Comparative Study of Techniques for Land Cover Classification and Mapping

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ABSTRACT:

Land cover classification and mapping are critical for environmental monitoring, urban planning, and sustainable development. Precise and scalable predictions of land cover enable decision-makers to have a data-driven understanding of how land is used and how it may evolve, leading to better policies, strategic resource allocation, and sustainable development. This study compares the performance of several machine learning techniques, including Support Vector Machines (SVM), Deep Learning (CNN) and Transfer Learning (VGG-16) for accurately classifying land cover in geospatial images. Using a benchmark dataset derived from satellite imagery, the algorithms were evaluated based on classification accuracy, computational efficiency, and scalability. The results demonstrate that deep learning methods outperform traditional techniques in accuracy, albeit with higher computational demands. This research provides insights into selecting appropriate machine learning models for land cover analysis in diverse scenarios.

KEYWORDS: Data Mining, Machine Learning, Transfer Learning, Land Cover Classification

INTRODUCTION:

The rapid expansion of urban areas, agricultural activities, and environmental changes has made the need for accurate and efficient land cover classification more critical than ever. With the increasing availability of satellite imagery, accurately classifying land cover types has become achievable. Traditional machine learning, advanced deep learning and Transfer Learning methods have shown promising results in image classification tasks.

However, the choice of ML techniques impacts classification accuracy, computational cost, and practical implementation.

The project proposes conducting a comparative study of various image classification algorithms. This study has significant potential applications in fields such as urban planning, resource management, environmental monitoring, and geospatial analysis, enabling informed decision-making for sustainable development and effective resource allocation.

DATASET:

In this project we have used the EuroSAT dataset which consists of 27000 RGB Images of various types of land covers. These images have been captured by the Sentinel2 satellite and have dimensions of 64x64 pixels with a Ground Sampling Distance of 10m. All these images have been categorized in 10 different classes.

This dataset is split into a training set which constitutes 70% (18900 images) of the entire dataset, a validation set that constitutes 20% and a test set containing 10% images of the entire dataset. We also have 3 csv files for each set containing paths to images belonging to the respective set.

Dataset Link: https://www.kaggle.com/datasets/apollo2506/eurosat-dataset

METHODS:

In this project we have chosen algorithms from each of the 3 different technologies, viz, Machine Learning, Deep Learning and Transfer Learning.

1. **Common Data Preprocessing:**
   1.1. Image augmentation
   Used various Image augmentation techniques like image resizing, rotation, flipping, zooming and other changes in hue, contrast and saturation values. Also turned images into tensor slices for better pre-processing. These techniques help the model with better generalization.
   1.2. Normalization
2. **Machine Learning:** From the current advanced Machine Learning algorithms, we choose to study the performance of the Random Forest due to its ability to handle multi-class classification accurately and efficiently.
   2.1. **Process Followed:**
   - **Data Preprocessing:**
     - **Feature extraction:**
       Flattened images to 1-D array to use them as features
     - **Feature scaling**
       Scaling ensures that features with larger ranges don't dominate the decision tree splits. Although Random Forests handle this internally by splitting based on feature thresholds, if features have drastically different scales, some features might end up being favored in splits.
     - **Label Encoding:**

Since Random Forests work with numerical data, even if they can handle categorical variables during training, they require numeric labels for the target variable (dependent variable).

- **Model training**
  - **Initialization**:
    - n_estimators=100: Creates 100 decision trees in the forest.
    - random_state=42: Ensures reproducibility by fixing the random seed.
    - n_jobs=-1: Uses all available CPU cores to parallelize tree training.
  - **Training**:
    - The model is trained on the scaled feature data (X_train_scaled) and corresponding labels (y_train).
    - Each tree is trained on a random subset of data (bootstrapping) and random features (feature randomization).
  - **Ensemble Learning**:
    - After training, predictions from all trees are aggregated by majority voting for classification.
  - **Parallelization**:
    - n_jobs=-1 speeds up training by training trees in parallel.

2.2. **Results**

- **Classification report**

Classification Report:

	precision	recall	f1-score	support
AnnualCrop	0.63	0.74	0.68	300
HerbaceousVegetation	0.71	0.83	0.76	300
PermanentCrop	0.62	0.52	0.57	300
Industrial	0.45	0.21	0.29	250
Pasture	0.67	0.86	0.75	250
Highway	0.56	0.63	0.59	200
Residential	0.47	0.36	0.41	250
River	0.50	0.57	0.53	300
SeaLake	0.50	0.51	0.50	250
Forest	0.81	0.79	0.80	300
accuracy			0.61	2700
macro avg	0.59	0.60	0.59	2700
weighted avg	0.60	0.61	0.60	2700

Figure 1: Classification Report - SVM

1. **High-Performing Classes:**
   - Forest **(F1-score: 0.80)** and **HerbaceousVegetation (F1-score: 0.76)** performed the best, with both high precision and recall. This indicates that the model effectively identifies forests and vegetative areas, which are likely visually distinct and well-represented in the training data.
   - Pasture **(F1-score: 0.75)** also had a strong performance, particularly in recall (0.86), meaning most pasture instances were correctly classified.
2. **Moderate-Performing Classes:**
   - Annual **Crop (F1-score: 0.68)** and **Highway (F1-score: 0.59)** showed reasonable performance but left room for improvement, especially in precision for Highway (0.56), possibly due to confusion with Industrial or Residential areas.
   - Permanent **Crop (F1-score: 0.57)** and **Sea Lake (F1-score: 0.50)** had lower recall, meaning some instances were missed, possibly due to overlap with visually similar classes or variability in the imagery.
3. **Problematic Areas:**
   - **Industrial (F1-score: 0.29)** and **Residential (F1-score: 0.41)** were the weakest, both with low precision and recall. These may have overlapping features with other built-up classes or insufficient representation in training.
   - **River (Recall: 0.57)** had poor recall and low F1-score (0.53), suggesting it was often confused with Sea Lake or misclassified due to its linear and narrow structure in satellite images.
4. **Overall Model Accuracy**
   - **Accuracy:** 0.61 → 61% of total predictions were correct.
   - **Macro avg:**
     - Precision: 0.59
     - Recall: 0.60
     - F1-score: 0.59 → Treats all classes equally, regardless of support.
   - **Weighted avg:**
     - Precision: 0.60
     - Recall: 0.61
     - F1-score: 0.60 → Takes class imbalance into account.

