LAND COVER AND CROP CLASSIFICATION In SATELLITE IMAGES

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Dedication

All praise and thanks to Allah Almighty, the most gracious and the most merciful. This thesis is dedicated to all my teachers, mother, father and all family, for their never ending love, faith and motivation.

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Abstract

The classification of land cover and crop types through the analysis of satellite imagery is a fundamental task with wide-ranging implications in the fields of agriculture, environmental monitoring, and urban planning. This research embarks on a comprehensive journey to explore advanced methodologies for precise land cover classification and crop type identification, utilizing high-resolution satellite images as its primary data source. Leveraging the EuroSat dataset as a valuable resource, we harness the potential of cutting-edge deep learning models, with a focal point on DenseNet, renowned for its capacity to extract intricate features from remote sensing data. A meticulous data preprocessing pipeline is applied, encompassing image resizing, normalization, and class aggregation, to optimize the input data for superior model performance. The outcomes of this study underscore the remarkable ability of modern neural networks to capture the nuanced characteristics of land cover and crop types within satellite imagery, emphasizing their effectiveness in addressing real-world challenges across diverse applications. Moreover, this research outlines promising avenues for future exploration, including the development of fine-grained crop classification techniques, temporal analysis methods, and the integration of multi-sensor data fusion, all aimed at further enhancing the precision, adaptability, and practicality of land cover and crop type classification models.

TABLE OF CONTENTS

LIST OF TABLE

List of Figures

LIST OF ABBREVIATIONS

Land cover and Crop Classification (LCCC)
Remote Sensing (RS)
Residual Network (ResNet)
Convolutional Neural Network (CNN)
Rectified Linear Unit(ReLU)
Densely Connected Convolutional Network (DenseNet)
Geographic Information Systems (GIS)
IEEE International Geoscience and Remote Sensing Symposium(IGARSS)
Artificial Intelligence (AI)
Red Green Blue (color channels) (RGB)
Binary Cross-Entropy (BCE)
Feature Extraction (FE)
Near-Infrared (NIR)
True Positive (TP)
True Negative (TN)
False Positive (FP)
False Negative (FN)
Infrared (IR)
Deep Learning (DL)
Natural Language Processing (NLP)
Deep Convolutional Neural Networks (DCNN)
Summation (+)
Concatenation (.)
Intersection over Union (IoU)
Machine Learning (ML)
Inverted Residual Blocks (IRB)
Residual Blocks (RB)
Fully Connected (FC)
Dense Block (DB)
Parameter Efficiency (PE) Efficient Neural Network Architecture (EfficientNet)
Visual Geometry Group (VGG)
Linear Discriminant Analysis (LDA)

CHAPTER 1

1 INTRODUCTION

The process of recognizing and classifying various types of land cover and crops existing in a specific location is referred to as land cover and crop type categorization. Aerial photography, satellite imaging, and ground surveys are frequently used in this process. The improvement of the current systems for gathering and developing agricultural maps and data sources relies heavily on satellite and geographic information data. Remote sensing (RS), a popular method for gathering required data, provides a practical method for obtaining accurate information about the land cover that is affordable and practical. RS has been employed extensively over the past few decades, particularly for agricultural techniques to obtain sustainable agricultural goals [1]. The key methods for estimating the degree of geographical diversity inhabited by different crops are crop identification and classification.

1.1 The Land Cover

In satellite images, the classification and identification of different types of land on the Earth's surface are known as Land Cover (LC). The presence of water bodies, the type, and density of vegetation, as well as the extent of human-made features such as roads, buildings, and houses, can be observed with details in satellite data of the land cover. The spectral characteristics of various surface features are often used to classify land cover [2]. Satellite sensors can monitor the distinct spectral signature of each surface feature that measures the reflected radiation from the surface of earth.
Environmental monitoring, disaster management, resource management, and agriculture are just a few of the many uses for satellite-based land cover classification. Vegetation cover, determining locations that might be utilized for crop production, and the estimation of natural disasters can be monitored by using land cover classification. In general, understanding and monitoring the Earth's surface land cover classification is the best tool. Land cover classification also supports a variety of applications that require information about the different types of land[3].

1.1.1 Types of Land Cover

Several types of land cover can be recognized and divided into separate groups using their spectral characteristics, including forest, grassland, farmland, aquatic bodies, and urban regions. There are many types of land cover but we are focusing on three major types as shown in Figure 1. The green color represents grasslands, the yellow color represents cereal crops, and the red color shows the unused area on Earth's surface.

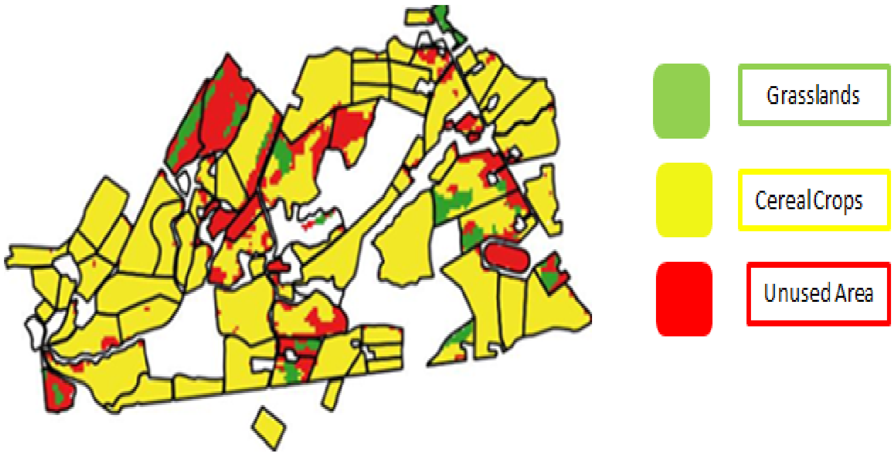

Figure 1: "Map of Land Cover Types" Wikipedia Commons.

The term "Land Cover" refers to both biological and physical features that cover the surface of the earth. Three most prevalent types of land cover are grasslands, cereal crops, and unused areas[4].

1.1.2 Grasslands

The large area of flat, open, or rolling ground that is covered by grasses and non-woody plants is defined as grassland. Except for antarctica, they are found on every continent. Grasslands can be divided into two main types: tropical and temperate grasslands.

