Transfer Learning on EuroSat Dataset

(CA550 Small Industrial Training)

A Report

Submitted in partial fulfilment of the requirements for the award of the Degree of

Master of Computer Application

By

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APPROVAL OF THE GUIDE

I recommended that the MCA Minor Project titled **Transfer Learning on EuroSat Dataset** submitted by **Dibyanshu Kiro (MCA/10028/22)** is approved by me for submission. This should be accepted as fulfilling the partial requirements for theaward of Degree of Master of Computer Application. To the best ofmy knowledge, the report represents work carried out by the student in **Birla Institute of Technology, Mesra** and the content of this report is not form a basis forthe award of any previous degree to anyone else.

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ABSTRACT

This project delves into the realm of transfer learning by leveraging the EfficientNetB1 model in conjunction with the EuroSAT dataset, encompassing satellite imagery across ten distinct classes. Employing subsets of the EuroSAT dataset, each comprising 60, 70, 80, and 90 images per class, aggregating to a total of 3000 images, our primary aim was to scrutinize the model's performance across varying dataset sizes. To achieve comparable accuracy with both smaller and larger datasets, an additional dense layer was introduced to the model.

Beyond dataset size considerations, our investigation extended to experiments involving batch normalization, regularization techniques, and the incorporation of supplementary layers within the model architecture. The outcomes of these experiments furnish valuable insights into the efficacy of these methodologies in enhancing overall model performance.

This research contributes to the understanding of transfer learning's adaptability to diverse dataset sizes and sheds light on strategies for optimizing model accuracy, particularly when confronted with limited data resources. The findings presented herein underscore the significance of thoughtful model modifications and offer guidance for practitioners seeking to improve the performance of convolutional neural networks on satellite imagery dataset.

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CHAPTER 1

INTRODUCTION

1.1 PROJECT OVERVIEW

In the quest to harness the power of artificial intelligence for Earth observation, this project presents a comprehensive study on the application of transfer learning using the EfficientNetB1 model, tailored to the EuroSAT dataset. The EuroSAT dataset, a collection of satellite imagery spanning 10 distinct classes, serves as the foundation for this exploration. The dataset's unique composition of varying image quantities per class—60, 70, 80, and 90—totals an impressive 3000 images, offering a rich ground for experimentation.

Table 1.1 Dataset Information

Dataset Size	Images per Class	Total Images
60	60	600
70	70	700
80	80	800
90	90	900

1.2 OBJECTIVES

The primary objective of this research is to dissect the relationship between dataset size and model performance. The study delves into strategies aimed at achieving comparable accuracy with smaller datasets as opposed to larger ones. This endeavor is marked by the innovative addition of an extra dense layer to the EfficientNetB1 model, a modification anticipated to bridge the performance gap.

1.3 SIGNIFICANCE

The significance of this project lies in its potential to provide insights into the optimization of machine learning models for satellite image classification. By experimenting with various techniques such as batch normalization, regularization, and the integration of additional layers, the project sheds light on the effectiveness of these methods in enhancing model performance.

1.4 RELEVANCE OF THE STUDY

The relevance of this study is underscored by the burgeoning demand for advanced machine learning techniques in the field of satellite image analysis. As Earth observation becomes increasingly critical for environmental monitoring, disaster response, and urban planning, the need for efficient and accurate image classification models is paramount. This project not only contributes to the scientific community's understanding of transfer learning's impact on model performance but also addresses practical challenges faced by researchers and practitioners in the field. By optimizing the EfficientNetB1 model for the EuroSAT dataset, this research paves the way for more effective utilization of satellite imagery in real-world applications.

1.5 SCOPE AND REPORT

The scope of this report encompasses a detailed examination of the EuroSAT dataset through the lens of the EfficientNetB1 model, augmented by transfer learning techniques. The experiments conducted are not only pivotal in understanding the model's adaptability to different dataset sizes but also instrumental in formulating strategies for efficient model training with limited data.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION TO LITERATURE REVIEW

The literature review is foundational for this research, delving into existing scholarly works aligned with the study's focus. In this project, it critically establishes a theoretical basis for applying transfer learning to the EuroSAT dataset, utilizing the EfficientNetB1 model. Beyond a mere overview, this section provides a nuanced backdrop for the research objectives.

By scrutinizing prior research, the literature review ensures the study contributes significantly to the field, serving as a robust intellectual anchor. This deliberate grounding sets the stage for subsequent exploration and analysis, providing a platform for meaningful conclusions.

As we navigate the literature, it's evident that transfer learning in satellite imagery, especially with EfficientNetB1, is a nuanced and evolving domain. Insights from prior studies shape this project's methodology, focusing on how different dataset sizes impact model performance—critical with diverse subsets of the EuroSAT dataset, ranging from 60 to 90 images per class.

The literature review informs the study and bridges gaps, guiding decision-making. As subsequent chapters unfold, the review's theoretical foundation echoes in methodologies, experiments, and discussions, leading the research to a profound understanding of transfer learning dynamics with the EuroSAT dataset and EfficientNetB1 model.

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2.2 HISTORICAL CONTEXT

In the realm of satellite image analysis, the trajectory of evolution traces back to the groundbreaking milestone of Landsat 1's launch in 1972 during the nascent era of space exploration. This mission marked a transformative chapter, providing humanity with unprecedented perspectives of the Earth's surface. Since then, the field has witnessed a continuum of technological strides, particularly the development of high-resolution imaging and the integration of machine learning techniques.