- **ROC-AUC Curve**

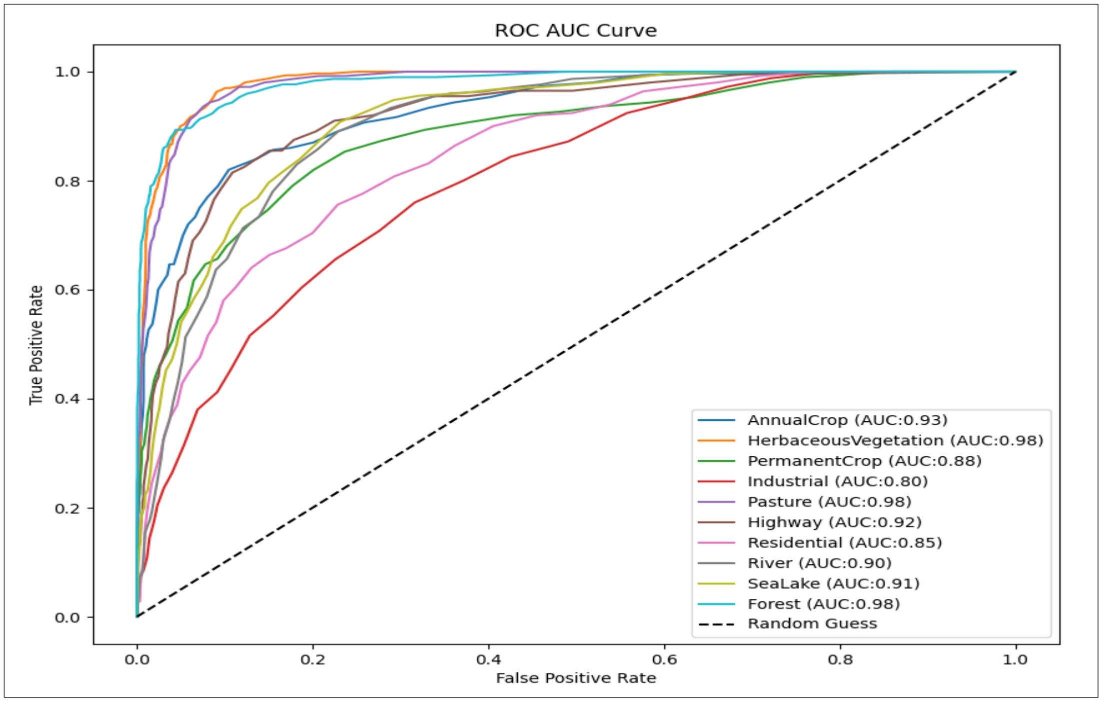

Figure 2: ROC-AUC Curve for all classes- SVM

- The ROC curve demonstrates the classifier's robust performance across land-cover classes, with AUC values ranging from **0.80 to 0.98**.
- **HerbaceousVegetation, Forest, and Pasture** each achieve an **AUC of 0.98**, indicating excellent class separation with minimal confusion from other categories. **AnnualCrop (0.93)** and **Highway (0.92)** also show strong discriminative power.
- Classes like **SeaLake (0.91)**, **River (0.90)**, and **PermanentCrop (0.88)** display slightly lower AUCs, suggesting some degree of overlap with visually similar categories.
- The model struggles most with **Industrial (AUC: 0.80)** and **Residential (AUC: 0.85)**, indicating these classes are harder to distinguish and may require enhanced feature extraction or more training examples.
- Overall, the model exhibits excellent classification capability, with minor weaknesses in distinguishing built-up or visually complex land types. These insights can guide further improvements in model tuning or data augmentation.

➢ Confusion Matrix

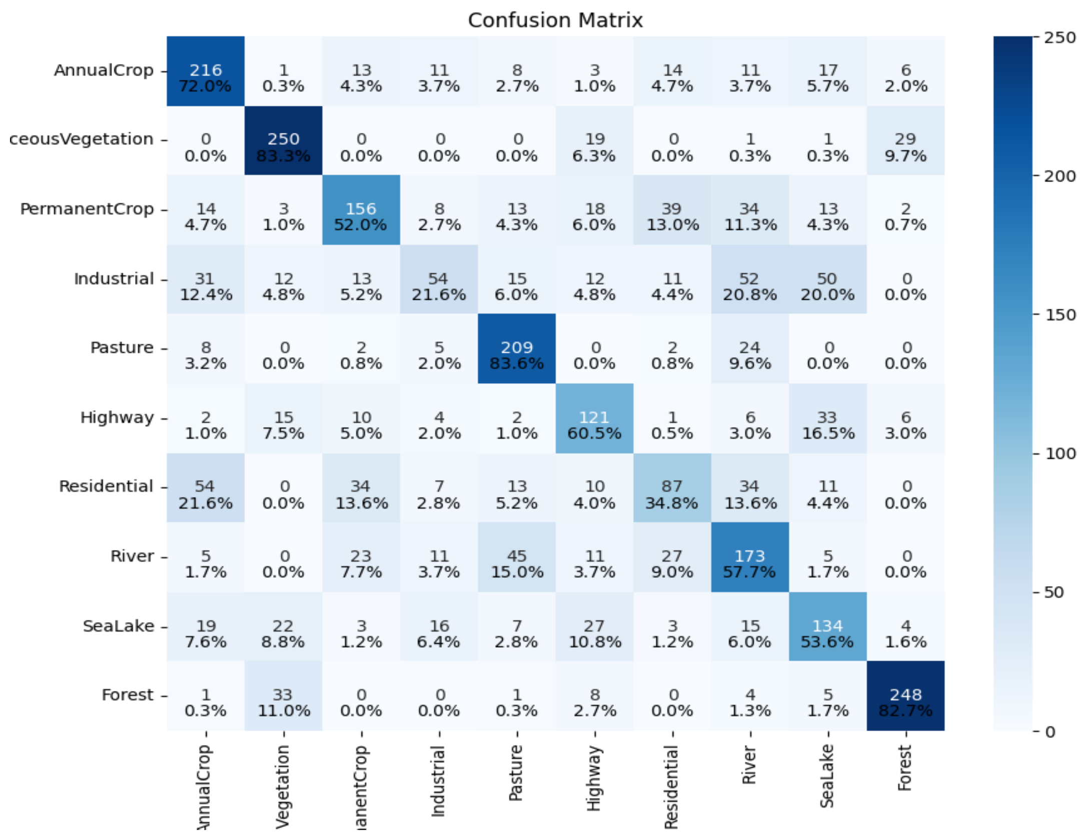

Figure 3: Confusion Matrix - SVM

- Inference:
  - The confusion matrix evaluates the **Random Forest Classifier's** performance on the test set, with **true class labels on the y-axis** and **predicted labels on the x-axis**.
  - Strong performance is seen for classes such as **HerbaceousVegetation (83.3%)**, **Pasture (83.6%)**, **Forest (82.7%)**, and **AnnualCrop (72%)**, where most predictions fall along the diagonal, indicating correct classifications.
  - Misclassifications are evident in several areas:
    - **PermanentCrop** is frequently confused with **HerbaceousVegetation, Industrial, and SeaLake**, showing substantial off-diagonal values.
    - **Industrial** shows major confusion with **Residential, Highway**, and even **Pasture**, indicating overlapping visual patterns or underfitting.
    - **Residential (34.8% correct)** suffers from significant misclassification with **AnnualCrop (21.6%)**, **PermanentCrop**, and **Highway**.