A. Tropical grasslands

Tropical grasslands have a distinct dry and rainy season as well as usually mild temperatures. This is also sometimes called savannas. Wildebeest, zebra, and giraffes are large feeding species and they live there along with carnivores like jackals and lions. Tropical grasslands get 500 to 1500 mm of rain per year. They have large expanses of grass and a few scattered trees.

B. Temperate grasslands

In comparison to tropical grasslands, temperate grasslands also referred to as prairies, can be found in areas with lower temperatures and more moderate rainfall. Along with wild animals like coyotes and wolves, they are home to grazing animals like bison and antelope.

Grasslands are a crucial component of the ecosystem since they are utilized for grazing, agriculture, and the sustenance of a diverse range of plant and animal species. Yet, issues including overgrazing, climate change, and human growth also pose a threat to them [5].

1.1.3 Cereal crops

A group of grasses cultivated largely for their edible seeds or grains are known as cereal crops. Many crops are growing in the world but cereal crops are some of the most important staple crops. These crops also contributed significantly to the world's food supply. Rye, maize, wheat, oats, barley, and wheat are a few examples of cereal crops as shown in Figure 2.

Figure 2: "Examples of Cereal Crops, First image represents Corn, second Rice, Third Wheat, Fourth Soybean, Fifth Potato" Data Source: Wikipedia[6], Last access: 02/03/2023).

These crops are grown on farms in large quantities and can be used for many purposes. These crops are also used for biofuels, and industrial applications, as well as for animal feed and human consumption. Furthermore, cereal crops are an important component of many national economies and this is also an important source of income for farmers.

Seasons of Cereal Crops

The planting and harvesting season of these crops is dependent on the specific crop and the area in which it is grown. Typically, cereal crops are separated into two types: winter cereals and spring cereals.

1) Winter Cereals

Winter cereals like barley, oats, and wheat are usually planted in the fall. This is allowed to grow in all winter months. As I early discussed, these crops are planted in the winter season but these crops can only survive the winter months before maturing. These crops are harvested in the spring or early summer.

2) Spring Cereals

These crops are planted in the spring when the risk of frost has passed, and the soil h has warmed up. Corn and sorghum are examples of spring cereals. Typically these crops flourish and are harvested at the end of summer.
Weather patterns, regional agricultural methods, and soil quality are only a few examples of variables that may have an impact on the specific time period of planting and harvesting cereal crops.

1.1.4 Unused Areas

The areas of land that are not currently being used for a specific purpose or that are not being significantly managed are referred to as unused areas in land cover. Deserted farmland, clear-cut woods, fallow fields, and regions damaged by natural disasters like floods, degraded terrain, or wildfires are examples of unused areas in land cover. Active management and restoration techniques have the capability to be rehabilitated and restored these areas. This can help to improve ecosystem services, soil quality, and biodiversity.

Types of Unused areas in land cover

There are several types of unused areas in land cover, including:

1) Fallow fields

The earth may recover and restock its nutrients because these fields have not been planted for a period.

2) Degraded land

Human activities like poor land management techniques, overgrazing, or mining are the biggest reason for harming specific areas. These suffering areas are known as degraded land.

3) Urban vacant lots

The areas that are not being used for any specific purpose are located within urban areas like parks or buildings known as urban vacant lots.

4) Clear-cut forests

The areas of forest that have been fully cleared of trees, mainly for timber or agriculture purposes.

5) Natural disaster sites

The areas are unsuitable for human activities because they have been damaged by natural disasters like landslides, wildfires, or floods.

1.2 Introduction to Crop Classification

The process of identifying the different crops planted in a specific area using satellite images is known as crop classification. It is one of the important applications of remote sensing technology. It can provide useful information for yield estimation, land-use planning, and crop management. This process involves pre-processing the satellite data, then extracting features from the image, and after that identifying the crop type by using classification algorithms. Numerous techniques and approaches are used for crop classification, such as object-based classification, and supervised and unsupervised classification[7]. It can be challenging due to a number of factors including cloud cover, seasonal variations in vegetation cover, and mixed-crop regions. Moreover, recent developments in remote sensing technologies have increased the accuracy and effectiveness of crop classification.

1.2.1 Approaches to Classifying Crop Types

Crop-type classification can be done by using multiple approaches and these approaches provide meaningful information about crop selection, yield optimization, land use planning, and agricultural planning and management. Following are some typical methods for categorizing different types of crops.

1) Seasonal classification

The crops that are planted at a specific time of year are known as seasonal-based classification. Kharif crops or Rabi crops are examples of seasonal based classification.

Kharif crops

The crops planted in the rainy season and harvested in the fall are known as kharif crops. This classification is frequently employed in those countries that have monsoon climates. In these countries, the rainy season lasts from june to september. Rice, maize, cotton, soybean, and sugarcane are some examples of kharif crop types.

Rabi crops

Crops known as rabi those are planted in winter season (between october to december) and are harvested in the spring season (between february to april). These crops are grown in those countries where the rainy season ends by september or october, and the winter season is suitable for cultivation. Wheat, mustard, peas, barley, and gram are the examples of rabi crops. These crops dependent on irrigation facilities, and require less water compared to kharif crops.

2) Agronomic classification

This classification based on cultural practices. Crops can grow on the bases of cultural practices like fertilization, pest management, and irrigation.

3) Botanical classification

This method classifies crops on the bases of their taxonomic properties, like genus, species and family.

4) Commercial classification

In commercial classification, crops classify on the base of their end use or market value, like industrial crops, food crops, and cash crops.

5) Climatic classification

Climatic classification classifies crops based on their adaptability to different environmental conditions, such as arid crops, temperate crops, or tropical crops.

Each of these methods offers a different viewpoint on various crop types and can help with decisions about crop management and production. Researchers and decision-makers can gain a more thorough understanding of crop production and the variables affecting its performance by integrating several methodologies[8].

1.3 Applications of Land Cover and Crop Classification

Identifying potential dangers, keeping track of troop movements, and identifying regions of interest are just a few examples of how Land Cover Classification can be used in military applications.

