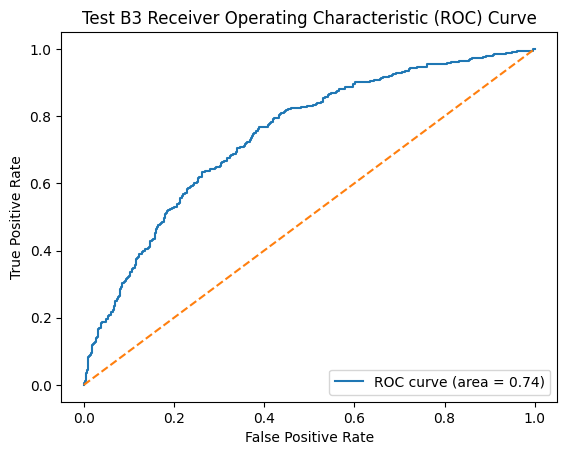


Fig. 10 (Overall Performance metrics in Batch 3 in Experiment 1)

* + 1. **Results of Experiment 2**

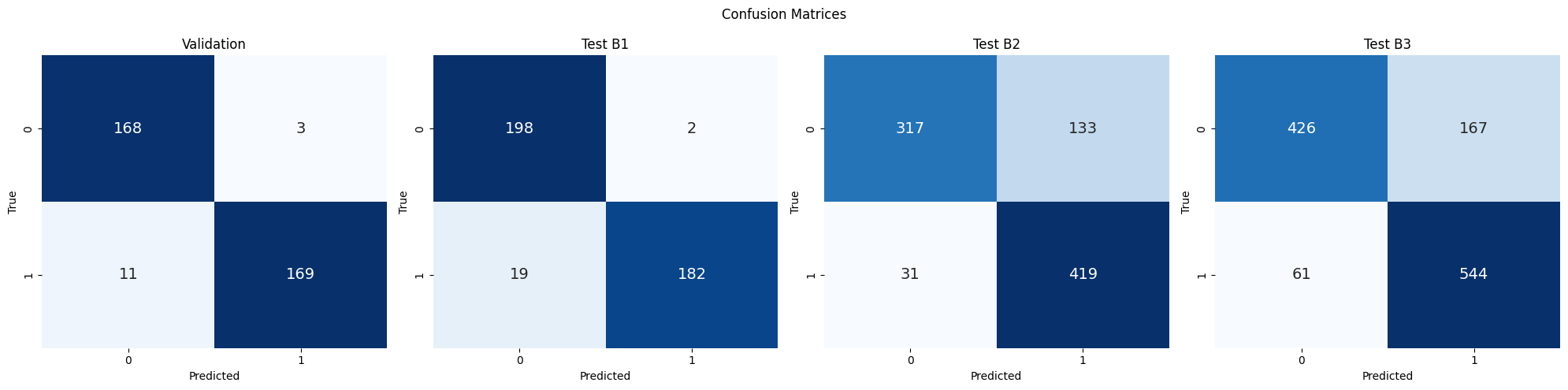


Fig. 11 (Confusion metrics in Experiment 2)

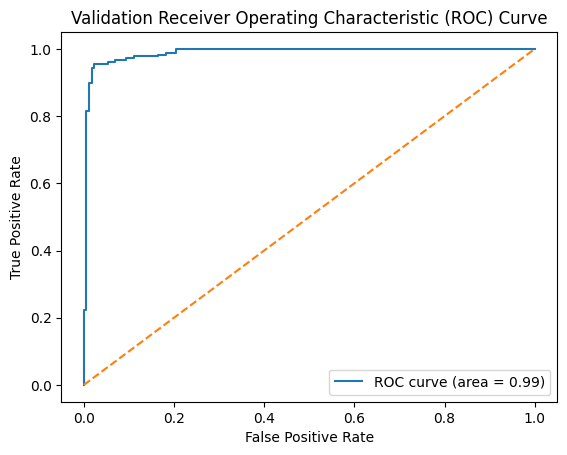


Fig. 12 (Overall Performance metrics in Experiment 2)