These technological advancements have redefined the landscape of satellite image analysis, allowing for more nuanced and sophisticated interpretations of the vast troves of satellite data. The fusion of machine learning with satellite imagery has become a catalyst for unlocking deeper insights into the dynamic landscapes of our planet. As researchers harness these innovations, the field continues to expand, pushing the boundaries of our understanding and enabling more intricate analyses of Earth's diverse terrains.

The historical context presented here forms a backdrop for the contemporary exploration in this project, where the application of transfer learning on the EfficientNetB1 model intersects with the rich tapestry of advancements in satellite image analysis. Understanding this historical journey is paramount for contextualizing the significance of the present research within the broader evolution of the field.

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2.3 TRANSFER LEARNING IN IMAGE CLASSIFICATION

The evolution of transfer learning represents a paradigm shift in image classification, offering a transformative approach, especially in the face of constraints imposed by limited labeled datasets. This methodology, rooted in the extraction of knowledge from pre-trained models, stands as a catalyst for expediting the training process, ultimately resulting in elevated accuracy levels. In the intricate domain of satellite imagery, characterized by its inherent diversity and data complexity, transfer learning emerges as an indispensable tool.

The literature unfolds a rich tapestry, detailing the nuances and successes of transfer learning in the context of image classification. Researchers globally have harnessed this approach, revealing its adaptability and efficacy in addressing the unique challenges posed by satellite imagery. By distilling valuable insights from pre-existing models, transfer learning not only streamlines the training process but also enhances the model's capacity to discern complex patterns within the data.

In satellite image analysis, the application of transfer learning becomes paramount, allowing for the leveraging of knowledge acquired from broader datasets. This proves especially beneficial in scenarios where obtaining large labeled datasets specific to satellite imagery is impractical. The adaptability of transfer learning to the idiosyncrasies of satellite data underscores its significance in bolstering the accuracy and efficiency of image classification models. As this project traverses the landscape of transfer learning applied to the EfficientNetB1 model with the EuroSAT dataset, it stands on the shoulders of the successes and insights gleaned from the broader body of literature in this pivotal domain.

2.4 EFFICIENT MODELS

The EfficientNet architecture stands as a transformative paradigm in the realm of convolutional neural networks (CNNs), introducing a systematic and innovative approach to scaling model dimensions. Encompassing a series of variants from B0 to B7, each tier within the EfficientNet spectrum offers a finely tuned balance between model complexity and performance, providing a versatile toolkit for a diverse array of image classification tasks. This architectural finesse has positioned EfficientNet as a revolutionary force, redefining the landscape of CNN design.

The efficiency and accuracy embedded within the EfficientNet architecture have propelled its widespread adoption across various domains, showcasing particular prominence in the intricate field of satellite image analysis. The literature surrounding EfficientNet meticulously scrutinizes the nuances of these models, unveiling the architectural brilliance that underpins their success and delving into their practical applications.

EfficientNet's systematic scaling approach, which optimizes depth, width, and resolution, caters to the increasing demands of diverse image classification challenges. This not only ensures adaptability to a broad spectrum of tasks but also attests to its efficiency in resource utilization. In the specific context of satellite image analysis, where computational efficiency is crucial, EfficientNet models emerge as a beacon of innovation, offering a sophisticated solution to the complexities inherent in interpreting satellite data.

As this project embarks on the application of transfer learning to the EfficientNetB1 model with the EuroSAT dataset, it leverages the architectural brilliance and proven efficacy of EfficientNet models, as elucidated by the wealth of literature. This chapter sets the stage for an exploration that integrates the cutting-edge advancements encapsulated within EfficientNet architectures, paving the way for insightful contributions to the field of satellite image analysis.

2.5 PREVIOUS STUDIES ON THE EUROSAT

The EuroSAT dataset, a pivotal focus of this research, has been the subject of numerous comprehensive studies, illuminating its versatility and intrinsic value in training models for nuanced land cover classification. Researchers, captivated by the dataset's richness, have embarked on diverse investigations employing a spectrum of methodologies, spanning from traditional machine learning algorithms to state-of-the-art deep learning architectures.

These extensive studies serve as a testament to the EuroSAT dataset's adaptability and significance in the domain of remote sensing. Traditional machine learning approaches have delved into the dataset's intricacies, uncovering patterns and relationships between features that contribute to effective land cover classification. Concurrently, cutting-edge deep learning architectures have pushed the boundaries of what is achievable, leveraging the dataset's complexity to train models capable of discerning subtle and intricate features within the satellite imagery.

Each research endeavor, irrespective of the chosen approach, contributes a unique set of insights, enriching our collective understanding of the EuroSAT dataset's untapped potential and its practical applicability in real-world scenarios. From the delineation of urban areas to the identification of agricultural patterns, these studies collectively form a mosaic of knowledge, expanding the horizons of what can be achieved through the effective utilization of the EuroSAT dataset. As this project assimilates the findings and methodologies from previous studies, it not only builds upon this rich tapestry but also aims to carve new pathways in exploring the dataset's capabilities, particularly in the context of transfer learning with the EfficientNetB1 model.

