Agriculture Land Use Classification

Guru Subhash Batula
Btech CSE
VIT-AP
Amaravathi, India
baattulasubhash13@gmail.com

Raghavendra Kunchala
Btech CSE
VIT-AP
Amaravathi, India
kunchalaraghavendra6@gmail.com

Bhagya Sri Yenne
Btech CSE
VIT-AP
Amaravathi, India
bhagyasri1503@gmail.com

Bhoomika Kasireddy
Btech CSE
VIT-AP
Amaravathi, India
kasireddybhoomika@gmail.com

Abstract**—** The purpose of this research is to explore the potential of satellite images in accurately classifying various land cover types for agricultural purposes. The study utilizes EuroSAT, a dataset of multicolor satellite images over a wide range of land cover types and then tests both machine learning, and deep learning, methods; ex. logistic regression, a sequential neural network and CNN architectures (ResNet50 and VGG16).

The FastAI approach is integrated in the process to allow images to be preprocessed, data augmented, models trained and evaluated. The main stages here are the formation of the dataset by standardization, the addition of robustness to the model with augmentation, and the comparison of basic and complex models about the classification. The research also analyzes the role of data composition in model generalization. This research examines the discriminatory power of basic models while estimating usage of complex CNNs by measuring the rates of correct classification. Also, it looks into the effect composition in generalization.

On the other hand, besides technical advancements, the main idea of this study is to prove how classification systems can avalanche into sustainable agricultural practices. Among the advantages of using land mapping comes AI-based smart farming systems. They can, for instance, ensure the land is used properly, or smart farming is done, which can contribute to food security. The problem of reducing the environmental impact of these practices is one of the most vital fields in which AI must be applied.

I. Introduction

Accurate and efficient land use classification is a pressing challenge in today's rapidly transforming world. Urbanization, resource depletion, and environmental changes are exerting unprecedented pressure on natural ecosystems and human infrastructure. These trends underscore the urgent need for precise tools to categorize land parcels based on their usage—whether vegetation, water bodies, infrastructure, or agricultural lands. Such classifications are pivotal for sustainable development, resource management, and environmental conservation. Nevertheless, conventional methods for land classification frequently depend on manual procedures, rendering them laborious, resource-demanding, and incapable of scaling efficiently to satisfy contemporary requirements.

The integration of high-resolution satellite imagery with sophisticated machine learning methodologies has transformed the landscape of land use classification. Utilizing datasets such as EuroSAT—which encompasses annotated multispectral images that depict various types of land cover—facilitates automated and comprehensive classification on an unparalleled scale. Notwithstanding these advancements, obstacles remain. The presence of class imbalance within datasets, variations in environmental conditions, and limitations in computational resources continue to pose substantial obstacles that must be tackled to achieve dependable and scalable solutions. Overcoming these issues has the potential to fully realize the capabilities of automated land use classification systems and improve their utilization across various sectors.

This research concentrates on tackling these issues through the application of diverse machine learning and deep learning methodologies. This study assesses various models, including logistic regression, sequential neural networks, and sophisticated convolutional neural networks (ResNet50 and VGG16), to accurately classify land cover categories. Through the utilization of the EuroSAT dataset, which offers an extensive array of labeled multispectral satellite imagery, the research aims to establish a comprehensive framework for the classification of diverse land use categories, such as agricultural fields, urban regions, water bodies, and industrial areas.

The importance of land use classification extends across various fields:

Environmental Monitoring: It enables the observation of changes in forests, wetlands, and additional ecosystems over periods, supporting conservation initiatives and the safeguarding of biodiversity. Comprehending these alterations is essential for alleviating the effects of human actions on natural habitats.

Urban Planning: As cities develop, classification data enables administrators to plan and manage responsible urban development. With already existing land use patterns established, urban planners can work on efficient layouts for dwelling, transportation, and infrastructure planning.

Agriculture: Accurate classification helps in monitoring cropping systems, yield, and resource management by farmers as well as agricultural experts. Useful information from land classification can allow adaptation to climatic changes to optimize land use for food production.