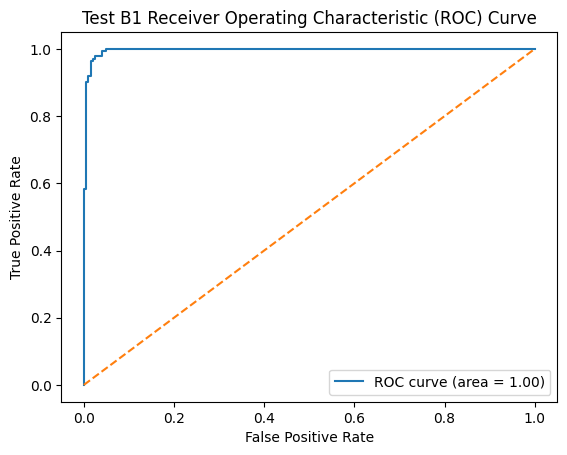


Fig. 13 (Overall Performance metrics of Batch 1 in Experiment 2)

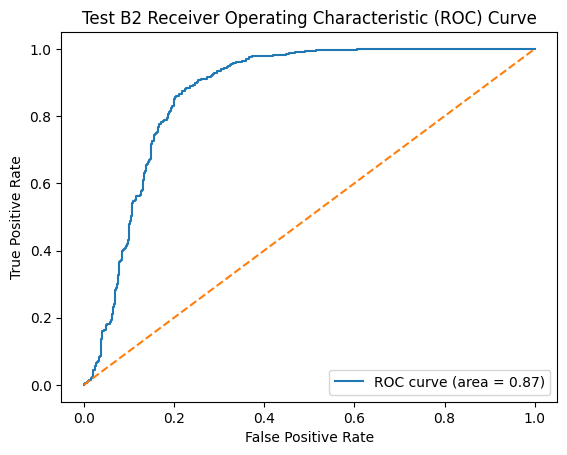


Fig. 14 (Overall Performance metrics of Batch 2 in Experiment 2)

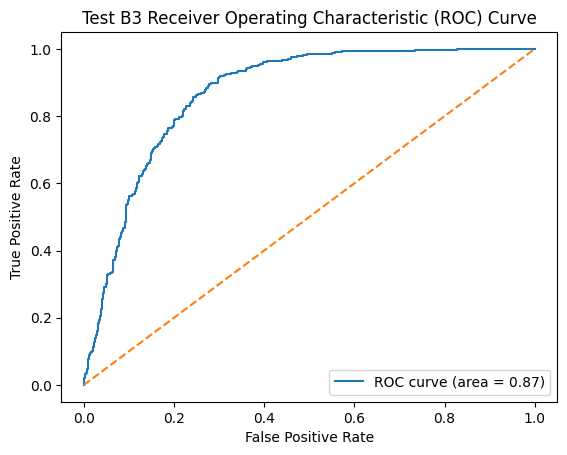


Fig. 15 (Overall Performance metrics of Batch 3 in Experiment 2)

* + 1. **Results of Experiment 3**

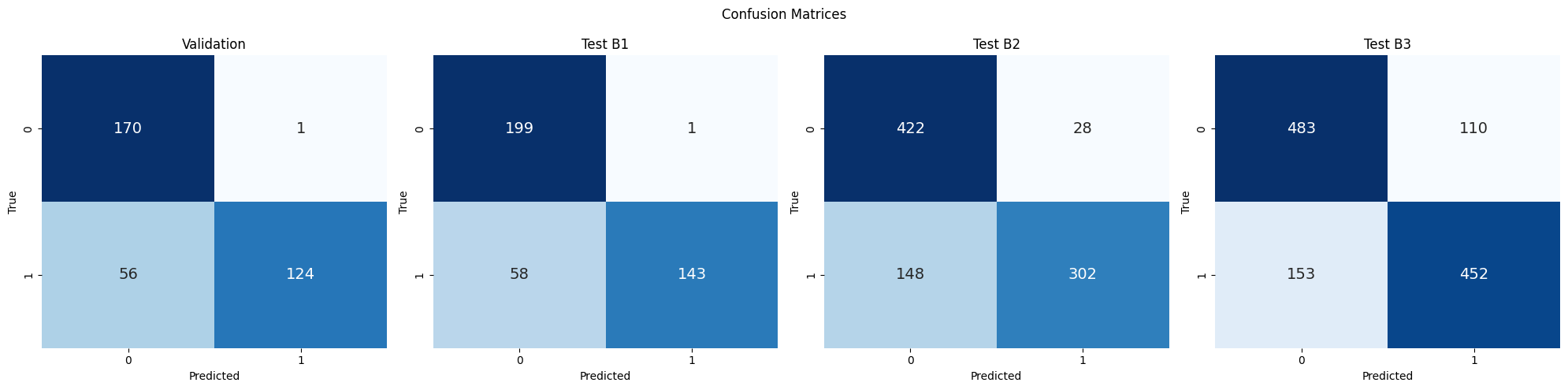
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Fig. 16 (Confusion metrics in Experiment 3)