1.3.1 Environmental monitoring

Land Cover Classification is a useful tool that can provide information on the distribution and extent of natural resources, such as grasslands, water bodies, and wetlands. This information is useful for environmental monitoring and management purposes.

1.3.2 Urban Planning

In urban planning, Land Cover Classification can provide valuable information about the distribution and extent of urban areas. This information is very beneficial for disaster management, urban planning, and infrastructure development.

1.3.3 Forestry

The classification of Land Cover can provide valuable information regarding the overall health of the forest, forest cover, and forest cover. This information can prove beneficial for monitoring of reforestation and deforestation activities, management of forests, and conservation efforts.

1.3.4 Agriculture

In the agriculture field, crop type classification provides insights into the type of crops. It also gives information about crop distribution. This information is very useful for resource allocation, crop management, and yield prediction.

1.3.5 Supply Chain Optimization

Classification assists in identifying regions with suitable conditions for potato cultivation, aiding in procurement and supply chain management. Monitoring crop types and land cover helps ensure a consistent supply of high-quality potatoes for chip production.

1.3.6 Yield Prediction

Classification provides data for predicting wheat yields, helping governments and organizations prepare for potential shortages and plan import/export strategies accordingly.
In Conclusion, Land Cover and Crop Classification can provide useful information for different fields, like environmental monitoring, urban planning, forestry, agriculture, military applications, and climate change.

1.4 Dataset Details

RS has been employed extensively over the past few decades, particularly for agricultural techniques to obtain sustainable agricultural goals. Many researchers and scientists have contributed to the development of LC and CC techniques. According to my best knowledge, Anderson et al. in the 1970s first contributed to the Land Cover and Crop classification system. Jensen in the 1980s contributed to the image processing approach for land cover mapping. The development of machine learning algorithms for land cover classification started in the 2000s[9].
Land Cover and Crop Classification is a challenging task for researchers due to mixed pixels, crop variability, and spectral confusion. For several years, land cover and crop type classification studies have been interested in Remote Sensing.

1.4.1 EuroSAT Dataset

In Paper [10] EuroSAT dataset was created by the Technical University of Munich in Germany, led by Johannes Schmidhuber. This dataset was created using sentinel-2 satellite imagery which is operated by the European Space Agency (ESA). The satellite can capture images in 13 spectral bands, including visible and near-infrared wavelengths because the satellite is equipped with Multi-Spectral Instrument (MSI).
The euroSAT dataset consists of 27,000 images, which is divided into 10 different Land Cover Classes such as agricultural land, forest, urban areas, permanent crops, industrial areas, pastures, water bodies, railway tracks, meadows, and highways.The EuroSAT dataset is roughly balanced.
In EuroSat dataset Annual Crop and River Class contains 3000 labeled images, Forest class contains 2300 images, Vegetation class has 3500 images, Residential class has 2900 images, SeaLake and Highway class contains 2500 images, Industrial class has 1500 images, PermanentCrop has 2000 images and Pasture class contains 3800 images. This information is also represented in Figure: 3. Graphically EuroSat dataset is represented in Figure 3.

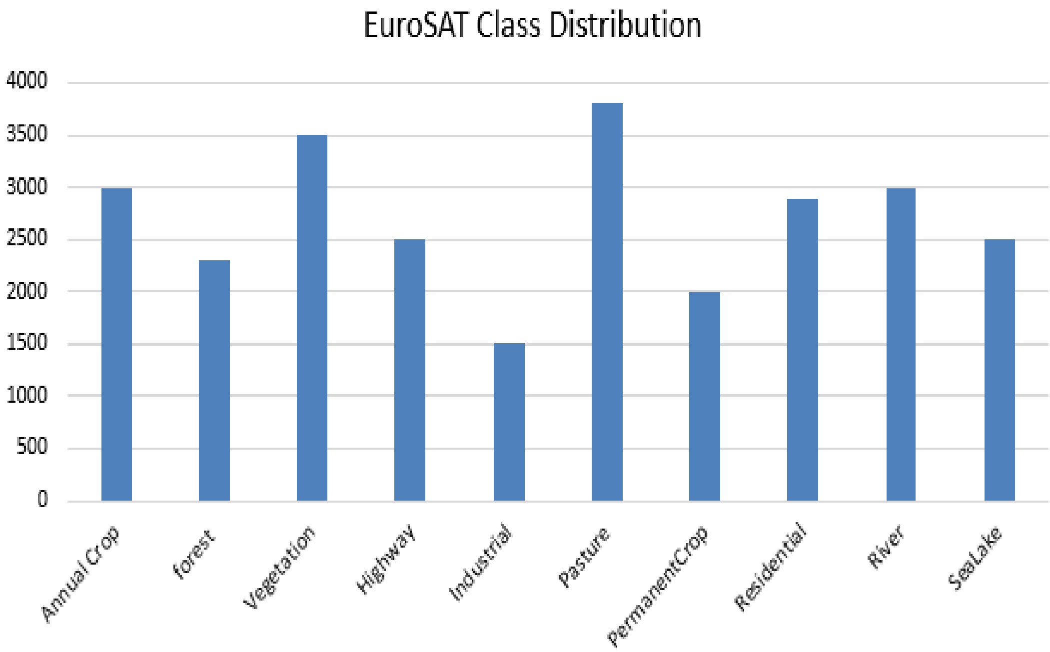

Figure 3: "EuroSat Class Graph: Number of images shown in the corresponding class"

Each image consists of a resolution of 64x64 pixels and is evenly balanced. All images in the dataset are labeled with their corresponding class. It was published in 2017 as part of the IEEE International Geoscience and Remote

Sensing Symposium (IGARSS) conference. This dataset can be used for land cover classification and also for different machine learning and deep learning applications like object detection, classification, and image segmentation. The EuroSAT dataset has become a popular benchmark dataset in the field of machine learning and remote sensing and has been used in many studies to evaluate the performance of various classification algorithms and models. This dataset can be accessed freely from the official website of the Technical University of Munich.
There are two versions of the EuroSAT dataset available: **EuroSAT RGB and EuroSAT NIR**.

1.4.2 EuroSAT RGB dataset v1.0

The EuroSAT RGB version contains 27000 labeled images that covering 10 different land cover classes in Europe. Each image consists of a resolution of 64x64 pixels and evenly balanced. Each image in the dataset is labeled with the corresponding land cover class, and the dataset is evenly balanced across all classes.