- The ‘**River’** class is often confused with **PermanentCrop** and **SeaLake**, and **Highway** is misclassified as **Residential (16.5%)** and **SeaLake**, showing weaknesses in identifying narrow, linear, or structurally complex regions.
- Overall, while the model performs reliably for well-separated classes, it struggles with visually or spatially similar categories, indicating potential for further enhancement via feature tuning or class-specific augmentation.

3. **Deep Learning:** From a wide range of Neural Networks, we choose to study the Convolution Neural Networks (CNNs). CNN is well known for working with images and is used in applications related to image classification, segmentation and recognition.

   3.1. **Process Followed:**

   - **Data Preprocessing**
     - **Normalization:** Dividing pixel values by 255, to bring them to the same scale of range [0,1]
   - **Model Training:**
     - **Model Architecture:** Following diagram represents the architecture of the CNN model. The input shape is (64,64,3).

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 64, 64, 3)	0
conv2d (Conv2D)	(None, 64, 64, 32)	896
max_pooling2d (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_1 (Conv2D)	(None, 32, 32, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 16, 16, 64)	0
conv2d_2 (Conv2D)	(None, 16, 16, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 8, 8, 128)	0
dropout (Dropout)	(None, 8, 8, 128)	0
conv2d_3 (Conv2D)	(None, 8, 8, 128)	147,584
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_1 (Dropout)	(None, 4, 4, 128)	0
conv2d_4 (Conv2D)	(None, 4, 4, 64)	73,792
max_pooling2d_4 (MaxPooling2D)	(None, 2, 2, 64)	0
conv2d_5 (Conv2D)	(None, 2, 2, 32)	18,464
max_pooling2d_5 (MaxPooling2D)	(None, 1, 1, 32)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 32)	0
dense (Dense)	(None, 64)	2,112
dense_1 (Dense)	(None, 10)	650

Total params: 335,850 (1.28 MB)
Trainable params: 335,850 (1.28 MB)
Non-trainable params: 0 (0.00 B)

Figure 4: Model Architecture/Parameters

- Used MaxPooling for reducing spatial dimensionality of the images.
- Used Dropout layer for preventing overfitting
- Used Global Average Pooling for reducing each feature map to a single number.

➢ **Hyperparameters:**
- Activation Function ReLU used in inner layers ensures that negative values are replaced with zeros, introducing non-linearity and sparsity into the model.
- Activation Function Softmax in the output layers is used since this is a multi-class classification.
- Number of epochs defined:100
- Number of epochs trained: 83
- Batch size: 32
- Early Stopping used with patience equal to 5
- LR Scheduler: ReduceLROnPlateau used with patience of 5 (monitoring validation loss)
- Used Checkpoints to save best model weights
- Used Adam as the optimizer as it handles sparse gradients.

➢ **Optimizer & Loss:** Calculated sparse_categorical_crossentropy loss, since the labels are integer encoded.

3.2. **Results**

➢ **Training and Validation Loss:**

The following Images represent the training loss (Figure 5) and validation loss (Figure 6), for measuring accuracy, over 28 epochs.

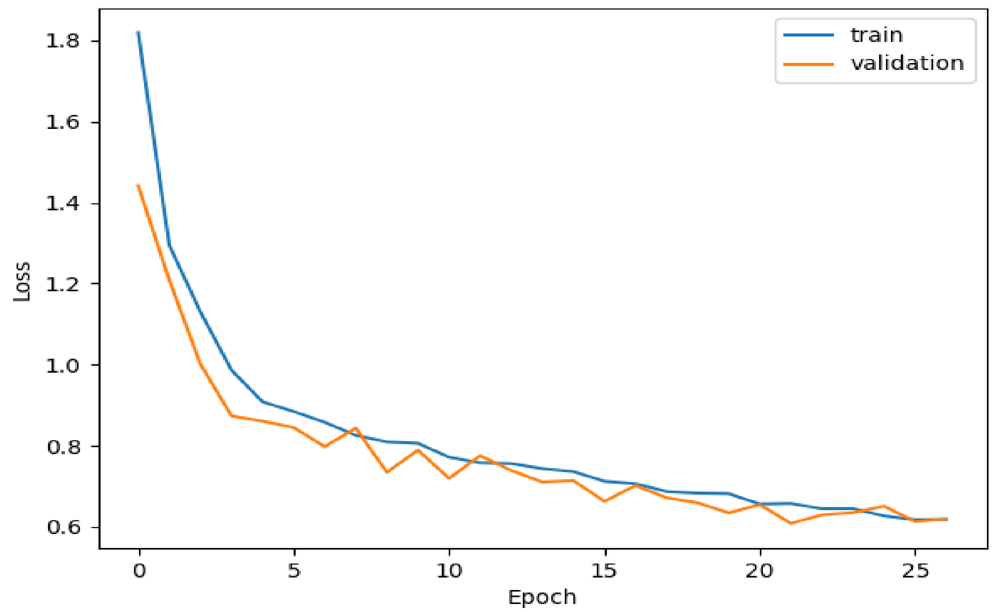

Figure 5: Training/Validation Loss

Figure 5 shows both the training and validation loss decline together; Validation loss is a bit noisy. Both the training and validation loss remain close to each other, indicating there is no significant overfitting. This indicates that the model generalizes well.