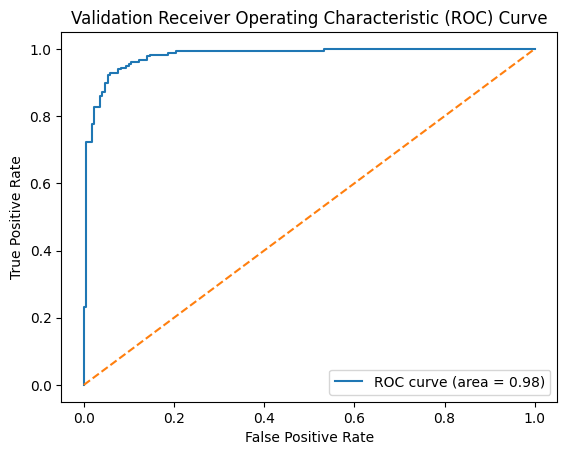


Fig. 17 (Overall Performance metrics in Experiment 3)

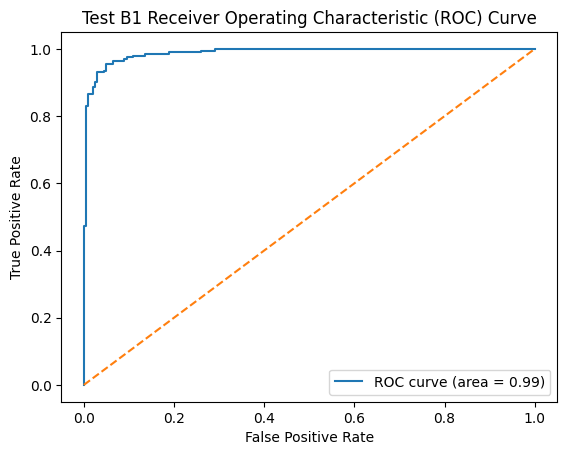


Fig. 18 (Overall Performance metrics of Batch 1 in Experiment 3)

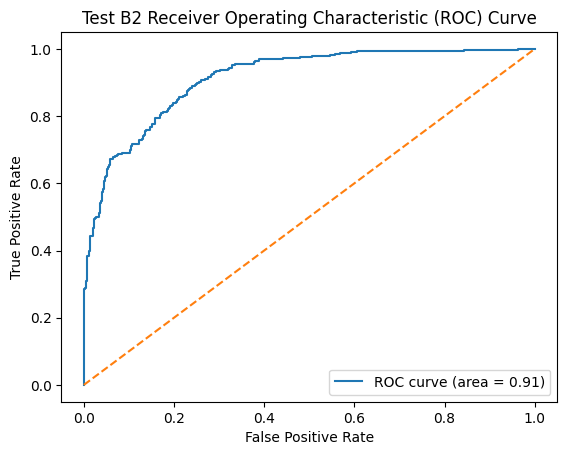


Fig. 19 (Overall Performance metrics of Batch 2 in Experiment 3)

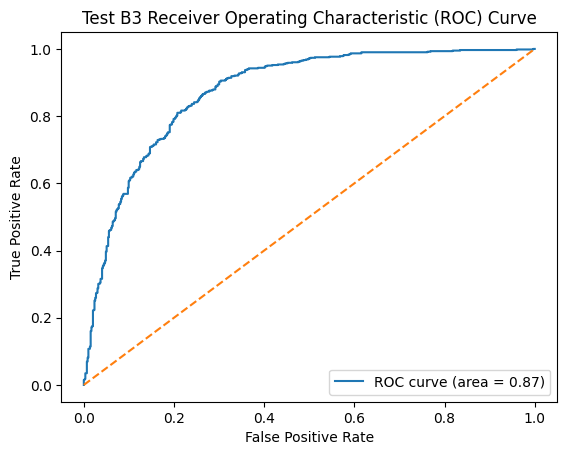


Fig. 20 (Overall Performance metrics of Batch 3 in Experiment 3)