2.6 IMPACT OF DATASET SIZE ON PERFORMANCE

Exploring how the size of our dataset affects how well our model performs is like peeling back layers of research. Normally, having more data is thought to make our model better, but studies show we can be smart about it. Tricks like making more diverse versions of our data (data augmentation) and learning from already smart models (transfer learning) are like secret weapons. They help our model do well even when we don't have tons of data.

Think of it as a game-changer! The research challenges the idea that having a huge dataset is the only way to success. Instead, it suggests that being clever with a smaller dataset, using tricks like making it more varied and learning from what's already known, can be just as powerful.

As we dive into our project with the EuroSAT dataset and the EfficientNetB1 model, we're not just looking at the amount of data. We're also considering smart tricks from the research that can make a big impact with our limited dataset, helping us understand how our model performs with satellite images.

2.7 TECHNIQUES OF MODEL OPTIMIZATION

In the pursuit of achieving the best possible model performance, a comprehensive exploration of optimization techniques unfolds, with a spotlight on batch normalization, regularization, and the augmentation of model complexity. These techniques stand as pillars in fine-tuning models for heightened efficiency and robustness.

Batch normalization takes center stage by revolutionizing how each layer of the model processes information. By standardizing inputs, it mitigates internal covariate shift, a phenomenon that can hinder the learning process. This not only enhances model stability but also ensures that the model adapts more efficiently during training, contributing to improved overall performance.

Regularization techniques, embodied in L1 and L2 penalties, emerge as crucial guardians against overfitting. While the model learns from data, there's a risk it becomes too tailored to the training set, making it struggle with new, unseen data. L1 and L2 penalties act as wise constraints, preventing the model from becoming overly complex and fostering a more generalizable understanding. This is fundamental for the model to perform well not just on the data it learned from but on new, real-world situations.

The literature further unravels the strategy of augmenting model complexity through the strategic addition of extra layers, such as dense layers. This augmentation empowers models to delve deeper into data intricacies, enhancing their ability to discern and capture complex patterns within the dataset.

As this project integrates these optimization techniques into the methodology, it draws inspiration from the rich insights of the literature. The exploration of these techniques sets the stage for a sophisticated model that not only performs well but is also adaptable and resilient in the face of diverse challenges presented by the EuroSAT dataset and the EfficientNetB1 model.

2.8 SUMMARY

In summary, this literature review has taken us on a journey through the historical development of satellite image analysis, unraveling the revolutionary impact of transfer learning in image classification. It has dissected the architectural brilliance of EfficientNet models and delved into the nuanced relationship between dataset size and model performance. The exploration extended to vital optimization techniques, including batch normalization and regularization, crucial for fine-tuning model accuracy.

These in-depth discussions serve as the cornerstone for the upcoming methodology and experiments, offering a solid and nuanced theoretical foundation for the research undertaken in this project. By blending historical context, cutting-edge methodologies, and optimization insights, this literature review not only sets the stage but also illuminates the path forward, ensuring a robust and informed approach to the exploration of transfer learning with the EuroSAT dataset and the EfficientNetB1 model.

METHODOLOGY

3.1 TRANSFER LEARNING

The methodology employed in this research is structured into four distinct sections, each representing a unique experimental setup aimed at enhancing the model's performance. The primary focus revolves around transfer learning using the EfficientNetB1 model, followed by three subsequent experiments: Adding Extra Dense Layer and Batch Normalization, Adding Extra Dense Layer and Regularization, and Adding Extra Dense Layer without Batch Normalization.

3.1.1 DATA PREPARATION

The process of data preparation involved the meticulous division of the EuroSAT dataset, consisting of satellite images categorized into 10 classes, into subsets. These subsets were strategically designed, encompassing 60, 70, 80, and 90 images per class, respectively. This deliberate partitioning aimed to systematically investigate and gauge the model's adaptability to varying dataset sizes, providing a nuanced understanding of its performance dynamics.

Figure 3.1 Dataset (Classes)

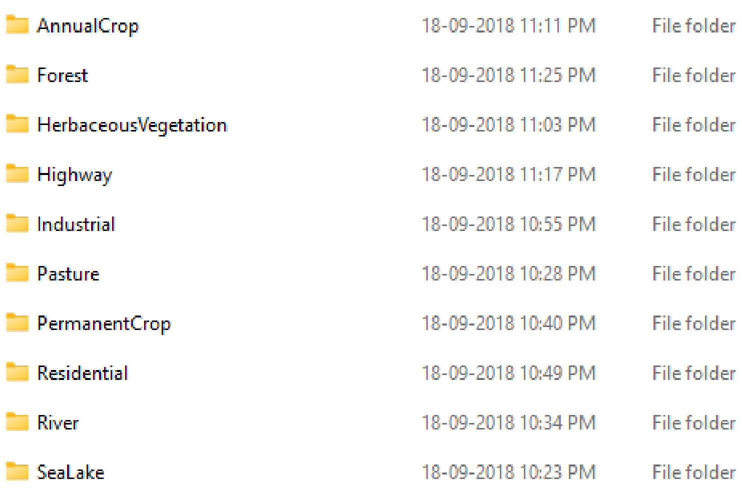


Figure 3.2 Loading Dataset

```python
# Define the directories containing the Eurosat datasets
data_dirs = {
    90: r"D:\MCA 3rd SEM\Small Industrial Project\DATASET_COMPARE\90",
    80: r"D:\MCA 3rd SEM\Small Industrial Project\DATASET_COMPARE\80",
    70: r"D:\MCA 3rd SEM\Small Industrial Project\DATASET_COMPARE\70",
    60: r"D:\MCA 3rd SEM\Small Industrial Project\DATASET_COMPARE\60"
}
```