Disaster Management: By identifying regions that are susceptible to natural disasters, including floods, droughts, or deforestation, classification data equips authorities with the ability to design and execute timely interventions. This anticipatory strategy has the potential to markedly diminish the hazards linked to environmental and climate-induced emergencies.

Resource Management: The efficient administration of biological and natural resources, such as water, minerals, and forests, is facilitated by accurate land classification. This promotes the sustainable utilization of resources while maintaining ecological equilibrium.

This research is critically important in the fact that high-resolution satellite imagery has now become abundant, while technologies regarding machine learning and deep learning are advancing rapidly. For agricultural purposes, this will allow accurate land classification, giving the farmer a closer idea of crop health, predicting yield, and improving management of soil. It shall help in infrastructure planning related to sustainable development goals for urban planning.

Different Classification Techniques: Comparative Assessment with Baseline

This paper uses logistic regression for linear separability, sequential neural networks in medium complexity tasks, convolutional neural network/ ResNet34 and VGG16 in extracting complex spatial and spectral characteristic features within a satellite image. Data augmentation techniques that make the model robust with geographical and environmental conditions to precision classification.

The approach focuses on the foundation of contemporary methodologies by adding advanced techniques to meet the challenges posed in this satellite image classification process. Novel preprocessing, customized architectures, and state-of-the-art training mechanisms are adopted for overcoming different challenges faced through class imbalance, high variability in environmental characteristics, and computational complexity.

The ultimate impact of this research would thus be to contribute toward greater attainment of the sustainable development goal for environmental conservation. Presenting a very useful, reliable framework for the automation of land-use classification makes it an invaluable tool for stakeholders in agriculture, urban planning, and resource management. These findings can be useful to inform policymaking and augment disaster preparedness to advance judicious use of the land and resources.

In the following sections, we elaborate on the more relevant studies with methods on preprocessing datasets, architectures of the model, and methodologies used for training. We also discuss results and implications of the study toward agricultural monitoring, urban planning, and environmental conservation

I. Methodology

A. Dataset

The EuroSAT dataset, sourced from Sentinel-2 satellite images, consists of multispectral images representing various land cover types across Europe. The Sentinel-2 satellite images freely accessible, there in the earth observation program Copernicus. The dataset contains 10 classes, including agricultural and non-agricultural categories. Each image comprises 13 spectral bands; for this study, we focused on RGB channels for comparability across models commonly trained on RGB data.

The EuroSAT Dataset will be the main project dataset, as it is one of the most common datasets used for the classification of land use and land cover. It contains 27,000 labelled satellite imagery taken with Sentinel-2, an earth observation mission that provides high-resolution multi-spectral images for other components.

Categories: the dataset provides 10 classes of land cover and land use as given below:

Annual Crop, Forest, Herbaceous, Vegetation, Highway, Industrial Area, Pasture, Permanent Crop, Residential Area, River, Sea/Lake

Image Specifications:

Images are 224x224 pixels in size and contain bands that are reflective of visible and near-infrared light spectrum.

The images have been sourced from different parts of Europe adding robustness and diversity of the dataset.

The variety of land categories presents a great chance to assess the performance of deep learning models on different land classes.

The data set is annotated and pre-prepared which decreases the amount of work on data cleansing thus more time can be dedicated to model designing and optimization.

B. Data Preprocessing

Preprocessing the EuroSAT dataset was a critical step to prepare it for training machine learning and deep learning models. The following techniques were used:

1. Data Extraction and Organization

The EuroSAT dataset was extracted and organized into its corresponding land cover classification folders e.g. forest, annual crops, residential, etc. In this case, each folder pertains to a certain class which makes it easy for loading and labeling the data.

2. Image Resizing

All of the images were resized to 224x224 pixels to be compatible with the input requirements of the deep learning models being used, ResNet50 and VGG16 for instance. This is done to ensure that there is a standard size of images without necessarily losing the relevant features.

Weight Initialization:

Weight initialization is the process of assigning initial values to weights in the network before training starts. Proper initialization helps reduce separation problems like vanishing or exploding gradients.