1.4.3 EuroSAT NIR dataset v2.0

In addition to the 13 bands of the RGB version, the Near-Infrared (NIR) band is included in the EuroSAT NIR version. The NIR band is helpful for monitoring vegetation since it can give information on the health and density of the vegetation. The same 10 land use types from the RGB version are covered by the 27,000 annotated photos in the EuroSAT NIR version. The photos have the same spatial resolution and coverage area as the RGB version. The EuroSAT datasets are both freely accessible for academic study and are widely used as benchmark datasets in the fields of remote sensing and machine learning.

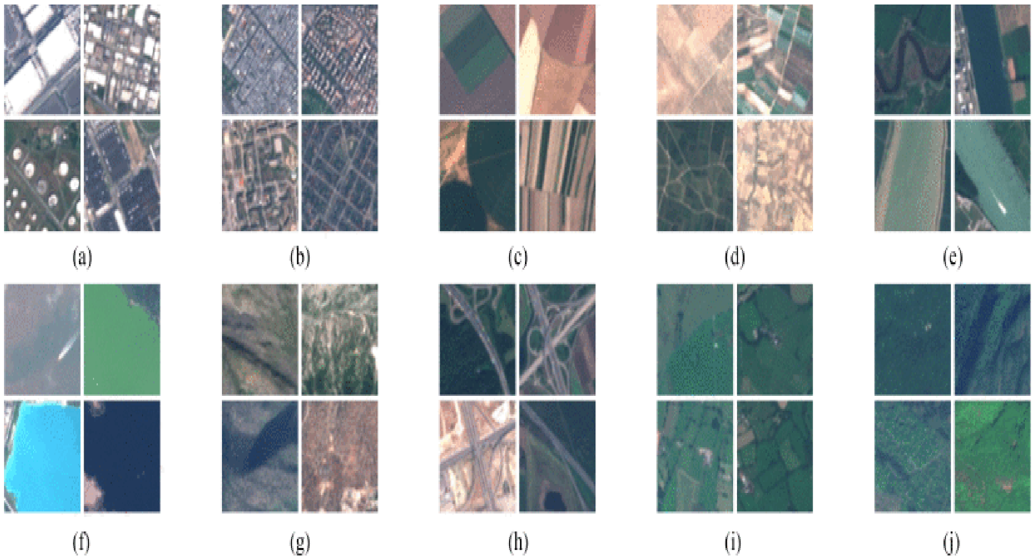

Figure 4: "Sample image patches of EuroSAT Dataset"

Sample image shown in Fig: 4, patches of all ten classes covered in the proposed EuroSAT dataset. The images measure 64 × 64 pixels. Each class contains 2000–3000 images. In total, the dataset has 27,000 geo-referenced images. (a) Industrial buildings. (b) Residential buildings. (c) Annual crop. (d) Permanent crop. (e) River. (f) Sea and lake. (g) vegetation. (h) Highway. (i) Pasture. (j) Forest.

1.4.4 Band Characteristics

The 13 spectral bands of the EuroSAT dataset, which is presented in Table:1 offer a wealth of data for the classification of land use and other machine learning applications. The reflectance of vegetation, water, and man-made buildings are only a few examples of the various landscape characteristics that each spectral band records and can be used to differentiate between various land use classes.

Table 1: All 13 bands covered by sentinel-2's multispectral imager (MSI)

Bands	**Central-Wavelength (nm)**	**Resolution (m)**
Band 1(B1) —Coastal	443	60
Band 2(B2) — Blue	490	10
Band 3(B3) —Green	560	10
Band 4 (B4)— Red	665	10
Band 5(B5)—Vegetation Red Edge	705	20
Band 6(B6)—Vegetation Red Edge	740	20
Band 7(B7)—Vegetation Red Edge	783	20
Band 8 (B8)— NIR	842	10
Band 8A (B8A)— Narrow NIR	865	20
Band 9 (B9)— Water Vapor	945	60
Band 10 (B10) — SWIR	1375	60
Band 11 (B11) —SWIR	1610	20
Band 12 (B12) — SWIR	2190	20

The EuroSAT dataset's spectral bands typically offer a distinctive perspective of the environment that can be utilized to differentiate between various land use groups. A more precise and thorough representation of the landscape can be made by merging data from several bands. This representation can then be utilized for a variety of purposes, including land use classification, vegetation monitoring, and urban development planning[11].

1.5 Problem Statement

Current methods struggle to accurately classify Land Cover and Crop types from satellite images, which are essential for applications like crop monitoring and environmental assessment. However, Land Cover and Crop type classification is a challenging task due to factors like mixed pixels, crop variability, and spectral confusion. Our current focus lies in utilizing deep learning techniques to improve the accuracy of land cover and crop type classification by effectively managing both the dataset and the model.

1.6 Objectives of Research

The following are the study's particular objectives:

1) The focus of the proposed work is to first perform land cover classification by identifying fields from the surroundings.

2) The focus is to identify the area in which a particular crop is cultivated based on its type.

3) A significant objective is to support companies like Lays in optimizing their supply chains.

4) The goal is to establish a proper classification with a high degree of accuracy.

CHAPTER 2

2 RELATED WORK

In this section, we explore the studies that utilize conventional machine learning algorithms, such as random forest, support vector machines (SVM), and logistic regression. We will also explore the advancement into deep learning algorithms, specifically applied to data collection techniques and satellite imagery.

2.1 Land Cover Classification

In this paper [12] H. Fahmi et.al explores computer vision for land cover mapping, emphasizing patch-based change detection over pixels. Three CNN architectures, LeNet-5, VGG-16, and ResNet-50 are compared for euroSAT land cover classification. ResNet-50 achieves the highest validation accuracy of 0.877 with reasonable training time. LeNet-5 is quick but inaccurate, while VGG-16 has the longest training time with the highest test score of 0.878. ResNet-50 is the recommended model for patch-based land cover classification using EuroSAT data.