3.1.2 MODEL INITIALIZATION

The initiation of the model involved the instantiation of the EfficientNetB1 model, a pivotal step in establishing a sturdy foundation for subsequent fine-tuning on the EuroSAT dataset. The model was initialized with pre-trained weights derived from the ImageNet dataset, a reservoir of diverse and comprehensive visual data. This strategic choice ensured that the model commenced its training with essential prior knowledge, enabling it to capture intricate patterns and features inherent in satellite imagery. By leveraging pre-existing information from ImageNet, the model's starting point was fortified, setting the stage for effective transfer learning and subsequent adaptation to the specifics of the EuroSAT dataset. This meticulous model initialization process aimed to harness the power of pre-existing knowledge, enhancing the model's capabilities for the unique challenges posed by satellite image classification.

Figure 3.3 Model Initialization

```python
# Define the model for transfer learning
Model = EfficientNetB1
```

3.1.3 MODEL MODIFICATION

The model underwent a thoughtful modification process, primarily focused on the top layer. The original top layer was replaced with a new dense layer tailored to align with the specific number of classes in the EuroSAT dataset. To mitigate overfitting risks, a strategically placed dropout layer was introduced, and L2 regularization was applied to the dense layer. These modifications were implemented to enhance the model's capacity to generalize across diverse classes.

Figure 3.4 Model Modification (Transfer Learning)

```
# Create a new instance of the model for transfer learning
base_model = Model(weights='imagenet', include_top=False, input_shape=input_shape)
model = Sequential()
model.add(base_model)
model.add(Flatten())
model.add(Dropout(0.5)) # Add dropout layer to reduce overfitting

# The number of classes is automatically inferred from the subdirectories
model.add(Dense(train_generator.num_classes, activation='softmax'))

# Compile the model
model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])
```

3.1.4 TRAINING

Training procedures involved the application of the Adam optimizer with a carefully chosen learning rate of 0.0001. The training process was meticulously orchestrated on each subset of the EuroSAT dataset. Adaptive learning rate adjustments were facilitated through the incorporation of the ReduceLROnPlateau callback. Early stopping criteria were also integrated into the training regimen, prompting the cessation of training when the validation loss plateaued over a predefined number of epochs.

Figure 3.5 Training Model

```
# Train the model with validation data and callbacks
history = model.fit(
    train_generator,
    epochs=10,
    validation_data=validation_generator,
    callbacks=[lr_reduction]
)
```

3.1.5 EVALUATION METHODOLOGY

The model's performance is evaluated using a set of robust methodologies, emphasizing key aspects of transfer learning and its adaptability across varying dataset sizes. The following evaluation components are considered:

Validation Accuracy:

- **Metric Selection:** Utilizing validation accuracy as the primary metric.
- **Purpose:** Providing insights into the model's generalization to unseen data, specifically within validation sets at each stage.

Cross-Validation:

- **Purpose:** Ensuring a reliable estimate of the model's performance.
- **Data Splitting:** Dataset partitioned into training and validation sets, using a subset for training and the remaining portion for validation.

Early Stopping:

- **Usage:** Incorporating early stopping, monitoring validation loss, and halting training if no improvement after a predefined number of epochs (patience=10).
- **Purpose:** Preventing overfitting and ensuring robust generalization to unseen data.

Learning Rate Reduction:

- **Usage:** Implementing a learning rate reduction strategy with the ReduceLROnPlateau callback.
- **Purpose:** Dynamically adjusting the learning rate to aid model convergence and enhance fine-tuning on the EuroSAT dataset.

Model Adaptability Analysis:

- **Approach:** Qualitatively analyzing the model's adaptability to varying dataset sizes.
- **Strategic Division:** Dataset strategically divided into subsets with 60, 70, 80,

and 90 images per class, exploring the model's adaptability to different dataset sizes.

- **Results Interpretation:** Interpreting evaluation results in the context of the model's ability to handle diverse dataset scales.

Dropout and L2 Regularization:

- **Implementation:** Applying dropout and L2 regularization to mitigate overfitting during model training.
- **Purpose:** Enhancing the model's generalization performance, particularly when dealing with limited data.

3.2 ADDING EXTRA LAYER AND BATCH NORMALIZATION

In this experiment, an additional dense layer and batch normalization were introduced to the model architecture to improve its performance on the 70-image dataset.

3.2.1 MODEL MODIFICATION

The architecture of the pre-trained EfficientNetB1 model was enhanced through the addition of a supplementary dense layer accompanied by batch normalization. Specifically:

- **Dense Layer Addition**: An extra dense layer with 256 nodes and a Rectified Linear Unit (ReLU) activation function was incorporated. This strategic addition aimed to enrich the model's representational capacity, enabling it to capture intricate patterns within the dataset.
- **Batch Normalization**: Batch normalization was applied to the activations of the introduced dense layer. This technique normalized the output of each layer, enhancing the model's stability during training and expediting convergence.