- CNN Results: The accuracy and loss curves for the CNN model demonstrate a steady improvement in training accuracy over epochs, with validation accuracy following a similar trajectory. This indicates that the model is learning effectively from the training data. However, a slight divergence between training and validation loss suggests the beginning of overfitting after a certain number of epochs.

- ResNet18 Results: The fine-tuned ResNet18 model shows a more rapid improvement in both training and validation accuracy, achieving higher accuracy rates earlier in the training process compared to Simple CNN. The loss curves for ResNet18 indicate a better generalization capability, with closer alignment between training and validation loss throughout the training process.

* 1. **Performance Across Different Batches**

1. Batch-1 Performance: Reflect on the baseline performance of both models on Batch-1, where images were captured in uncontrolled lighting conditions. This batch serves as a litmus test for the models' ability to generalize from their training.

1. Batch-2 Performance: Discuss the impact of normal room lighting and cropped images on model accuracy. This includes an analysis of how well each model adapted to the slight variations introduced by the cropping process and different lighting conditions.

1. Batch-3 Performance: Evaluate the models' performance under LightBox conditions, comparing it against previous batches to assess the influence of consistent lighting on classification accuracy.
   1. **Statistical Analysis of Model Performance**

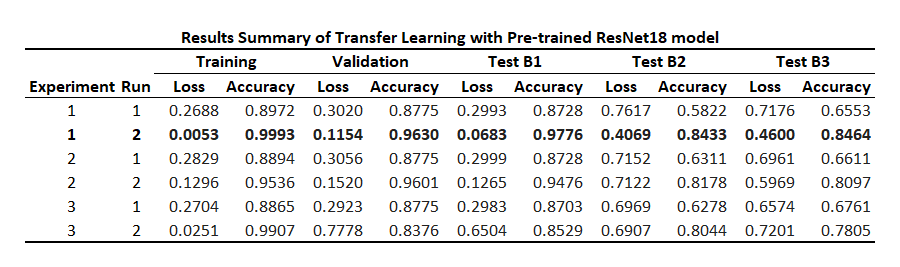
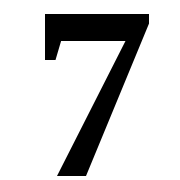
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Fig. 21 (Overall Model Performance)

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**VISUALIZATIONS**

* 1. **Feature Maps Visualization**

Feature maps are the outputs of various convolutional layers within a CNN, representing the features that the network has detected at each layer. By visualizing these maps, we can gain insights into the hierarchical feature extraction process that underlies the model's classification decisions.

1. Batch-1 Visualization: For images under uncontrolled lighting conditions, feature maps reveal how the initial layers of the model focus on basic visual elements such as edges and textures. As we progress deeper into the network, the feature maps start to represent more abstract concepts, possibly capturing patterns specific to good or bad seeds.