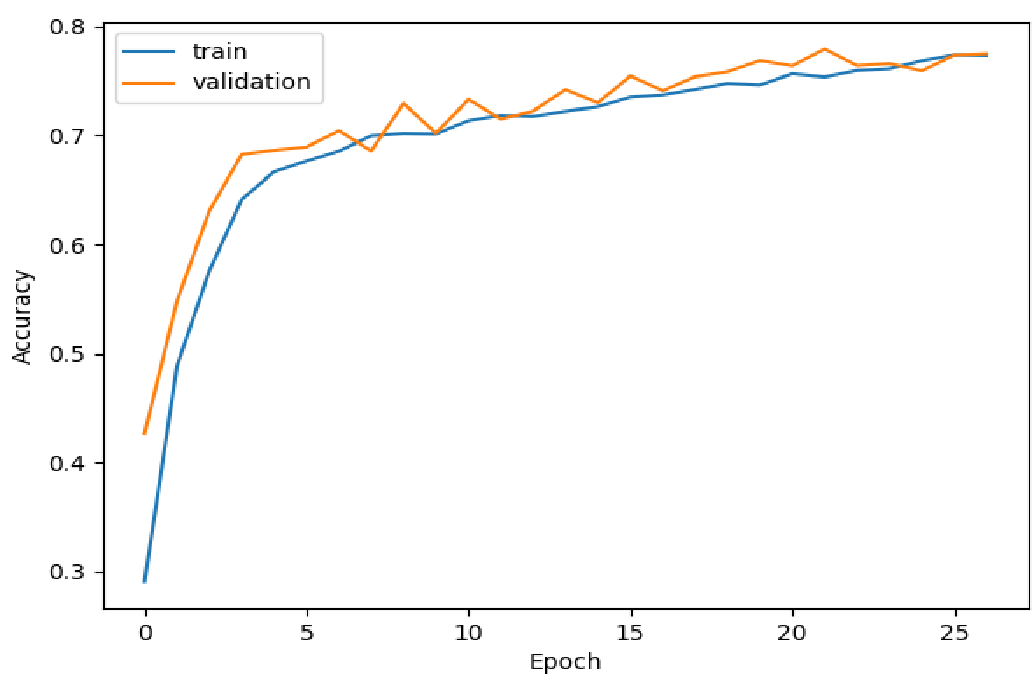

Figure 6: Training/ Validation Accuracy

Figure 6 shows both the training and validation accuracy increase gradually together with the increasing number of epochs. Up to 5 epochs the accuracy increases rapidly, then increases gradually further. After the 10th epoch, the accuracy reaches a plateau and reaches around 77%, indicating that model has learned most of the patterns well.

- Training Accuracy: 77.5%, Training Loss: 17.9%
- Validation Accuracy: 77.39%, Validation Loss: 19.7%
- Testing Accuracy: 77.7%, Testing Loss:21.1%

➢ **Classification Report:**

	precision	recall	f1-score	support
AnnualCrop	0.84	0.89	0.86	300
HerbaceousVegetation	0.94	0.91	0.93	300
PermanentCrop	0.75	0.54	0.63	300
Industrial	0.56	0.53	0.55	250
Pasture	0.93	0.89	0.91	250
Highway	0.58	0.72	0.65	200
Residential	0.60	0.76	0.67	250
River	0.90	0.99	0.94	300
SeaLake	0.66	0.53	0.59	250
Forest	0.94	0.94	0.94	300
accuracy			0.78	2700
macro avg	0.77	0.77	0.77	2700
weighted avg	0.78	0.78	0.78	2700

Figure 7: Classification report- CNN

1. **High-Performing Classes:**
   - **Forest (F1-score: 0.94)** and **River (F1-score: 0.94)** – Excellent classification, with both high precision and recall.
   - **Pasture (F1-score: 0.91)** – Very strong performance, especially high precision and recall.
   - **HerbaceousVegetation (F1-score: 0.93)** and **AnnualCrop (F1-score: 0.86)** – Reliable and consistent predictions.
2. **Moderate-Performing Classes:**
   - **Highway (F1-score: 0.65)** – Decent recall (0.72) but low precision (0.58), meaning it's often confused with other classes.
   - **Residential (F1-score: 0.67)** – Moderate scores, though recall (0.76) suggests it's often correctly identified when present.

3. **Low-Performing Classes:**
    - **Industrial (F1-score: 0.55)** and **PermanentCrop (F1-score: 0.63)** – Poorer classification, with lower precision and recall, suggesting overlapping features with other land use types.
    - **SeaLake (F1-score: 0.59)** – Low recall (0.53) indicates many SeaLake images are misclassified.
4. **Overall Summary**
    - **Accuracy**: **0.78** – The model correctly classifies 78% of the test samples**.**
    - **Macro avg (0.77)** – Average performance across all classes, treating them equally.
    - **Weighted avg (0.78)** – Performance weighted by support (class size)

- **ROC Curve:**

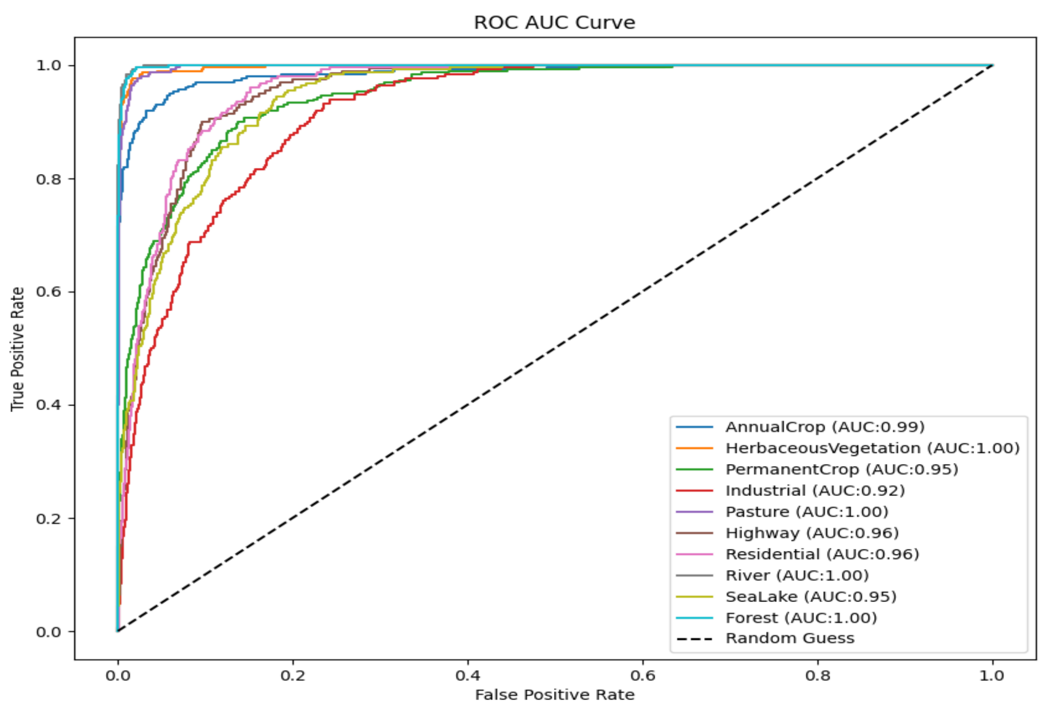

Figure 9: ROC- AUC Curve- CNN

- The ROC curve demonstrates the CNN classifier's **excellent ability to distinguish between land cover classes**, with **AUC values ranging from 0.92 to 1.00**.
- **HerbaceousVegetation, Pasture, River, and Forest** each achieve a **perfect AUC of 1.00**, indicating the model is highly confident and consistent in correctly identifying these classes without significant overlap.

- **AnnualCrop (AUC: 0.99)**, **Highway (0.96)**, and **Residential (0.96)** also show **strong discriminative power**, reflecting the model's effectiveness in separating these from other categories.
- **PermanentCrop (AUC: 0.95)** and **SeaLake (AUC: 0.95)** maintain high performance, although slight confusion may exist with visually similar classes.
- **Industrial (AUC: 0.92)**, while still well above chance, has the **lowest AUC**, suggesting it is the most challenging class for the CNN to differentiate — likely due to similarities with Residential or Highway regions.
- Overall, the CNN model achieves **exceptional classification performance**, with nearly all classes exhibiting near-perfect AUC values, indicating well-learned features and strong generalization on the test set.