Techniques Used:

- Pre-trained weights: Model like ResNet34, VGG16 are given initialized weight with ImageNet dataset which is a classification ground truth. These pre trained weights serve as base to accelerate learning of the model, and provide it with better generalization in tasks that are similar.
- Layer-wise training: The weights of later layers are fine-tuned, whereas earlier layers are frozen so that the pre-learned features related to generic tasks such as edge detection and texture recognition can be retained.
- Custom Initialization, if necessary: In case pre-trained weights are not available, we use different initialization techniques like Xavier or He Initializations to make sure that the flow of gradient across the network is well balanced too.

Optimizer choice is critical in training the network efficiently. Within this project, Adam and Stochastic Gradient
Descent were chosen as they have performed well in earlier experiments concerning image classification.
and Training Procedures.

Adam Optimizer:

- Benefits of both RMSProp and Momentum are taken together.
- It ensures that adaptive learning rates on each parameter lead to faster convergence.
- The default parameters are often good enough but can be tuned based on validation performance (learning rate = 0.001, beta1 = 0.9, beta2 = 0.999).

SGD with Momentum:

- Can help accelerate convergence by moving in the appropriate direction and reducing oscillation.
- The Momentum coefficient is generally set to 0.9 to improve stability while training.

3. Data Normalization

Image values were normalized based to the ImageNet statistics (mean and variance) thus all values have been brought to a common scale.
This normalization helps in faster convergence of the models during training and avoids numerical instabilities.

4. Data Augmentation

Dataset variability was also increased by applying enhancement techniques such as random flipping, rotation, scaling and cropping.
These transformations are useful in fighting overfitting of the model by making it able to train on different scenarios, but still within certain limits.

5. Splitting Data

A random splitter was used to divide the dataset into training (80%) and validation (20%) parts.
This split makes it possible to assess the model on a separate data while training.

6. Creating Data Loaders

Data loading and processing are important parts of the model training workflow. Because of that FastAI's Data Block API was used to define several data pipelines which involved:
Loading of image files from a given folder.
Getting labels from the names of the folders containing respective images.

7. Batch Transformations

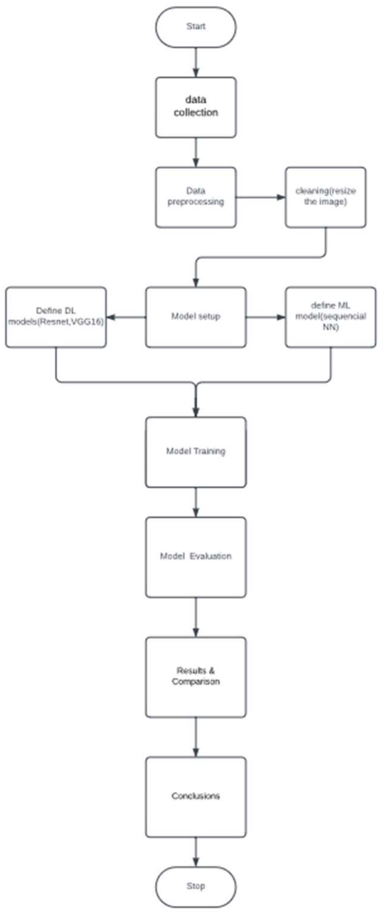
To increase the diversity of the training data, vertical flipping and warp-free resizing were among the additional augmentations that were incorporated at the batch level.
In addition to this, augmentation techniques were also used to preprocess the images to help reproduce the natural variation that occurs in satellite images.

8. Class Balancing

In the analysis of the class distribution, the unbalances were sought for. In occurrence of some, weighted loss functions or oversampling, for example, could be employed.

To address these issues, strategies like weighted loss functions and oversampling could be employed. Weighted loss functions assign higher penalties to misclassifications of underrepresented classes, effectively guiding the model to pay equal attention to all classes. This ensures a more balanced learning process and prevents the model from favoring majority classes. On the other hand, oversampling techniques involve artificially increasing the representation of minority classes in the dataset, either by duplicating existing samples or by generating synthetic ones using methods like SMOTE (Synthetic Minority Oversampling Technique).