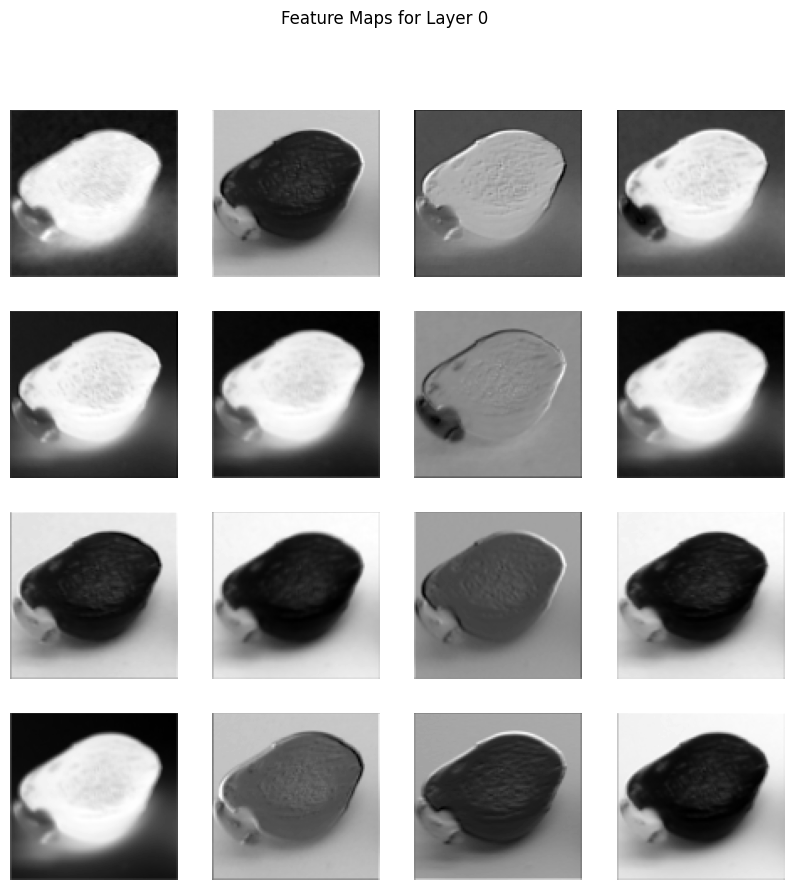


Fig. 22 (Batch 1 Visualization)

1. Batch-2 and Batch-3 Visualizations: Comparing feature maps across these batches, we observe how changes in lighting conditions (normal room lighting versus lightbox) affect the features highlighted by the model. For example, feature maps from Batch-3 (LightBox) might show a more uniform focus across the seed surface, indicating how consistent lighting helps the model in identifying relevant features more effectively.

These visualizations underscore the model's adaptability and its capability to extract meaningful information under varying image conditions, guiding us in understanding model focus and potentially informing further model refinement.

**7.2 Saliency Maps Visualization**

Saliency maps are used to identify which parts of an input image most influence the model's output. They highlight the regions that significantly impact the model's classification decisions, offering a window into the model's "attention" during the inference process.