➢ **Confusion Matrix:**

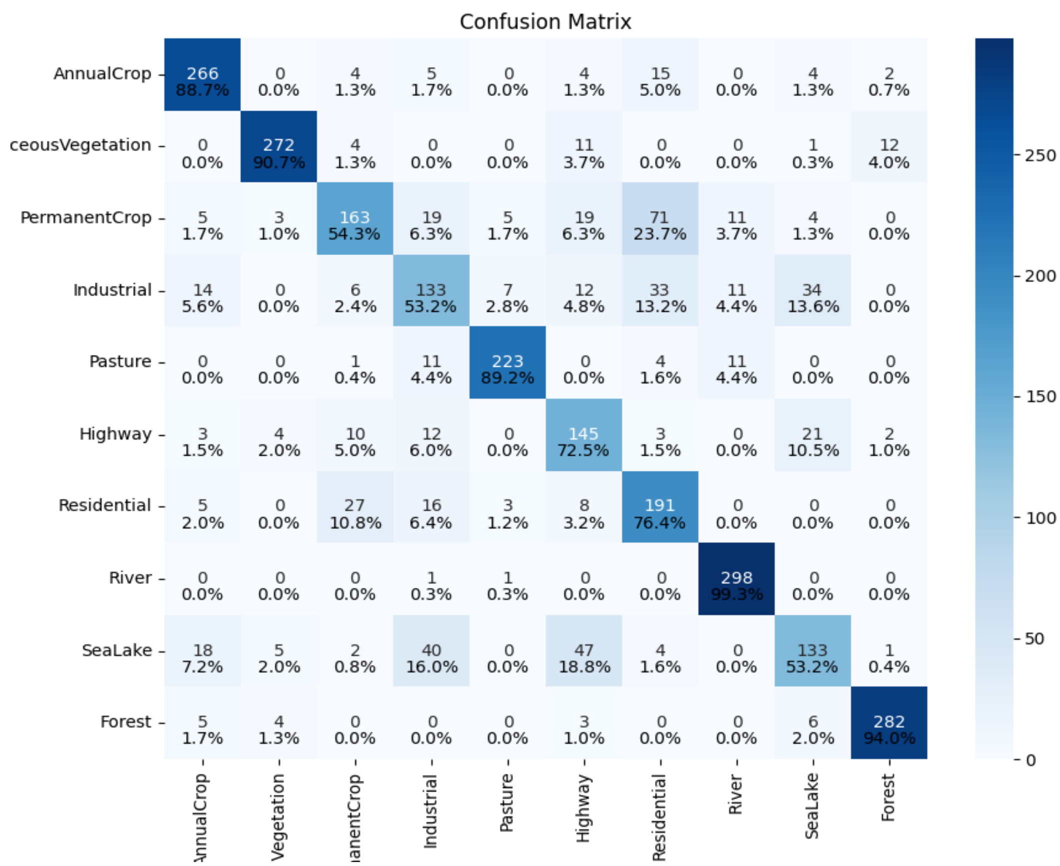

Figure 8: Confusion Matrix - CNN

- **Inference:**
  - The **diagonal values** represent the number of correctly classified samples for each class. From the matrix, the classifier performs very

well for most classes, with **accuracy above 85%** for many and above **90% for several key classes**.

- **River** shows exceptional accuracy at **99.3%** (298 correctly classified out of 300), followed by **Forest (94.0%)**, **HerbaceousVegetation (90.7%)**, and **AnnualCrop (88.7%)**, indicating the CNN model effectively recognizes these land types.
- **Pasture** and **Residential** also show strong performance with accuracies of **89.2%** and **76.4%**, respectively.
- Misclassifications are more frequent in some classes:
- **PermanentCrop** is often misclassified as **SeaLake (71 samples)** and **HerbaceousVegetation (19 samples)**, suggesting visual overlap.
- **Industrial** is confused with **Residential (34 samples)** and **SeaLake (33 samples)**.
- **SeaLake** shows considerable confusion with **PermanentCrop (71 samples)** and **Residential (47 samples)**.
- Overall, while the model handles natural land covers like Forest, River, and Vegetation very effectively, improvements are needed for classes like **Industrial**, **SeaLake**, and **PermanentCrop** due to their higher rates of confusion with visually similar categories

4. **Transfer Learning**: Transfer learning using ResNet50 is a popular method to leverage a pre-trained model for tasks like image classification. We choose this pretrained model as lower-level features (e.g., edges and textures) learned by ResNet50 are highly relevant and can be adapted for the EuroSAT image classification task.

   4.1. **Process Followed:**

   - **Model Training:**
     - **Model Architecture:** The first 30 layers of the ResNET50 pre-trained model were unfrozen to achieve the maximum accuracy.Following diagram represents the architecture of the model. The input shape is (64,64,3).

Model: functional

Layer (type)	Output Shape	Param #
input_layer (Inputla..	(None, 64, 64, 3)	0
conv2d (Conv2D)	(None, 64, 64, 3)	996
max_pooling2d (MaxPo..	(None, 32, 32, 3)	0
conv2d_1 (Conv2D)	(None, 32, 32, 64	73 896
max_pooling2d_1 (MaxP..	(None, 16, 16, 64	0
dropout (Dropout)	(None, 16, 16, 64	73 856
conv2d_2 (Conv2D)	(None, 16, 16,128	73 856
max_pooling2d_2 (MaxP..	(None, 8, 8, 128)	0
dropout_1 (Dropout)	(None, 8, 8, 128)	0
conv2d_3 (Conv2D)	(None, 8, 8, 128)	147 584
max_pooling2d_3 (MaxP..	(None, 4, 4, 128)	0
global_average_pooli…	(None, 2, 2, 128)	0
dense (Dense)	(None, 126)	1 290

Total params: 335,850 (1.28 MB)
Trainable params: 335,850 (1.28.MB)
Non-trainable params: 0

Figure 10: VGG16 Architecture

- Used MaxPooling layers throughout the model to reduce the spatial dimensionality of the images after convolutional operations.
- Used BatchNormalization layers to

➢ **Hyperparameters:** Following diagram represents the architecture of the CNN model.

- The input shape is (64,64,3).
- **Activation Functions:**
  - **ReLU:** Used in inner layers to replace negative values with zeros, introducing non-linearity and sparsity into the model.
  - **Softmax:** Used in the output layer for multi-class classification.
- **Number of Epochs :** 20 epochs in the code.
- **Batch Size :**32.
- **Early Stopping**
  - Patience: 10 epochs.
  - Monitoring: Validation sparse categorical accuracy (`val_sparse_categorical_accuracy`).
  - Restores best weights when validation accuracy does not improve.
- **Checkpoints**
  - Used to Save Best Model Weights**:** Saved model weights based on the best validation categorical accuracy (`val_sparse_categorical_accuracy`).
- **Optimizer**
  - Adam: Used as the optimizer to handle sparse gradients effectively.