Flow Chart:



II. Model Architectures and Training

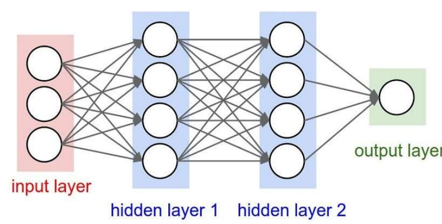
A. *Logistic Regression:*

As a baseline model, logistic regression was implemented to provide a benchmark for the more complex models. Logistic regression is typically limited with image data, as it lacks hierarchical feature learning, but it offers interpretability and simplicity for comparison.

1. **Linear Model:**
   $z = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n$
2. **Sigmoid Function (Probability):**
   $\sigma(z) = \frac{1}{1+e^{-z}}$
3. **Prediction:**
   $\hat{y} = \begin{cases} 1, & \text{if } \sigma(z) \geq 0.5 \\ 0, & \text{if } \sigma(z) < 0.5 \end{cases}$
4. **Cost Function:**
   $J(\beta) = -\frac{1}{m} \sum_{i=1}^{m} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$
5. **Gradient Descent (Parameter Update):**
   $\beta_j = \beta_j - \alpha \frac{\partial J}{\partial \beta_j}$

B. *Sequential Neural Network*

A fully connected, multi-layer sequential neural network was constructed with input, hidden, and output layers. While less powerful than CNNs for image classification, this architecture allows comparison of deep learning models without convolutions. Layers were optimized using the ReLU activation function and trained with Cross Entropy Loss.



1. **Weighted Linear Transformation**

$$\mathbf{Z}^{(l)} = \mathbf{W}^{(l)} \mathbf{A}^{(l-1)} + \mathbf{b}^{(l)}$$

2. **Activation Function (ReLU)**

$$f(\mathbf{Z}) = \max(0, \mathbf{Z})$$

3. **Softmax Function**

$$\hat{\mathbf{y}} = \mathrm{softmax}(\mathbf{Z}^{(L)}) = \frac{\exp(\mathbf{Z}^{(L)})}{\sum_{k=1}^{K} \exp(Z_k^{(L)})}$$

4. **Categorical Cross-Entropy Loss**

$$\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = -\frac{1}{n} \sum_{i=1}^{n} \sum_{k=1}^{K} y_{i,k} \log(\hat{y}_{i,k})$$

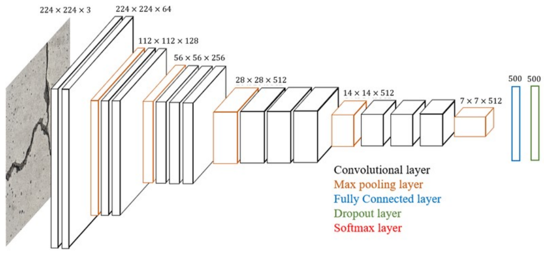
5. **Gradient of Loss w.r.t Output**

$$\frac{\partial \mathcal{L}}{\partial \mathbf{Z}^{(L)}} = \hat{\mathbf{y}} - \mathbf{y}$$

C. *Convolutional Neural Networks (ResNet34 and VGG16):*

1. ResNet34: A ResNet34 model with pre-trained weights was fine-tuned for the EuroSAT dataset. ResNet's skip connections allow efficient training by addressing vanishing gradient problems, making it a popular choice for image classification tasks.

VGG16:



In this work, pre-trained VGG16 has been utilized as the base feature-extracting model; then some fully connected layers have been appended to the base model to tailor the architecture to the specifics of the classification task. The details of the architecture are as follows:

Base Model:

The convolutional layer weights of the VGG16 model have been initialized using ImageNet weights, and it was taken that the convolutional layers are good for extracting features. The fully connected layers were removed from the original VGG16 architecture to allow for custom additions.