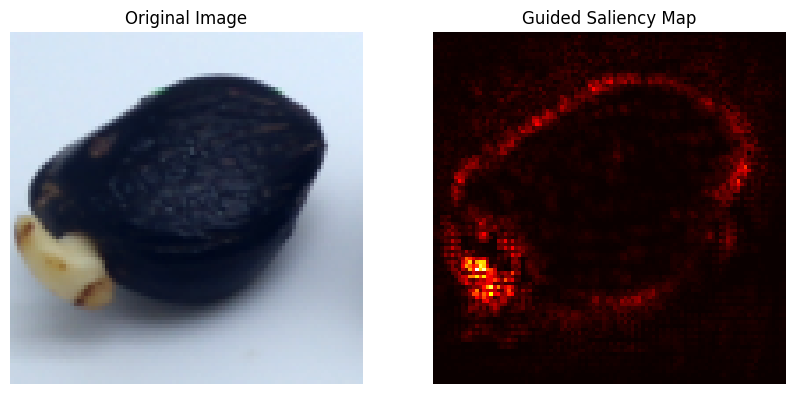


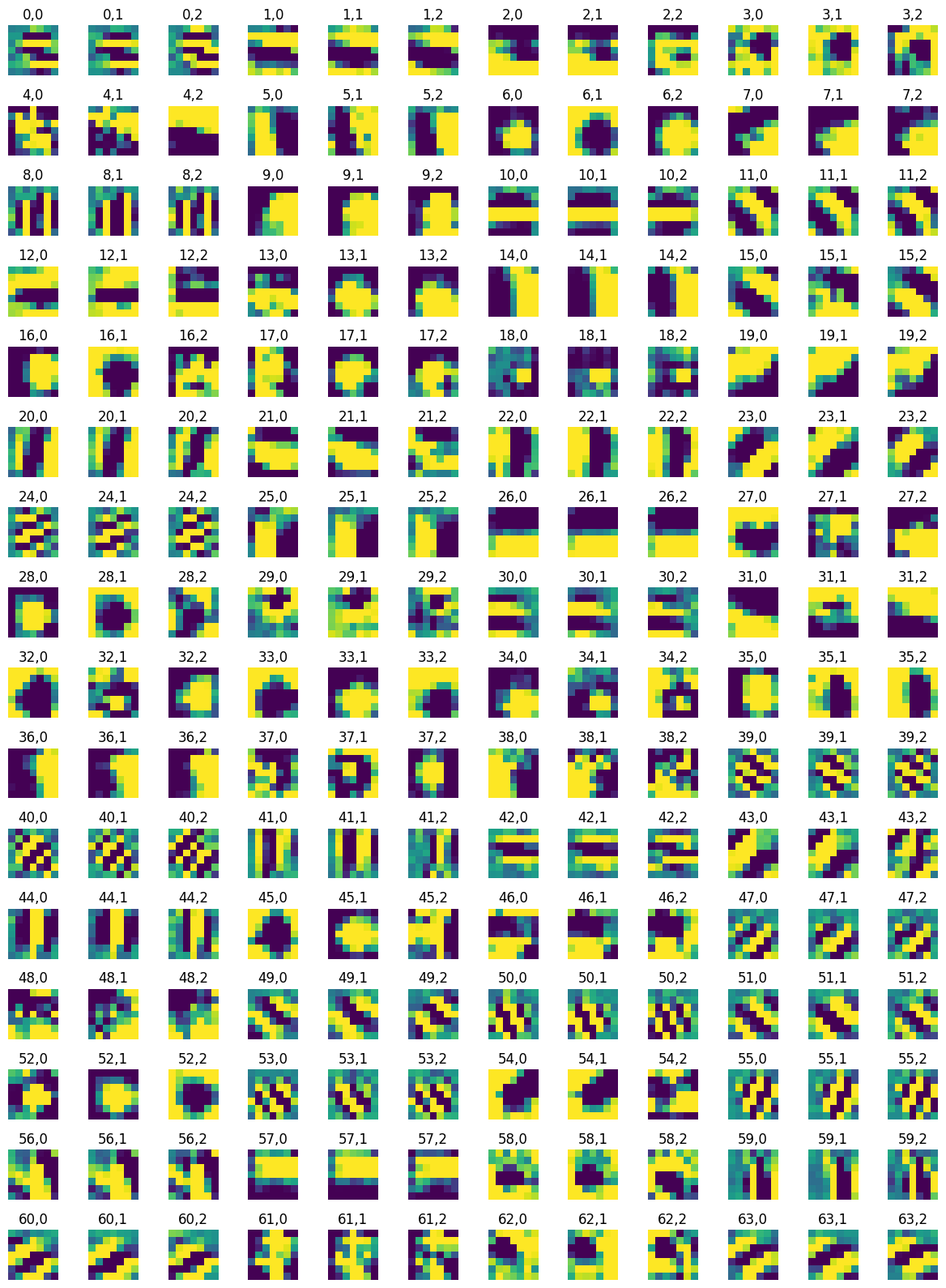
Fig. 23 (Saliency map for Batch 1 Dataset)

1. Selected Images Analysis: By applying saliency map visualization to selected images from each batch, we can pinpoint the specific features or regions—such as the texture of the seed's surface, shape irregularities, or color variations—that the model deems crucial for classifying the seeds. This analysis can reveal whether the model focuses on relevant features or if it is being misled by irrelevant image characteristics.