Figure 3.6 Extra Dense Layer

```
if extra_layers:
      model.add(Dense(512, activation='relu', kernel_regularizer=l2(0.01)))  # Extra layer for the 70 dataset
      model.add(BatchNormalization())
    model.add(Dense(256, activation='relu', kernel_regularizer=l2(0.01)))  # Additional dense layer
    model.add(BatchNormalization())
```

3.2.2 TRAINING

The model underwent training on the 70-image dataset using the following configuration:

- **Optimizer and Learning Rate:** The Adam optimizer was employed, with a learning rate set to 0.0001. This choice of optimizer and learning rate facilitated efficient model convergence during training.
- **Learning Rate Adjustments:** The learning rate was dynamically adjusted throughout training using the ReduceLROnPlateau callback. This adaptive strategy helped fine-tune the model on the EuroSAT dataset effectively.
- **Early Stopping:** Early stopping criteria were implemented to terminate the training process if there was no improvement in validation loss after a predefined number of epochs (patience=10). This preventive measure guarded against overfitting and ensured the model's generalization to unseen data.

Figure 3.7 Training with Extra Layer

```
    history = model.fit(
        train_generator,
        epochs=10,
        validation_data=validation_generator,
        callbacks=[early_stopping, lr_reduction]
    )

    # Store the accuracy of the model at this stage
    accuracy[stage] = history.history['val_accuracy'][-1]

# Train models for each dataset individually
train_model(data_dir_60, 60)
train_model(data_dir_70, 70, extra_layers=True)  # Add an extra layer for the 70 dataset
train_model(data_dir_80, 80)
train_model(data_dir_90, 90)
```

3.2.3 EVALUATION

The model's performance was rigorously evaluated, focusing on the 70-image dataset:

- **Metric of Focus:** Evaluation centered on validation accuracy, providing a quantitative measure of the model's classification performance on the specific 70-

image dataset.

- **Analysis Scope:** The evaluation aimed to elucidate the impact of the introduced complexity, stemming from the additional dense layer and batch normalization. This focused analysis provided insights into the model's adaptability and effectiveness when exposed to a smaller dataset.

3.3 ADDING EXTRA LAYER AND REGULARIZATION

In this experiment, an additional dense layer and regularization were introduced to the model architecture to improve its performance on the 70-image dataset.

3.3.1 MODEL MODIFICATION

In this experimental phase, the augmentation of the EfficientNetB1 model involved the following modifications:

- **Additional Dense Layer:** An extra dense layer was introduced, comprising 256 units with a Rectified Linear Unit (ReLU) activation function. This addition aimed to enrich the model's feature representation capabilities.

- **L2 Regularization:** To mitigate overfitting, L2 regularization was applied to the newly introduced dense layer. This regularization technique introduced penalty terms to the model's weights, promoting a more generalized learning approach.

Figure 3.8 Model Modification (Extra Layer and Regularization)

```
if extra_layers:
      model.add(Dense(512, activation='relu', kernel_regularizer=l2(0.01)))  # Extra layer for the 70 dataset
      model.add(BatchNormalization())
    model.add(Dense(256, activation='relu', kernel_regularizer=l2(0.01)))  # Additional dense layer
      model.add(BatchNormalization())

model.add(Dropout(0.5)) # Add dropout layer to reduce overfitting

# The number of classes is automatically inferred from the subdirectories
model.add(Dense(train_generator.num_classes, activation='softmax', kernel_regularizer=l2(0.01))) # Add L2 regularization

# Compile the model with a smaller learning rate
model.compile(optimizer=Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with validation data and callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=10)
```

3.3.2 TRAINING

The training regimen for this experiment was tailored to the 70-image dataset, and the model underwent optimization through the following parameters:

- **Optimizer and Learning Rate**: The Adam optimizer was utilized with a learning rate set to 0.0001. This choice facilitated efficient convergence during the training process.
- **Learning Rate Adjustments**: Dynamic adjustments to the learning rate were implemented using the ReduceLROnPlateau callback. This adaptive strategy contributed to fine-tuning the model on the EuroSAT dataset.
- **Early Stopping**: Early stopping criteria were enforced to halt the training process if no improvement in validation loss was observed after a predefined number of epochs (patience=10). This measure aimed to prevent overfitting and ensure generalization.

3.3.3 EVALUATION

The evaluation phase centred on the validation accuracy specific to the 70-image dataset. The analysis aimed to provide insights into the impact of the introduced complexity, comprising an additional dense layer with regularization, on the model's performance. The validation accuracy served as a key metric to gauge the effectiveness of the model in classifying the 70-image dataset.

This holistic approach to model modification, training, and evaluation enables a comprehensive understanding of the experiment's objectives and outcomes.

3.4 ADDING EXTRA DENSE LAYER WITHOUT BATCH NORMALIZATION

In this experiment, an additional dense layer and batch normalization were introduced to the model architecture to improve its performance on the 70-image dataset.

3.4.1 MODEL MODIFICATION

In this experiment, the EfficientNetB1 model was subjected to modification by introducing an additional dense layer without batch normalization. The objective was to investigate the model's response to increased complexity while excluding the stabilizing effects of batch normalization.