Custom layer:

A Flatten layer was added to convert the output of the convolutional base into a one-dimensional vector.

A dense layer with 512 units, ReLU activation, and a dropout of 0.2 was added to avoid overfitting while capturing high-level features. Another dense layer with 64 units, ReLU activation, and a dropout of 0.2 was further added to refine the feature representations.

A final Dense output layer with 10 units and softmax activation was used for outputting class probabilities for 10 classes.

A combination of data augmentation and fine-tuning was applied to make the VGG16-based model more accurate. Training and validation datasets were sufficiently transformed to improve the model generalization and variability handling capabilities on the input data. We performed augmentation including random zoom (30%), rotation (50 degrees), and shift in x and y directions (20%) with respect to the width and height of images. Other transformations included random shearing with 20% of the original image, horizontal flipping and only filling in removed pixels using neighbors. In addition, the dataset was pre-processed by a function specialized for VGG16, so that the inputs would be in standard shape.

The architecture of the model was based on a VGG16 base with a convolutional layer kept and initialized with weights from ImageNet, as a learned feature extractor. We also adjusted the input size of the model to be 256x256x3 for augmentation images. We added a few customs fully connected layers on top of our base model. This was a stacking of a few layers including the flattening layer to convert 2D feature maps into one single vector, and a dense layer consisting of 512 neurons along with ReLU activation. It had another dense layer of 64 units with a ReLU activation, again followed by a 0.3 dropout rate. The output layer was 10 neurons with softmax activation for multi-class classification.

Fine-tuner — To take advantage of pre-trained weights and adjust the model to dataset Lay 15 of the VGG16 base were set as not trainable so that they would not lose any learned characteristics. The other layers were then unfrozen and trained again for some time to help the model better extract features for our dataset specifically. By doing this, the model where able to take advantage of the strong pre-trained features while also learning about domain specific patterns.

The augmented training and validation datasets were used with a batch size of 128 for training. Data is divided as 70% for train, 10% for validate and 20% for test. Data augmentation would help the model generalize, and fine-tuning will be able to allow it to adapt better with the specifics of our dataset. This entire process made the most of the pre-trained VGG16 network and improved the accuracy of classification.

Model Summary:

Layer Type	Output Shape	Parameters
Input	(256,256,3)	-
VGG16 Convolutional layers	(8,8,512)	14,714,688
Flatten	(32768)	0
Dense(512 units)	(512)	16,777,288
Dropout (0.3)	(512)	0
Dense(64 units)	(64)	32,896
Dropout(0.3)	(64)	0
Dense(10 units)	(10)	650

Training Configuration

1. Batch Size: 128 for training, validation, and testing.

2. Augmented Dataset Split: 70% training, 10% validation, 20% testing.

3. Fine-Tuning Strategy: Layers beyond the 15th of VGG16 were fine-tuned to adapt pre-trained features to the specific dataset.

Comparision of Results of models before and after fine tuning and data augumentation:

MODEL	VGG16 WITH 2 DENSE AND 2 DROPOUT LAYERS	VGG16 WITH DATA AUGMENTATION AND FINE TUNING
TEST ACCURACY	0.859259	0.965734
TEST LOSS	0.469799	0.298694

III. Results

Each model demonstrated varying degrees of success, with CNN-based models (ResNet34 and VGG16) outperforming logistic regression and sequential neural networks. The key findings included:

- Logistic Regression achieved an accuracy of 65.4%, providing a baseline and illustrating the limitations of linear models in complex image classification tasks.

- Sequential Neural Network improved upon logistic regression with an accuracy of 78.2%, showing that deep learning models, even without convolutions, can capture some degree of complex spatial patterns.