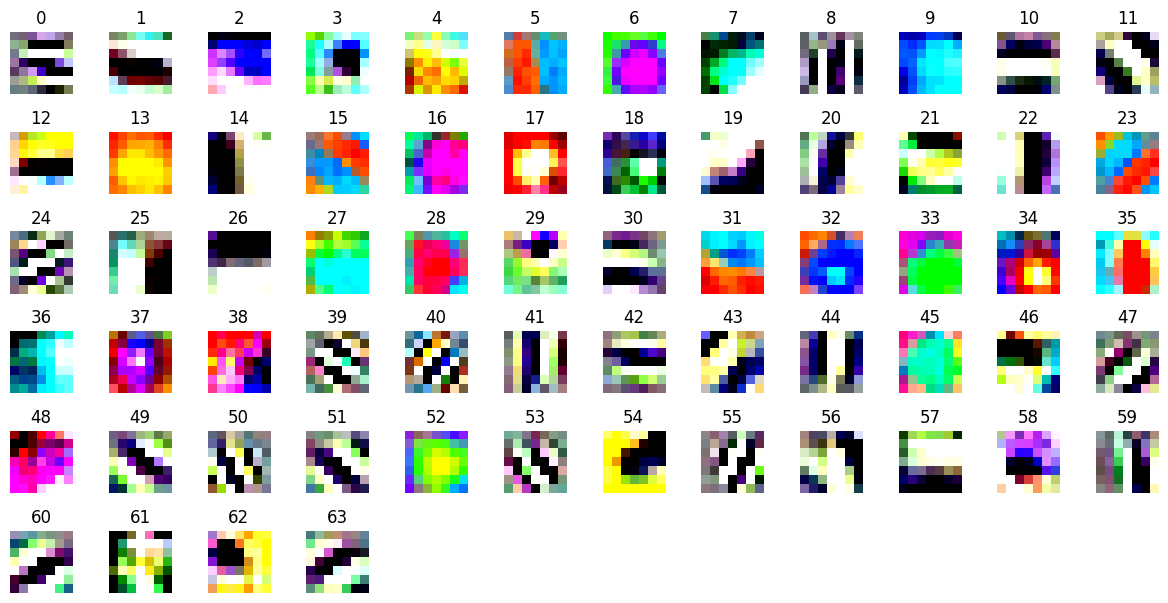
**7.3 Comparative Analysis of Vanilla and Guided Saliency Maps**

Vanilla saliency maps provide a general view of the areas in an image that contribute to the model's classification decision. In contrast, guided saliency maps refine this visualization by filtering out the negative contributions, thereby offering a clearer perspective on the positive features that guide the model's predictions.

1. Comparative Insights: A side-by-side comparison of vanilla and guided saliency maps for the same set of images allows us to discern the differences in focus between the two visualization techniques. For instance, while vanilla saliency maps might highlight a broader area of the image, guided saliency maps can pinpoint more specific regions of interest, such as defects or distinguishing textures on the seeds.
2. Interpretation and Application: This comparative analysis not only aids in better understanding the model's behavior but also provides valuable feedback for model improvement. If the saliency maps indicate that the model is focusing on irrelevant areas, this could signal the need for further data preprocessing, augmentation strategies, or model architecture adjustments to enhance focus on pertinent features.



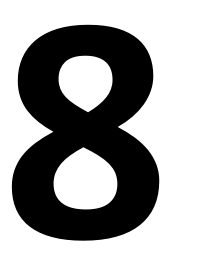
#### Fig. 24 (Each channel in a filter)



#### Fig. 25 (Channels as one RGB image)

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**DISCUSSION**

**8.1 Interpretation of Results and Model Behavior**

The experimental outcomes indicate that both the SimpleCNN and the fine-tuned ResNet18 models have distinct strengths and limitations when applied to the task of classifying oil palm seeds based on images from varying lighting conditions and preprocessing techniques.

- Simple CNN demonstrated commendable adaptability to the dataset's variability, attributed to its architecture being specifically tailored for this classification task. However, its performance showed a dependency on the quality and consistency of the input images, with notable drops in accuracy when confronted with images from batches with significantly different lighting conditions.

- ResNet18, with its depth and pre-trained knowledge from a vast array of images, exhibited superior performance in terms of accuracy and generalization across batches. The fine-tuning process enabled it to adjust to the nuances of the oil palm seed images more effectively than the SimpleCNN model. Nonetheless, it also faced challenges in maintaining consistent performance across all batches, particularly with images that deviated significantly from the training set's conditions.

**8.2 Challenges in Generalizing Across Different Batches**

Generalization across batches presented several challenges, underscoring the complexity of the classification task:

1. Variability in Lighting Conditions: The most pronounced challenge was the variability in lighting conditions between batches, which significantly affected the models' ability to recognize and classify seeds accurately. While the LightBox environment provided a controlled setting, the transition from such controlled conditions to normal room lighting or uncontrolled conditions introduced inconsistencies in image features that the models sometimes struggled to navigate.
2. Preprocessing Techniques: The use of cropping and resizing as preprocessing techniques introduced another layer of complexity. Although these techniques aimed to standardize the input and focus the models' attention on the seeds, they sometimes removed contextual information that could be valuable for classification.