➢ **Results:**

- The following Images represent the training loss (Figure 11) and validation loss (Figure 12), for measuring accuracy, over 32 epochs.

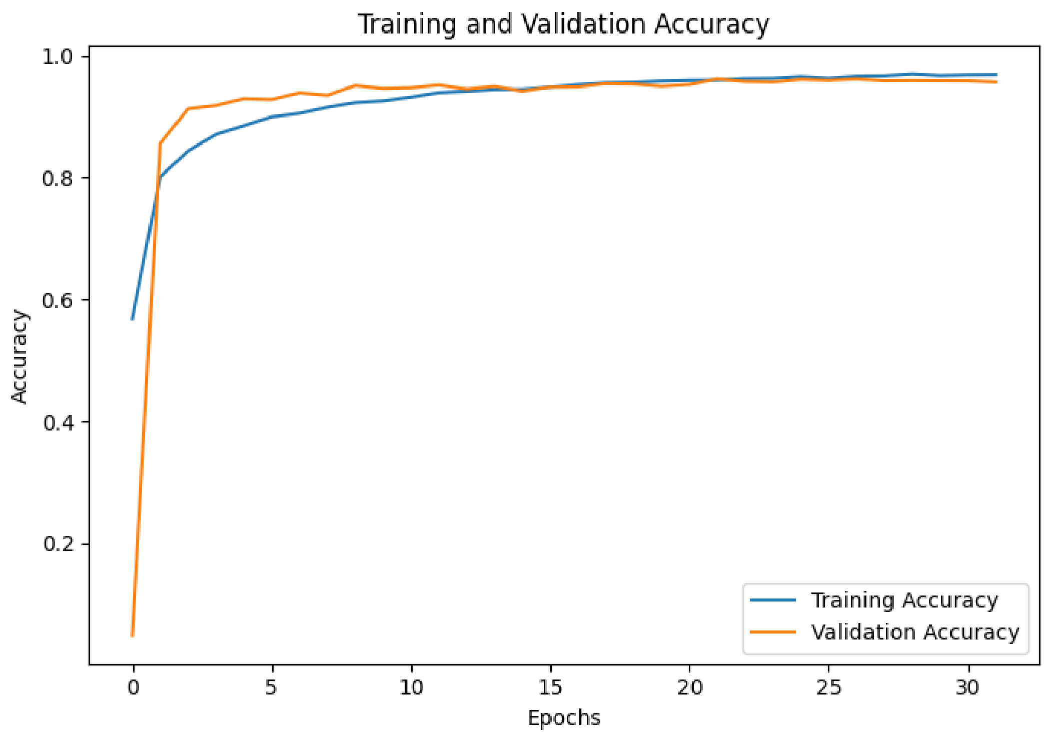

Figure 11: Training/ Validation Loss: VGG16

Figure 5 displays the training and validation accuracy curves over 32 epochs. The training accuracy begins around 0.6 and gradually increases, reaching close to 0.98 by the end of training. The validation accuracy starts very low at approximately 0.05 but quickly rises within the first few epochs, closely aligning with the training accuracy thereafter. From epoch 5 onward, both curves remain consistently high, fluctuating slightly between 0.94 and 0.98. The close alignment between training and validation accuracy indicates minimal overfitting and suggests that the model generalizes well to unseen data.

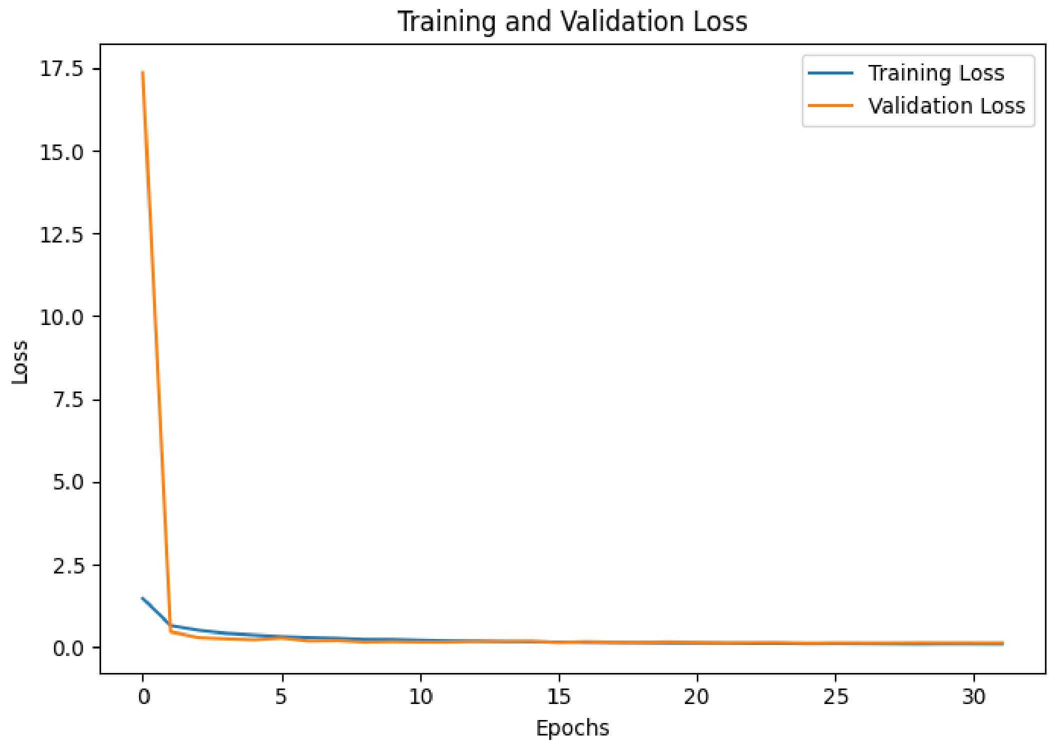

Figure 12: Training/Validation Accuracy: VGG16

Figure 6 illustrates the training and validation loss over 32 epochs. Initially, the validation loss spikes dramatically but quickly drop and aligns closely with the training loss after the first epoch. From that point onward, both losses steadily decrease and converge to near-zero values, indicating that the model's predictions are improving over time. The minimal gap between the training and validation loss curves suggests the model is not overfitting and is generalizing well to unseen data.