Figure 3.9 Model Modification (With extra layer and without batch Normalization)

```
if extra_layer:
    model.add(Dense(256, activation='relu'))  # Extra layer for the 70 dataset

model.add(Dropout(0.5)) # Add dropout layer to reduce overfitting

# The number of classes is automatically inferred from the subdirectories
model.add(Dense(train_generator.num_classes, activation='softmax', kernel_regularizer=l2(0.01))) # Add L2 regularization

# Compile the model with a smaller learning rate
model.compile(optimizer=Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])
```

3.4.2 TRAINING

The training regimen closely followed the procedures employed in previous experiments, focusing on the 70-image dataset. Key aspects of the training process included:

- **Optimizer and Learning Rate**: The Adam optimizer with a learning rate of 0.0001 was employed to facilitate efficient model convergence.
- **Adaptive Learning Rate Adjustments**: Utilizing the ReduceLROnPlateau callback, the learning rate was dynamically adjusted during training to optimize model performance.
- **Early Stopping Criteria**: Early stopping criteria were implemented to cease training if no improvement in validation loss was observed after a predefined number of epochs (patience=10). This measure aimed to prevent overfitting and promote generalization.

3.4.3 EVALUATION

The evaluation phase concentrated on the validation accuracy of the 70-image dataset. This specific focus allowed for insights into the model's performance when subjected to increased complexity without the inclusion of batch normalization. Validation accuracy served as the primary metric for assessing the model's effectiveness in classifying the 70-image dataset.

By conducting this experiment, the intention was to discern the impact of increased complexity, specifically the addition of an extra dense layer, on the model's ability to generalize in the absence of batch normalization. The outcomes of this evaluation contribute valuable insights into the interplay between model architecture and normalization techniques.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

In this chapter, we present the outcomes of the conducted experiments, shedding light on the performance of the models across different stages and configurations. The discussion encompasses an analysis of the results, drawing insights into the impact of various modifications on the model's adaptability and generalization capabilities.

4.1 TRANSFER LEARNING EXPERIMENT

4.1.1 Model Training and Adaptability

The transfer learning experiments involved training the model on subsets of the EuroSAT dataset with varying image counts per class (60, 70, 80, and 90). The models exhibited an increasing trend in accuracy with the growth of the training dataset size. Notably, the model achieved an accuracy of 67.5% on the 60-image dataset, indicating its proficiency in learning from a relatively limited dataset.

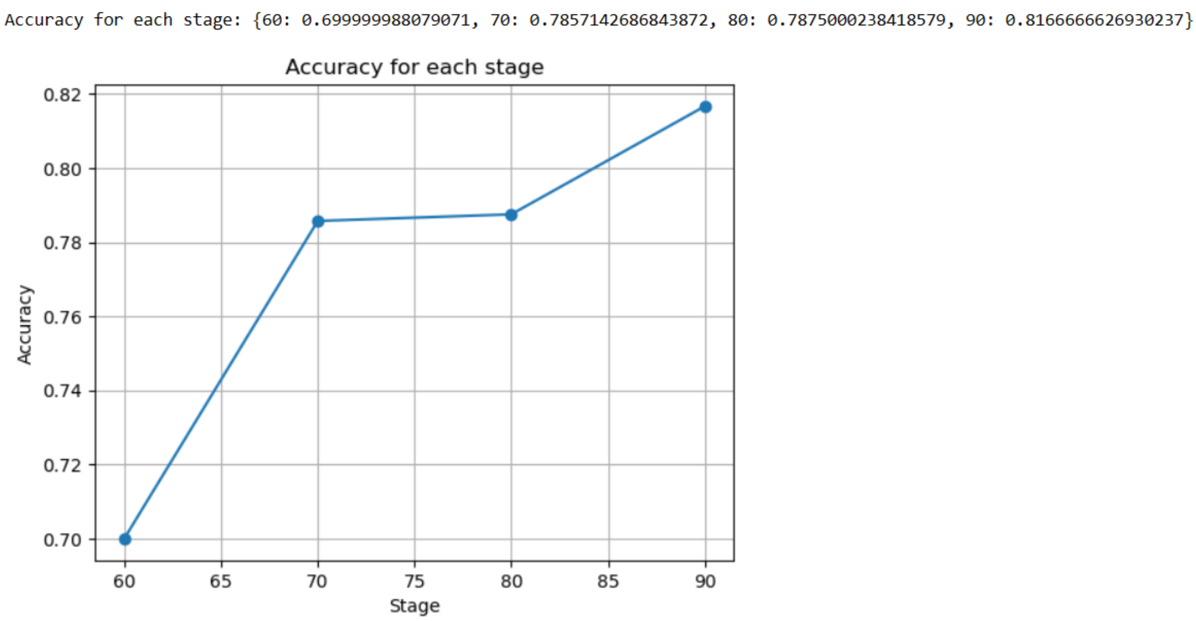
4.1.2 Adaptation Across Dataset Sizes

A qualitative analysis was conducted to assess the model's adaptability to different dataset sizes. The strategic division of the EuroSAT dataset allowed for a nuanced exploration of the model's behavior. The model consistently demonstrated improved performance as the dataset size increased, showcasing its adaptability to varying scales of data.