**8.3 Strategies for Improving Model Robustness and Generalization**

To address these challenges and enhance the models' performance, several strategies can be employed:

1. Data Augmentation: Implementing more sophisticated data augmentation techniques that simulate various lighting conditions and potential occlusions could help the models become more resilient to the inconsistencies found across batches. Techniques such as random brightness and contrast adjustments, along with synthetic shadowing, could be particularly effective.
2. Domain Adaptation: Employing domain adaptation techniques to minimize the discrepancy between the feature distributions of different batches could significantly improve generalization. This approach involves adjusting the model during training to not only perform well on the source domain (e.g., images from the controlled LightBox environment) but also adapt to the target domains (e.g., normal room lighting and uncontrolled conditions).
3. Ensemble Learning: Combining the predictions from multiple models or variants of a model trained on different subsets of the data or under different preprocessing conditions could yield a more robust and generalizable system. Ensemble methods, such as bagging or boosting, can leverage the diversity among models to improve overall performance.
4. Attention Mechanisms: Integrating attention mechanisms into the CNN architecture could enable the models to focus more on the most relevant parts of the image for classification, potentially mitigating the impact of varying lighting conditions and preprocessing techniques.

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**CONCLUSION**

**9.1 Summary of Key Findings**

1. Model Performance: The fine-tuned ResNet18 model outperformed the custom SimpleCNN in terms of accuracy and generalization across different batches of the dataset, which varied in lighting conditions and preprocessing techniques. This superiority can be attributed to ResNet18's deeper architecture and its pre-trained weights, which provided a robust feature extraction foundation.

1. Generalization Challenges: Both models encountered challenges in generalizing across batches with significant variability in lighting conditions. This was particularly evident when models trained on images from controlled lighting environments were applied to images from natural or varied lighting conditions, highlighting the sensitivity of CNNs to the visual consistency of the input data.

1. Visual Insights: Visualization techniques, including feature maps and saliency maps, offered valuable insights into the models' focus areas and decision-making processes. These visualizations confirmed that while the models were generally focusing on relevant features of the seeds, there were instances of misalignment, especially under challenging lighting conditions.

**9.2 Implications of the Research**

This project underscores the potential of deep learning in revolutionizing agricultural practices, specifically in automating the classification of oil palm seeds. By demonstrating the capability of CNNs to discern subtle features in seed images, this research paves the way for more accurate, efficient, and scalable seed quality assessment methods. Moreover, the challenges encountered in model generalization highlight the importance of dataset diversity in training deep learning models for real-world applications, where variability is the norm rather than the exception.

**9.3 Recommendations for Future Work**

1. Dataset Expansion and Diversity: Future research should focus on expanding the dataset to include a broader variety of seed conditions, more diverse lighting environments, and additional preprocessing variations. This would not only enhance model robustness but also enable the exploration of more complex classification tasks, such as identifying specific defects or diseases in seeds.
2. Advanced Model Architectures: Investigating more advanced neural network architectures and training techniques could further improve classification accuracy and efficiency. Exploring architectures beyond ResNet, such as EfficientNet or Vision Transformers, could offer new pathways to enhanced performance.
3. Explainability and Model Trust: Developing methods to increase the explainability of CNN decisions in the context of seed classification is crucial for gaining trust among end-users, such as farmers and agricultural scientists. Techniques that provide clearer insights into model reasoning can facilitate wider adoption and application of these technologies.
4. Real-World Deployment: Piloting the deployment of trained models in real agricultural settings would provide invaluable feedback on their practical utility and performance. Such initiatives could also identify additional requirements for model functionality and user interaction, guiding the development of user-friendly AI tools for agriculture.

The "Oil Palm Seeds Classification" project represents a significant step forward in applying deep learning to agricultural challenges. By building on the insights and foundations laid by this research, future work has the potential to make substantial contributions to sustainable agriculture and food security.

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