- Training Accuracy: 71.91%; Training Loss: 42.73%
- Validation Accuracy: 71.44%; Validation Loss: 43.14%
- Test Accuracy: 75.40%

- **Classification Report**

	precision	recall	f1-score	support
AnnualCrop	0.98	0.97	0.97	300
HerbaceousVegetation	0.98	0.97	0.98	300
PermanentCrop	0.93	0.96	0.95	300
Industrial	0.94	0.94	0.94	250
Pasture	0.98	0.99	0.99	250
Highway	0.95	0.95	0.95	200
Residential	0.95	0.90	0.92	250
River	0.99	1.00	0.99	300
SeaLake	0.95	0.96	0.95	250
Forest	0.98	0.99	0.99	300
accuracy			0.96	2700
macro avg	0.96	0.96	0.96	2700
weighted avg	0.96	0.96	0.96	2700

Figure 13: Classification report: VGG16

1. High-Performing Classes:
   - River (F1-score: 0.99), Pasture (F1-score: 0.99), and Forest (F1-score: 0.99) demonstrate near-perfect precision and recall, indicating the model can consistently and accurately identify these land cover types.
   - SeaLake, Highway, Residential, and HerbaceousVegetation all achieve F1-scores of 0.95 or higher, showcasing excellent class-wise performance with minimal misclassification.
   - AnnualCrop (F1-score: 0.97) also shows strong performance, with slightly lower recall (0.97) than precision (0.98), suggesting very few true samples were missed.
2. Moderate-Performing Classes (Relatively):
   - PermanentCrop (F1-score: 0.95) and Industrial (F1-score: 0.94) have marginally lower scores compared to other classes but still perform very well.
   - These classes may contain visually similar patterns that contribute to minor confusion with nearby categories, yet the model handles them with high confidence.
3. Overall Performance:
   - Accuracy: 0.96 – 96% of all predictions are correct.
   - Macro Avg / Weighted Avg:
     - Precision: 0.96
     - Recall: 0.96

        - F1-score: 0.96
    - These consistent averages across classes indicate balanced performance with no significant bias toward any particular class.

- **ROC Curve**

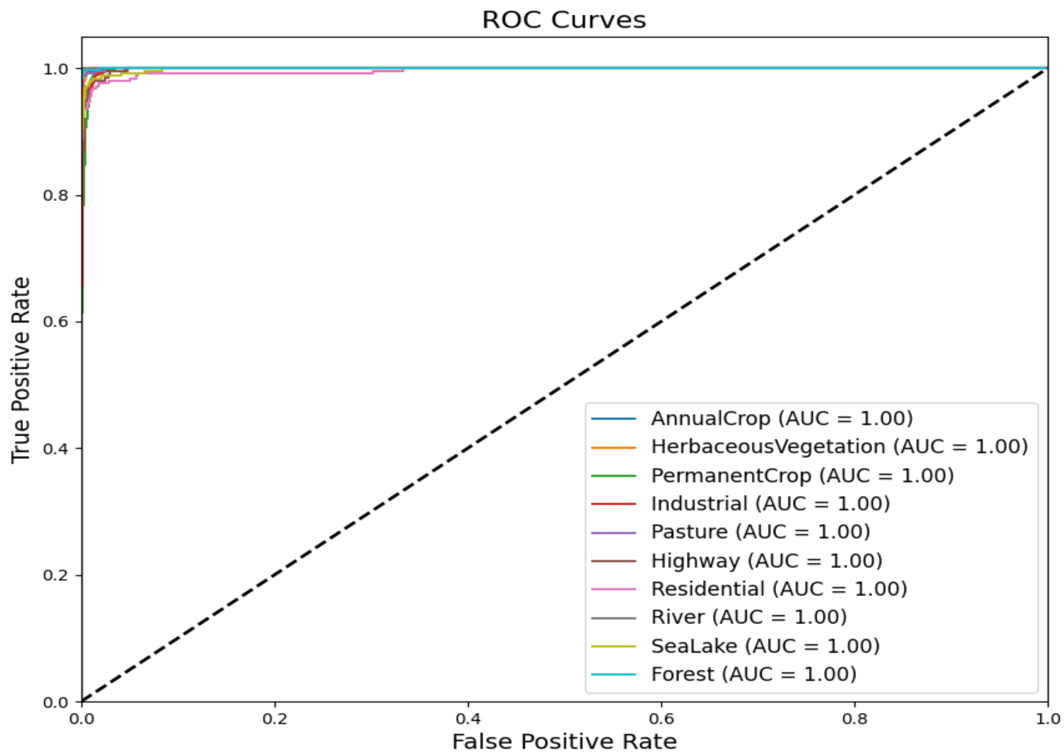

Figure 14: Confusion Matrix: VGG16

- **Figure X** displays the ROC curves for each class in the transfer learning model, plotting the **True Positive Rate** against the **False Positive Rate** across thresholds.
- All classes, including **AnnualCrop, HerbaceousVegetation, PermanentCrop, Industrial, Pasture, Highway, Residential, River, SeaLake**, and **Forest**, achieve an **AUC of 1.00**, indicating **perfect separability** between classes.
- The ROC curves hug the **top-left corner**, representing **optimal classification performance** with no trade-off between sensitivity and specificity.
- The absence of deviation from the ideal ROC shape across all classes suggests that the model **makes highly confident predictions** for every land cover type with virtually no false positives.