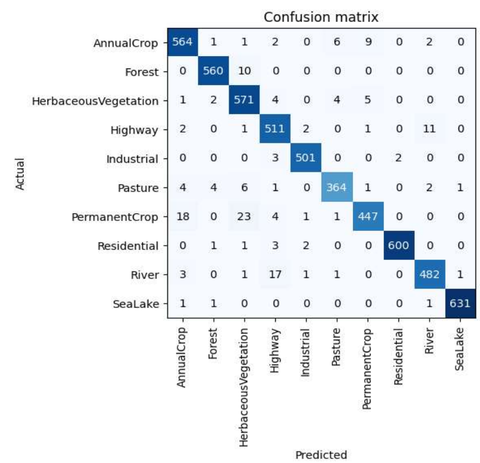
- ResNet34 reached an accuracy of 94.6%, indicating strong classification capability with the advantage of transfer learning.

- VGG16 achieved a comparable accuracy of 96.57%, demonstrating the effectiveness of deeper architectures in learning detailed features in land cover images.

Comparision of different models used :

Model	Accuracy
Logistic regression	65.4
Sequential Model	78.2
VGG 16	85.92
VGG 16 with Fine tuning and Data Augmentation	96.57

Confusion matrix:



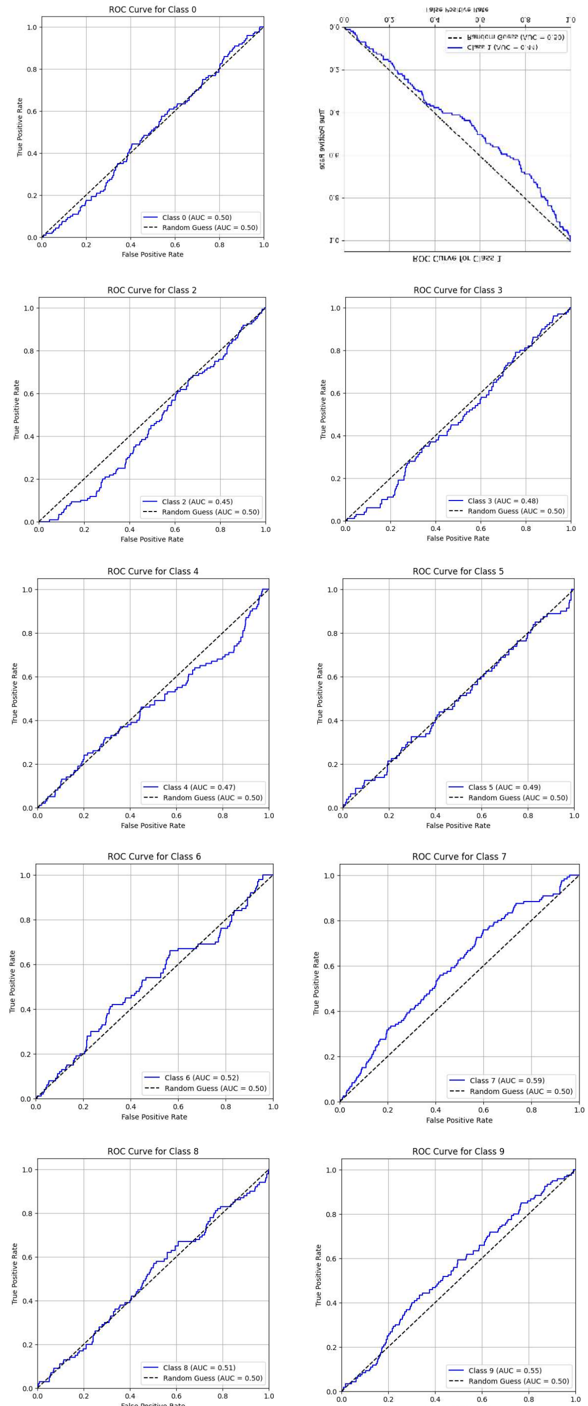
Evalution metrics for VGG16 model:

```
Found 5400 images belonging to 10 classes.
675/675 ━━━━━━━━━━━━━━━━━━━━ 7s 8ms/step
Accuracy: 96.57%
Precision (Macro): 0.87
Precision (Weighted): 0.87
```