Debella-Gilo et.al presented in [13] seasonal agricultural land cover types using deep learning on sentinel-2 image time series they used sentinel-2 satellite image time series (SITS) over the land area of Norway to map three agricultural land use classes: cereal crops, fodder crops (grass) and unused areas. The multilayer perceptron (MLP) and two variants of the convolutional neural network (CNN) are implemented on SITS data of four different temporal resolutions. The results obtained on held-out test data show up to 94% overall accuracy. It is further observed that cereal is predicted with the highest accuracy, followed by grass. Predicting the unused areas is difficult as there is no distinct surface condition that is common for all unused areas.

Vittorio Mazzia et.al in [14] Proposed a novel architecture for Land Cover and Crop Classification (LCCC). In this paper, they proposed a deep learning model for pixel-based that is developed and implemented based on Recurrent Neural Networks (RNN) in combination with CNN using multi-temporal sentinel-2 imagery of the central north part of Italy. They also tested widely used traditional machine learning algorithms for comparisons such as support vector machine SVM, random forest (RF), Kernal SVM, and gradient boosting machine. The overall accuracy achieved by the proposed R-CNN was 96.5%,

which showed considerable improvements in comparison with existing mainstream methods.
In this study [15] J. Pan et.al investigates the application of joint ICESat-2 and Landsat 8 OLI data for land cover classification in Yunnan province, China. The proposed method, which employs random forest, achieves greater accuracy for both five and four types of land cover, with further enhancements from feature selection. The researchers emphasize the importance of terrain factors, canopy photon count, and solar conditions in land cover classification in complex terrain areas. The findings suggest the potential of photon counting data in land cover classification.

In this research [16] Y. Cao et al investigate a two-step ensemble protocol for LULC classification proposed using a grayscale-spatial-based Genatic Algorithm (GA) model. Fuzzy c-means is used in the first ensemble framework to classify pixels into easy and difficult clusters, reducing the search space for evolutionary computation. The second ensemble framework uses neighborhood windows as heuristic information to adaptively modify the GA objective function and mutation probability, improving discrimination and decision-making. The proposed method achieves rapid convergence, reduces noise, and maintains image details in three research areas in Dangyang, China, with an overall accuracy of 88.72%, outperforming reference methods. Accurate LULC maps have potential applications in urban planning and precision agriculture.

2.2 Crop type Classification

Zhiwei Yi et.al presented in [17] crop classification in the shiyang river basin of China using multi-temporal sentinel-2 data. Multi-temporal sentinel 2 data were applied to the random forest algorithm to generate the crop classification map at 10 m spatial resolution. Four experiments with different combinations of feature sets were carried out to explore which sentinel-2 information was more effective for higher crop classification accuracy. The results showed that the augment of multi-spectral and multi-temporal information of Sentinel-2 improved the accuracy of crop classification. Compared with other bands, red-edge band 1 (RE-1) and shortwave-infrared band 1 (SWIR-1) of sentinel-2 showed a higher competence in crop classification. A relatively accurate classification (overall accuracy = 0.94) was obtained by utilizing the pivotal spectral bands and dates of the image.

Hongwei Zhao et.al presented in [18] five deep learning models for crop type mapping using sentinel-2 time series images with missing information. In this paper, they explored the performance of five deep learning models (i.e., the

1D CNN, LSTM, GRU, LSTM-CNN, and GRU-CNN) for crop type mapping using sentinel-2 time series data (TSD) with missing information. The results show that although the total missing rate of the sample TSD was approximately 43.5%, the 1D CNN, LSTM-CNN, and GRU-CNN all achieved acceptable classification accuracy (above 76%). Moreover, when compared with using filled TSD, they recalled more samples on crop types with small parcels than when using unfilled TSD. Although LSTM and GRU did not attain accuracies as high as the other three models using unfilled TSD, their results were almost close to those with filled TSD.

Teimouri N et.al presented in [19] a novel spatiotemporal fully convolutional network and a long short-term memory (FCN-LSTM) network for recognizing various crop types using multi-temporal radar images. Radar sensors are capable of imaging earth's surface independently. In this research, they proposed a novel network structure for combining an FCN and a ConvLSTM network. The proposed network can be trained by using c-band radar images and can extract spatiotemporal features from them. The average pixel-based accuracy and IoU of the proposed network were 86% and 0.64, respectively. The errors were mostly located at field boundaries. One of the main advantages of the proposed network is the detection of fields that are likely annotated incorrectly in the reference images. One of the important but complex classes in this research is the background, which includes extensive regions including lakes, sea areas, forests, buildings, and roads. The pixel-wise accuracy in this class was 88% despite the complexity of the class.

K. Kenduiywo et.al [20] present an approach to enhance crop classification by utilizing expert knowledge and TerraSAR-X multitemporal images. The method employs dynamic conditional random fields (DCRFs) with duplicated structures to encode phenology information from both image-based and expert-based sources. The results show that higher-order DCRFs (HDCRFs) offer the best accuracy, and the ensemble method outperforms conventional techniques. This approach has the potential to provide more accurate land cover information, which can aid in agricultural management and monitoring.

In this paper [21] Hengbin Wang et.al proposes the CC-SSL framework, a self-supervised learning crop classification method that can classify crops with few or no labeled samples. It incorporates the Sim-SCAN algorithm, a tensor transformation module, and a sample processing module to maintain sample balance. The experimental results indicate that richer tensor forms improve accuracy and better characterize crop growth patterns. Additionally, maintaining sample balance through data augmentation improves performance and produces classification results that exceed supervised learning. Even with reduced labeled samples, the CC-SSL framework can achieve comparable classification performance and robustness to supervised learning. Overall, this approach has the potential to reduce resource consumption while improving crop classification accuracy for agricultural management and monitoring.