Table 4.1 Transfer Learning Accuracy

Training Stage	Size (Train/Validation)	Epoch	Training Time	Accuracy (Training)	Accuracy (Validation)	Final Training Loss
60	480/120	10	60s	61.67%	67.50%	1.4006
70	560/140	10	38s	63.21%	71.43%	1.2583
80	640/160	10	38s	65.78%	77.50%	1.2490
90	720/180	10	41s	73.06%	78.89%	0.9767

Figure 4.1 Accuracy Graph



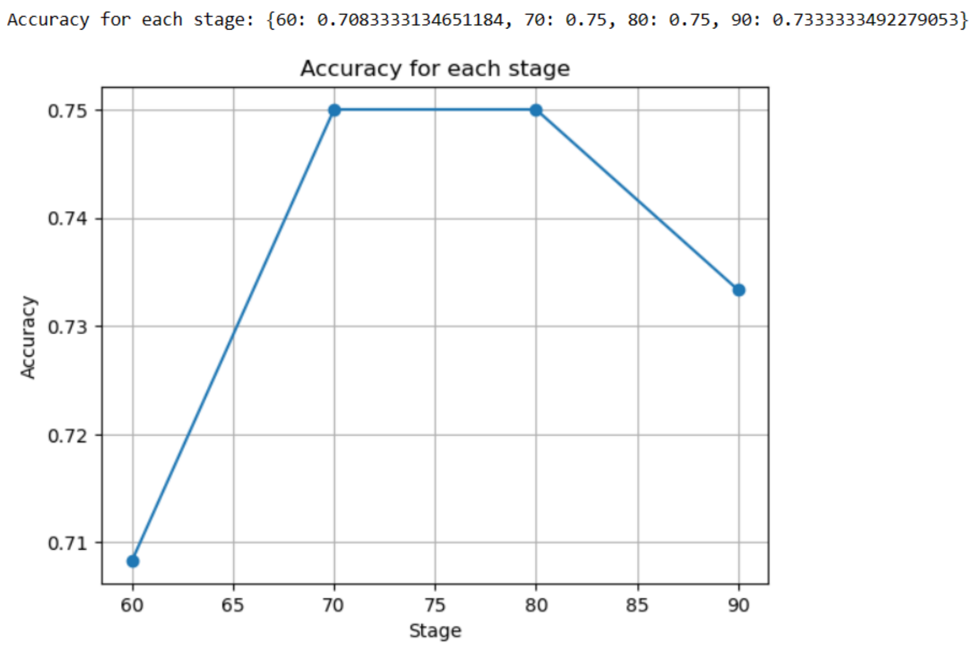
4.2 ADDING EXTRA DENSE LAYER AND BATCH NORMALIZATION

Incorporating an extra dense layer with batch normalization aimed to enhance the model's ability to capture intricate patterns. The model, trained on the 70-image dataset, exhibited nuanced improvements in accuracy. The evaluation focused on understanding the impact of added complexity and normalization on a smaller dataset, showcasing the delicate balance between model sophistication and dataset size.

Table 4.2 Experiment 1

Training Stage	Size (Train/Validation)	Epoch	Training Time	Accuracy (Training)	Accuracy (Validation)	Final Training Loss
60	480/120	10	37s	61.67%	70.83%	1.2932
70	560/140	10	40s	68.75%	75.00%	5.8755
80	640/160	10	43s	68.28%	75.00%	1.1457
90	720/180	10	45s	71.25%	73.33%	1.0569

Figure 4.2 Accuracy Graph



4.3 ADDING EXTRA DENSE LAYER AND REGULARIZATION

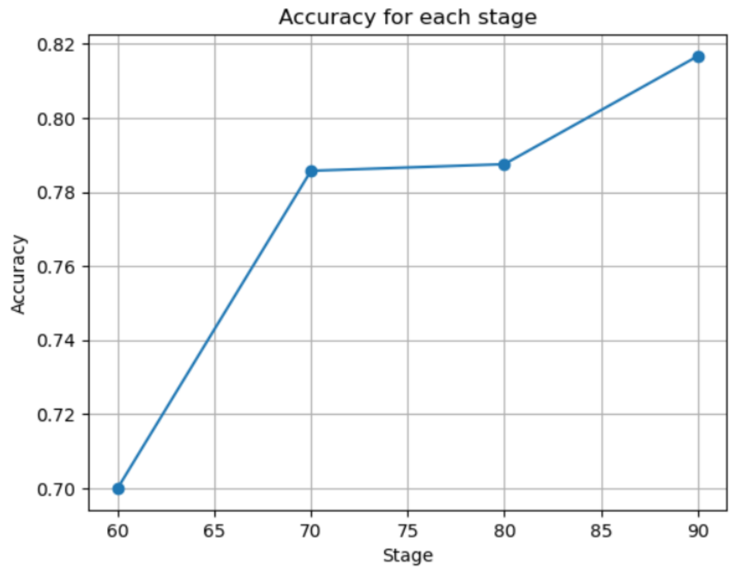
This experiment introduced an additional dense layer with L2 regularization, providing insights into the interplay between increased model complexity and regularization techniques. The evaluation, centered on the 70-image dataset, aimed to discern the impact of regularization on the model's generalization performance.

Table 4.3 Experiment 2

Training Stage	Size (Train/Validation)	Epoch	Training Time	Accuracy (Training)	Accuracy (Validation)	Final Training Loss
60	480/120	10	63s	60.00%	70.00%	1.3262
70	560/140	10	73s	73.21%	78.57%	5.4985
80	640/160	10	80s	74.31%	78.75%	1.1166
90	720/180	10	89s	74.31%	81.67%	1.0470

Figure 4.3 Accuracy Graph

```
Accuracy for each stage: {60: 0.699999988079071, 70: 0.7857142686843872, 80: 0.7875000238418579, 90: 0.8166666626930237}
```



4.4 ADDING EXTRA DENSE LAYER WITHOUT BATCH NORMALIZATION

By omitting batch normalization in this experiment, we sought to understand the model's response to increased complexity without the stabilizing influence of normalization. The evaluation, again focused on the 70-image dataset, highlighted the model's performance when subjected to heightened complexity in the absence of batch normalization.