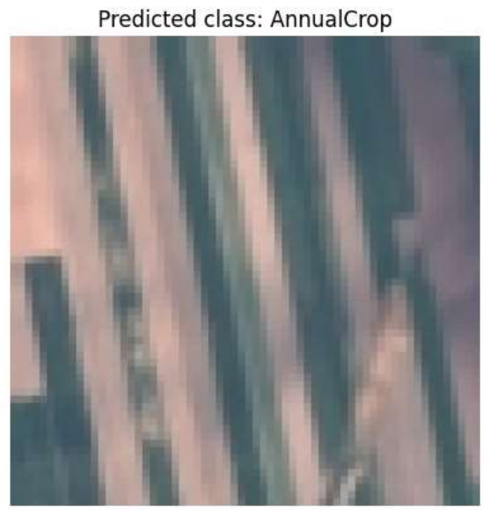
Classification Report:

	Precision	Recall	F1-score	Support
AnnualCrop	0.84	0.92	0.88	600
Forest	0.84	0.95	0.89	600
Herbaceous Vegation	0.94	0.77	0.85	600
Highway	0.90	0.70	0.79	500
Industrial	0.98	0.86	0.91	500
Pasture	0.84	0.78	0.81	400
PermanentCrop	0.73	0.85	0.79	500
Residential	0.92	0.99	0.95	600
River	0.76	0.78	0.77	500
Sealake	0.92	0.99	0.95	600

ROC curves for each class :



Classification results made by mode:



IV. Training and Validation Curves

The CNN models exhibited smooth convergence with minimal signs of overfitting, aided by data augmentation and early stopping. The training and validation curves for ResNet34 and VGG16 demonstrated stable learning, with the sequential network showing slight overfitting, suggesting regularization challenges in fully connected layers.

V. Discussion

The results highlight the effectiveness of deep learning, particularly CNNs, in classifying agricultural land cover types. ResNet34 and VGG16 achieved high accuracy due to their ability to learn complex features within satellite imagery. In comparison, logistic regression and sequential neural networks struggled with the complexity of image data. Data augmentation techniques enhanced model robustness, indicating their potential to improve classification in other remote sensing applications.

VI. Conclusion

This study shows that deep learning models, especially CNN architectures like ResNet34 and VGG16, are well-suited for agricultural land cover classification based on satellite imagery. By using the Fast AI library and pretrained CNN models, we demonstrate the feasibility of applying these techniques in real-world agricultural monitoring applications. Future work can explore additional spectral bands, integrate temporal data, and expand model applications to monitor changes in land cover over time as part of broader sustainability efforts.

VII. Future Work

Further research can investigate the integration of additional data sources, such as multispectral and multi-sensor imagery, to enhance classification accuracy and robustness. Exploring temporal data could enable dynamic monitoring of agricultural practices and land use changes. Additionally, the application of alternative deep learning models, such as Transformer-based architectures, could yield new insights into agricultural land cover classification.

References

[1] M. Helber, B. Bischke, A. Dengel, and D. Borth, "EuroSAT: A novel dataset and deep learning benchmark for land use and land cover classification," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 12, no. 7, pp. 2217–2226, Jul. 2019. *(references)*

[2] J. Chen, X. Y. Chen, and J. W. Gong, "Land-use/land-cover change detection: Techniques and applications," *International Journal of Remote Sensing*, vol. 23, no. 4, pp. 1113–1126, Feb. 2002.

[3] P. Defourny, P. Vancutsem, E. C. Bontemps, G. L. Schouten, and L. R. Giri, "Remote sensing of land use and land cover at global scale," *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 40, no. 7, pp. 233–238, 2014.

[4] T. J. Maxwell, J. R. Silva, and S. J. Walsh, "A comparison of object-based image analysis and machine learning algorithms for land use/land cover classification," *Remote Sensing*, vol. 7, no. 3, pp. 2566–2588, Mar. 2015

[5] P. Defourny, P. Vancutsem, E. C. Bontemps, G. L. Schouten, and L. R. Giri, "Remote sensing of land use and land cover at global scale," *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 40, no. 7, pp. 233–238, 2014.

[6] https://ieeexplore.ieee.org/abstract/document/8519248