Table 2: The land cover and crop classification summary of the related work. In this table the acronyms are used; DCNN: Deep Convolutional Neural Network;U-Net; R-CNN: Recurrent – Convolutional Neural Network

Authors	**Year**	**Sensor**	**Technique**	**No of Class**	**Main Findings**
Y. Cao et al (1)	2023	EuroSAT	Genetic Algorithm	6	Two-step ensemble-based genetic algorithm achieved overall good results
S. Ghosh et.al (2)	2022	EuroSAT	ResNet-50, LeNet-5, VGG-16	10	ResNet-50, achieve 0.777, LeNet-5 trains quickest but with low accuracy, VGG-16 has highest test score
J.Pan et.al (3)	2022	ICESat-2	Random Forest	7	hybrid classification achieves good result as compared to single
Vittorio Mazzia et.al (4)	2020	Sentinel-2	R-CNN	5	Incorporating temporal features from Sentinel-2 time-series data improved
DebellaGil et.al (5)	2021	Sentinel-2	U-Net	4	showed improved results with image time series data
Zhiwei Yi et.al (6)	2022	Sentinel-2	Random Forest classifier and SVM	4	Random Forest classifier achieved a good result as compared to SVM
Hengbin Wang et.al (7)	2022	Landsat 8 OLI	CC-SSL	11	This approach has the potential to reduce resource consumption while improving crop classification accuracy for agricultural management and monitoring.
Hongwei Zhao et.al (8)	2021	Sentinel-2 satellite	CNN, LSTM, GRU, RNN, LSTM-CNN	7	Models able to classify crop types accurately even with missing data
Teimouri N et.al (9)	2019	Radar Images	FCM-LSTM	6	FCN-LSTM achieved high accuracy for crop recognition using multi-temporal radar images.
K. Kenduiywo et.al (10)	2017	Radar images	HDCRFs	4	crop classification using expert knowledge and TerraSAR-X multitemporal images

2.3 Analysis of Related Work

A literature review of land cover and crop type classification would likely summarize the current state of research and development in this field. It would likely include studies on the various techniques used for analyzing land cover and crop images, including pixel-based, patch-based, and object-based techniques as well as the accuracy and reliability of these methods.
According to this literature review, Land cover and crop classification are still challenging tasks. Although there is a lot of work done before but there are still some gaps in accuracy that we can meet using the EuroSAT dataset. Some authors also used this data set and achieve good results, but we can improve it more with data preprocessing and filling in the missing information in the dataset. A lot of work is done before using machine learning and deep learning approaches but, for a more accurate land cover and crop classification, we need to handle the dataset and deep learning model by filling in the missing information.
The first research objective aligns with the identified gap by focusing on land cover classification, specifically by isolating fields from their surroundings. This step addresses the challenge of mixed pixels and contributes to refining the classification process. The second objective directly addresses the complexity of crop type classification by aiming to identify the specific areas where a particular crop is cultivated based on its type. This addresses the challenge of crop variability, contributing to more precise and detailed classifications. The third objective links the research to practical applications by highlighting the goal of supporting companies like Lays in optimizing their supply chains. This connection between research and real-world applications emphasizes the significance of accurate land cover and crop type classification in industries reliant on agricultural products. The fourth objective reinforces the overarching aim of the research, emphasizing the establishment of a proper classification with a high degree of accuracy. This aligns with the broader research gap of improving the accuracy of land cover and crop type classification through effective management of both the dataset and the model.

CHAPTER 3

3 Methodology

Deep Learning (DL) is a branch of artificial intelligence concentrating on instructing neural networks to extract information from immense quantities of information and make smart choices. It includes developing deep neural networks with several layers that are capable of autonomously picking up characteristics or interpretations that are structured from unprocessed data. Deep learning models can acquire these characteristics by analyzing the data, as compared to typical machine learning techniques, which depend on manually creating attributes. Deep learning works in a number of renowned fields, including bioinformatics, natural language processing (NLP), robotics and control, cybersecurity, processing medical data, remote sensing, and many others [22]. Health care, visual identification, fraud detection, self-driving cars, automatic handwriting production, language translation, and deep dreaming are a few examples of applications for deep learning. A simple pipeline is shown in the following figure: 5 for LC and CC.

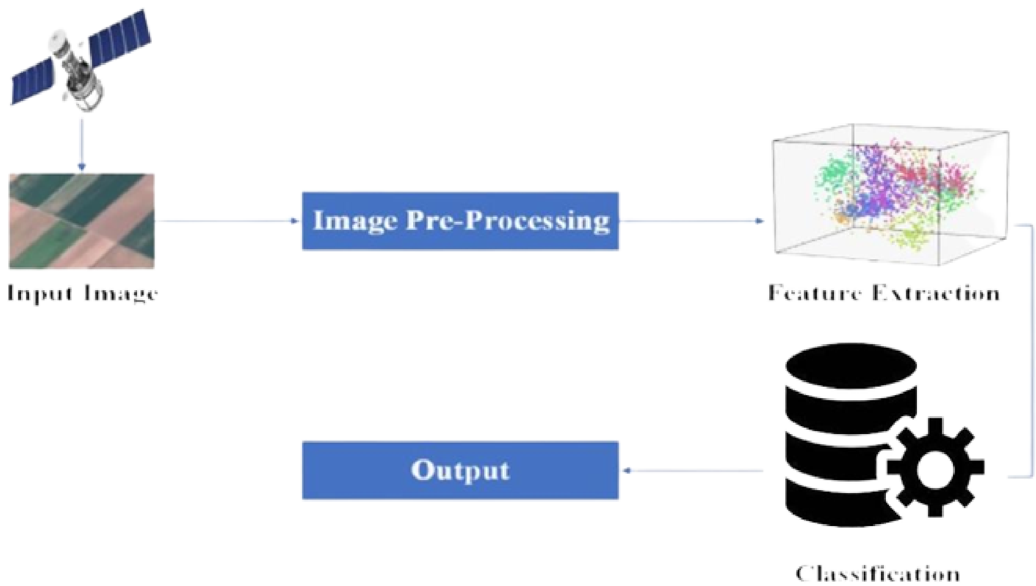

Figure 5: A simplified overview of Land Cover and Crop Classification process shown in this diagram

The classification of crop types and land cover also depends extensively on DL. Because of their capacity for handling extremely large and complicated information, DL models tend to be appropriate for tasks involving the classification of crop and land cover types. They are capable of successfully extracting and learning characteristics at different degrees of conceptualization, enabling the identification of local as well as global structures in pictures. Deep learning models are flexible and useful in many remote sensing applications because they can deal with variations of satellite sensor properties along with information resources. Deep learning has made major strides in the classification of crop types and land cover, allowing for more precise and effective tracking and mapping of farming practices and land resources. These developments have consequences in numerous fields, particularly agricultural precision, sustainable development, and managing land, and they allow for better resource allocation and making choices.