➢ Confusion Matrix

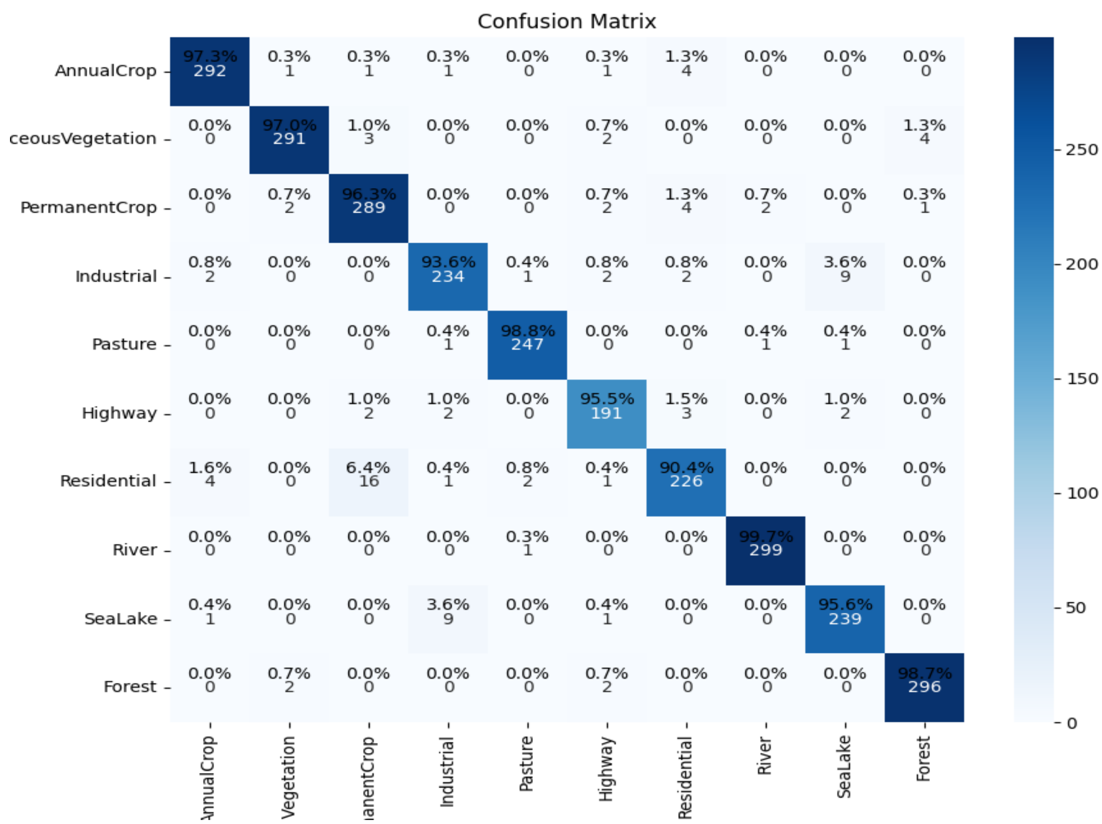

Figure 15: ROC-AUC Curve: Transfer Learning

- **Inference:**
  - Figure 14 presents the confusion matrix for a transfer learning-based classification model, where the true class labels are along the y-axis and the predicted labels are along the x-axis.
  - The diagonal elements represent correctly classified instances, and the high values along the diagonal indicate strong performance across all classes.
  - River (99.7%), Pasture (98.8%), Forest (98.7%), and AnnualCrop (97.3%) show excellent classification accuracy, suggesting the model is highly confident in identifying these land cover types.
  - HerbaceousVegetation (97.0%) and PermanentCrop (96.3%) are also predicted with very high accuracy, with only minor misclassifications into visually similar categories.

- SeaLake (95.6%) and Highway (95.5%) maintain strong performance, though a few samples are misclassified into classes like Industrial or Residential.
- Residential (90.4%) and Industrial (93.6%) show relatively lower diagonal values compared to other classes, indicating more frequent confusion, especially with each other and with similar-looking areas like PermanentCrop and Highway.

COMPARATIVE STUDY:

Criteria	SVM (Random Forest)	CNN	ResNet50 (Transfer Learning)
Training Time	40 minutes	23 minutes	25 minutes
Accuracy	61.0%	78.0%	96.0%
Precision (Macro Avg)	0.59	0.77	0.96
Recall (Macro Avg)	0.60	0.77	0.96
F1-Score (Macro Avg)	0.59	0.77	0.96
Variance in F1-Scores	High (e.g., Industrial: 0.29, Forest: 0.80)	Moderate (e.g., Industrial: 0.55, Forest: 0.94)	Very Low (Most classes above 0.94)
Memory Efficiency	High memory usage	Memory efficient	Memory intensive
Model Complexity	Simple preprocessing with Random Forest	Moderate complexity	High complexity
Scalability	Difficult to scale to large datasets	Scales well with larger datasets	Scales with computational cost

Generalization	Moderate, struggles with visually similar classes	Excellent generalization across diverse classes	Excellent generalization, robust across all classes
Key Strengths	Easy to implement, interpretable	High accuracy, faster training, good feature learning	Exceptional accuracy, perfect AUCs, effective transfer learning
Weaknesses	Poor with complex/overlapping classes	Struggles slightly with some similar classes	Longest training time, resource-intensive
Interpretability	Easy to interpret	Moderate (visualizable filters)	Complex due to deep residual layers
Suitability: Small Data	Good with proper preprocessing	Performs well with augmentation	May underperform without pretraining
Suitability: Large Data	Limited	Performs well	Performs well with GPU resources
Use Case Suitability	Basic classification tasks	General-purpose classification	High-accuracy, detail-critical classification
Preprocessing Needs	Extensive preprocessing & scaling	Light preprocessing + augmentation	Requires resizing, normalization, fine-tuning

Table 1: Comparison of Three Models.

CONCLUSION:

In conclusion, the comparative study of SVM, CNN, and ResNet50 models highlights that the **ResNet50 transfer learning model** is the most effective for classifying land cover images. With an accuracy of **96%**, it significantly outperforms both CNN (78.0%) and SVM (61.0%), showcasing superior classification performance across all classes.

The ResNet50 model demonstrates **perfect AUC scores** for all classes, indicating flawless class separation and strong generalization to unseen data. It also exhibits **minimal variance in F1-scores**, with most classes achieving scores above 0.94, suggesting consistent and highly reliable predictions.

While the CNN model provides a strong balance of accuracy and training efficiency, requiring only 23 minutes, ResNet50, despite its higher training time (25 minutes), delivers the most **robust and generalizable results**. On the other hand, the SVM model, though simpler and easier to interpret, lags significantly in performance, particularly for complex and visually similar classes.

Therefore, based on overall accuracy, consistency, class-wise balance, and model robustness, the ResNet50 transfer learning model is the optimal choice for accurate and scalable land cover classification.

REFERENCE:

[1] Ziming Li a, Bin Chen a b c, Shengbiao Wu a, Mo Su d, Jing M. Chen e f, Bing Xug;Deep learning for urban land use category classication: A review and experimentalassessment.

[2] Zhe Wang, Chao Fan, Xian Min, Shoukun Sun, Xiaogang Ma, Xiang Que; Cross-scaleUrban Land Cover Mapping: Empowering Classication through Transfer Learning andDeep Learning Integration.

[3] Giorgos Mountrakis, Shahriar S. Heydari; Harvesting the Landsat archive for landcover land use classication using deep neural networks: Comparison with traditionalclassiers and multi-sensor benets.

[4] Ava Vali,Sara Comai,Matteo Matteucci; Deep Learning for Land Use and Land CoverClassication Based on Hyperspectral and Multispectral Earth Observation Data: AReview.

[5] Suraj Sawant, Jayanta Kumar Ghosh; Land use land cover classication usingSentinel imagery based on deep learning models.

[6] Giorgos Mountrakis, Shahriar S. Heydari; Harvesting the Landsat archive for landcover land use classication using deep neural networks: Comparison with traditionalclassiers and multi-sensor benets.

[7] Enhancing land cover classication in remote sensing imagery using an optimal deeplearning model; Abdelwahed Motwake; Aisha Hassan Abdalla Hashim 1 ,Marwa Obayya, Majdy M. Eltahir
[8] Lou, Chen, Mohammed A. A. Al-qaness, Dalal AL-Alimi, Abdelghani Dahou,Mohamed Abd Elaziz, Laith Abualigah, and Ahmed A. Ewees. 2024. Land Use/LandCover (LULC) Classication Using Hyperspectral Images: A Review. Geo-SpatialInformation Science