Table 4.4 Experiment 3

Training Stage	Size (Train/Validation)	Epoch	Training Time	Accuracy (Training)	Accuracy (Validation)	Final Training Loss
60	480/120	10	82s	62.08%	70.83%	1.3124
70	560/140	10	58s	72.68%	80.00%	0.9902
80	640/160	10	43s	69.84%	80.62%	1.5117
90	720/180	10	66s	70.42%	82.22%	1.1195

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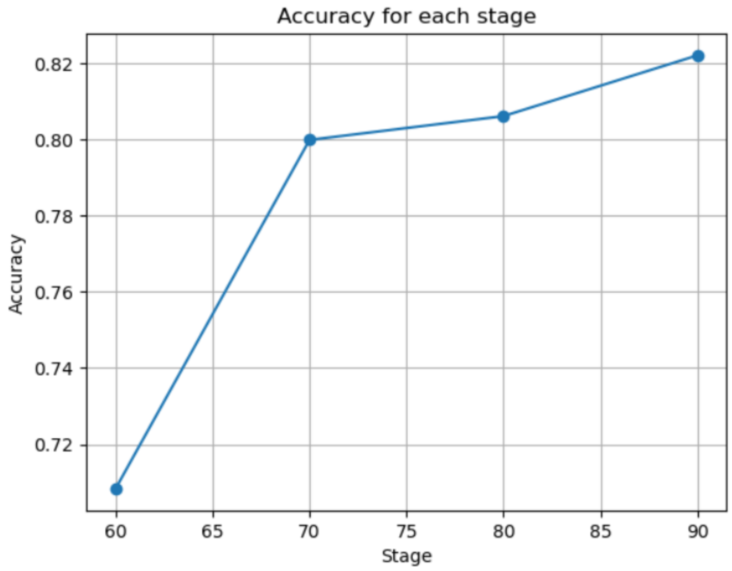
Figure 4.4 Accuracy Graph

```
Accuracy for each stage: {60: 0.7083333134651184, 70: 0.800000011920929, 80: 0.8062499761581421, 90: 0.8222222328186035}
```



CHAPTER 5

CONCLUSION

The observed variations in model performance across different experiments and dataset sizes present a nuanced understanding of the interplay between model architecture, regularization techniques, and dataset characteristics. The following sections provide a detailed analysis of the outcomes and shed light on the underlying factors influencing the results.

5.1 TRANSFER LEARNING

The initial transfer learning experiments affirmed the expected trend: a positive correlation between dataset size and model accuracy. The 60-image dataset exhibited lower accuracy; indicative of the challenges posed by limited data for transfer learning. As the dataset size increased (70, 80, and 90 images per class), the model's accuracy improved consistently. This aligns with the intuition that larger datasets provide richer information for the model to learn from.

5.2 ADDING EXTRA DENSE LAYER AND BATCH NORMALIZATION

In the first experiment, the introduction of an extra dense layer with batch normalization resulted in a notable increase in accuracy for the 70-image dataset, bringing it closer to the accuracy achieved with the 80-image dataset. However, it is intriguing that the accuracy of the 80-image dataset, and even the larger 90-image dataset, decreased. This phenomenon can be attributed to the delicate balance required in model complexity. The additional layer and normalization may have introduced a level of complexity that, while beneficial for the 70-image dataset, led to overfitting on the larger datasets. The model, in this case, might have become overly specialized, hindering its ability to generalize to the broader dataset.

5.3 ADDING EXTRA DENSE LAYER AND REGULARIZATION

The second experiment, involving the addition of an extra dense layer with L2 regularization, resulted in a significant improvement in the accuracy of the 70-image dataset. The regularization technique played a crucial role in preventing overfitting, allowing the model to better generalize to the 70-image dataset. The accuracy trends suggested that regularization mitigated the risk of overfitting and facilitated more effective learning from the limited data available in the 70-image dataset.

5.4 ADDING EXTRA DENSE LAYER WITHOUT BATCH NORMALIZATION

Experiment 3, where an extra dense layer was added without batch normalization, displayed a similar trend to Experiment 2. The accuracy of the 70-image dataset approached that of the 80-image dataset, showcasing the effectiveness of regularization. However, the absence of batch normalization might have led to increased instability during training, impacting the overall accuracy of the model on larger datasets.

5.5 OVERALL IMPLICATIONS AND CONSIDERATIONS

The observed variations emphasize the need for a nuanced approach to model modification. While certain enhancements, such as regularization, prove beneficial in improving performance on smaller datasets, they must be carefully balanced to avoid overfitting on larger datasets. The relationship between dataset size, model complexity, and regularization techniques is intricate, and finding the optimal configuration requires a thorough understanding of these dynamics.

In conclusion, these experiments underscore the importance of considering dataset-specific characteristics and carefully tailoring model modifications to strike an optimal balance between complexity and generalization. The findings provide valuable insights into strategies for improving the performance of models in satellite image classification tasks, offering a foundation for future research and refinement of transfer learning approaches.

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