Input Image: Input image describes either pre-processed or raw imagery from a satellite. It is used as the input of the algorithm for classifying crop types and land cover by representing visual information obtained by satellite sensors.

Image Pre-Processing: Different processes are applied to the input image during image pre-processing to improve the input picture's quality and prepare it for analysis. Improve the breadth of the training data, it might involve scaling the image to maintain a constant size, normalizing pixel values, minimizing noise, and performing methods for data augmentation such as rotations and flips.

Feature Extraction: In feature extraction, the pre-processed image is used to extract significant and useful features. For this objective, deep learning approaches are frequently employed. The model acquires the ability to identify hierarchical attributes at various degrees of abstraction, starting with basic features (e.g., boundaries and patterns) and gradually working up to more complicated and esoteric features.

Classification: A classification technique is then used to categorize the input image into a particular category of land cover or crop type after the relevant features have been retrieved. Deep learning and machine learning algorithms are typically employed for this.

3.1 Feature Extraction

The process of converting unprocessed data into a collection of representative features that successfully capture important details and patterns is known as feature extraction, and it is a critical stage in both machine learning and pattern recognition. A subset of relevant features is chosen from the raw data, and then they are changed into a more appropriate format. The overall dimension of data is reduced by eliminating unnecessary or redundant features. Approaches like statistical calculations, and techniques based on deep learning can all be used for feature extraction. Techniques for feature encoding are used to transform some non-numerical data types into numerical representations.

The amount of dimension is decreased through feature extraction, and the retrieved features offer a more accurate visualization of the data. The efficiency, accuracy, and generalization performance of machine learning algorithms are then enhanced by using these features as input.

3.2 DenseNet

DenseNet is another cutting-edge deep neural network architecture that is designed for computer vision tasks and image classification. DenseNet, short for "Densely Connected Convolutional Networks". It was first presented by Gao Huang and colleagues in their article titled "Densely Connected CNN" in 2017. DenseNet overcomes several of the drawbacks that plague traditional convolutional neural networks, including information flow, effectiveness of parameter usage and vanishing gradients. Each layer receives input from all previous layers within the same block and this is the core idea behind DenseNet is to create densely connected blocks of layers [23]. This dense connectivity improves feature reuse and information spread through the network, which improves potentially resolving the vanishing gradient issue and gradient flow. Due to the concatenation (.) function used by DenseNet; the output of feature map must contain the input that is used to produce that output.

3.2.1 DenseNet Architecture

The fundamental unit of the DenseNet design is referred to as a "Dense Block." A Dense Block is made up of a collection of layers. Each layer within a block receives as input the concatenated feature maps from all preceding layers Figure: 6 shows the architecture of DenseNet. This design offers the following notable advantages:

Feature Reuse: In dense architecture each layer has access to the features of all preceding layers. This connectivity enables feature reuse. By doing this, the network can use the input data to learn more discriminative features.

Gradient Flow: The vanishing gradient problem is mitigated by the dense connections within the network, which enable gradient signals to propagate through shorter paths during backpropagation. This characteristic significantly contributes to easing the challenges associated with training.

Parameter Efficiency: Dense connectivity promotes parameter sharing by allowing each layer to receive input from preceding layers, leading to a reduced total parameter count compared to traditional architectures.

DenseNet models are commonly identified by their depth and growth rate. The growth rate specifies the number of features generated by each layer in a dense block. Meanwhile, the network's depth is defined by the quantity of dense blocks and the layers they contain. Diverse versions of DenseNet, including DenseNet-121, DenseNet-169, and DenseNet-201, have been developed, each with distinct configurations. These architectures have demonstrated exceptional performance on multiple image classification benchmarks. Their strength lies in a fusion of skip connections and feature reuse, culminating in networks that are both efficient and remarkably expressive. Like other modern architectures, DenseNets are also available as pre-implemented models in popular deep-learning frameworks.

3.2.2 DenseNet Architecture layers

The DenseNet architecture comprises essential elements: dense blocks, transition layers, and auxiliary layers. Let's explore each component's intricacies.

Convolutional Layer (Initial Convolution): This layer functions as the initial access point of the network and is tasked with processing the input image. It encompasses a collection of convolutional filters that adeptly acquire low-level features from the provided image.

Dense Block: The central element of the DenseNet architecture is the dense block, a group of layers organized in a densely connected manner. Each layer in this block receives input from all prior layers within the same block, encouraging the sharing of features and information propagation. The outputs of these layers are concatenated along the channel dimension, forming a composite feature map that is information-rich. Each layer in a dense block typically encompasses operations like convolution, batch normalization, and activation, often ReLU. The growth rate parameter dictates the number of new feature maps produced by each layer, influencing the model's complexity and expressive capabilities.

Transition Layer: Transition layers regulate the spatial dimensions (height and width) of feature maps during their traversal through the network. These layers commonly incorporate a blend of 1x1 convolutional layers and down-sampling methods like average pooling, aimed at diminishing the spatial dimensions. Moreover, transition layers play a role in curbing the quantity of feature maps, effectively addressing the computational intricacy of the network.

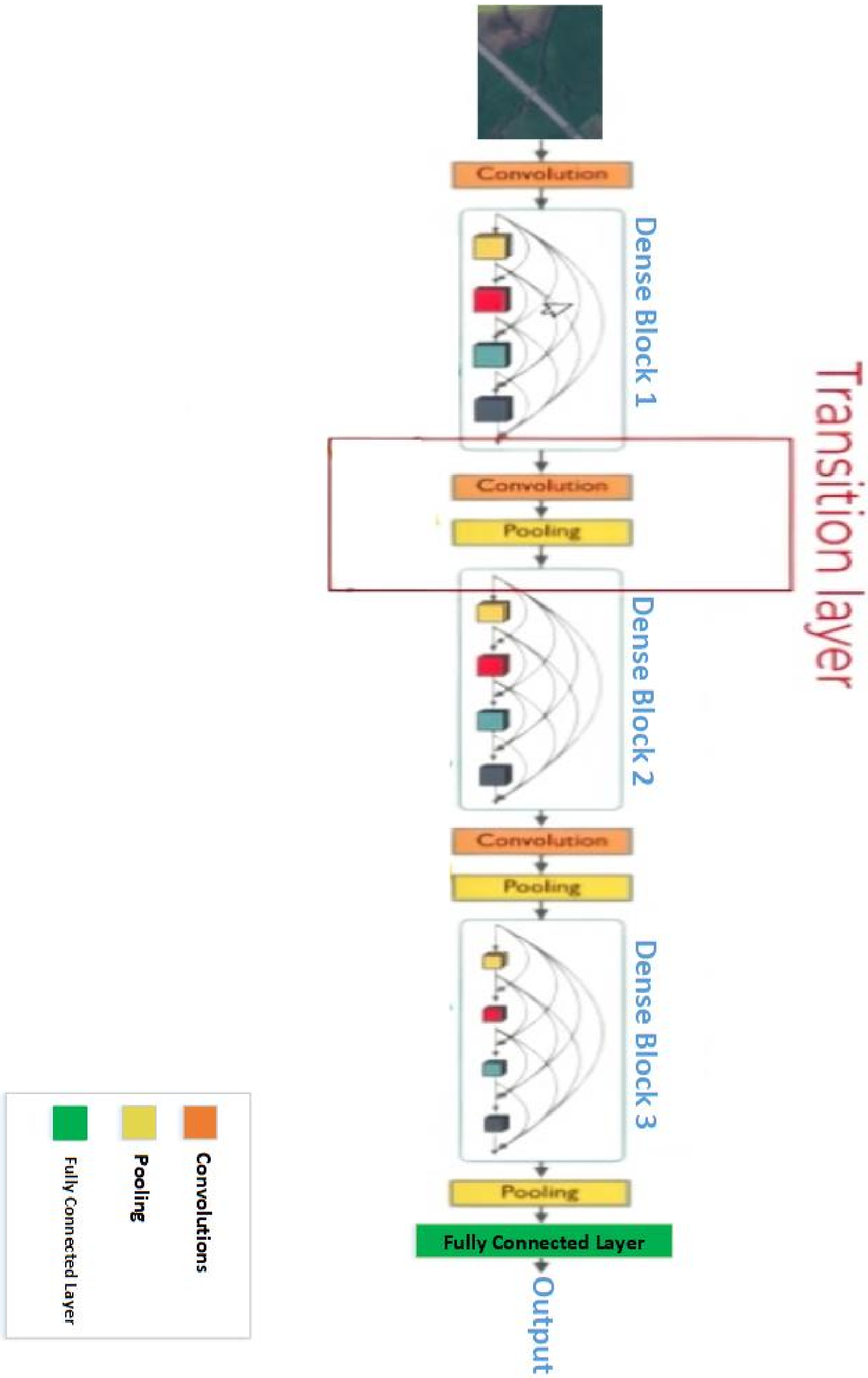

Figure 6: DenseNet: The orange block shows the convolution layers, yellow block show the pooling layer and Green block show the classification and there are three dense block

Global Average Pooling Layer: Towards the conclusion of the DenseNet architecture, following the final dense block, a common practice involves the implementation of a global average pooling layer. This step aims to transform the feature maps into a standardized representation of fixed dimensions. The procedure entails calculating the mean value for each channel across the spatial dimensions of the feature map. This strategic pooling operation accomplishes two objectives: capturing the holistic global context of the data and downsizing the spatial dimensions to a consistent size.

Fully Connected Layer (Output): The global average pooled features are typically linked to one or more fully connected layers, ultimately generating the network's output. In image classification scenarios, the last fully connected layer's neuron count aligns with the dataset's class number. This output is then processed through a SoftMax function to yield class probabilities.

In brief, the DenseNet architecture comprises linked dense blocks, with each block incorporating densely connected layers. These dense blocks are interwoven with transition layers that manage spatial dimensions and feature map scales. This design fosters feature reuse, tackles gradient vanishing concerns, and optimizes parameter utilization. DenseNets have showcased effectiveness across diverse computer vision tasks and have displayed remarkable performance on image classification benchmarks.

3.3 EfficientNet:

EfficientNet, an innovative convolutional neural network architecture, adeptly balances performance and computational efficiency. Proposed by Mingxing Tan and Quoc V. Le in their 2019 paper "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," this framework introduces a new paradigm for scaling neural networks [24]. Central to its effectiveness is compound scaling, which uniformly adjusts the network's depth, width, and resolution using a single scaling parameter. This holistic methodology ensures a harmonious growth across all dimensions, sidestepping the limitations of singular dimension focus.

3.3.1 EfficientNet Architecture:

Architecture employs depthwise separable convolutions to reduce computation while preserving essential features. Additionally, inverted residual blocks combine expansion layers, depthwise convolutions, and projection layers for efficient information processing. EfficientNet employs the Swish activation function for enhanced training, features global average pooling for context capture, and includes fully connected layers for classification. With variants denoted as EfficientNet-Bphi, the architecture adapts to diverse computational resources, excelling in various computer vision tasks. In essence, EfficientNet embodies a balance between precision and efficiency, reshaping deep learning model design.

3.4 ResNet

ResNet is a deep learning model that was unveiled in 2015 by the researchers at Microsoft research. It was created to tackle the issue of disappearing gradients in very deep neural networks, which may affect their efficacy and make training challenging. The utilization of residual blocks is the core concept of ResNet. The residual block performs as a network module that connects every layer of the network model. ResNet employs the summation method (+), which accepts input and output, with the first layer's output serving as the third layer's input. ResNet has been widely used for a variety of computer vision applications, including image segmentation, image classification, and object detection. It has attained outstanding results on numerous standard datasets [25].

3.4.1 ResNet Architecture

ResNet-50 or Residual Neural Network is a cutting-edge deep learning model. In the network architecture, ResNet (Residual Neural Network) introduces skip connections or shortcuts. In order to resolve the vanishing gradient issue and enabling the training of very deep networks, these skip connections allow the network to train the residual (difference) mapping of the output and input of a block. The residual block serves as the fundamental idea in ResNet. Following batch normalization and activation functions (usually ReLU), a residual block is based on several convolutional layers having smaller filter sizes. The skip connection, which connects the block's input and output immediately, is the most important new feature. The skip connections enable the gradient to flow directly through the block's input to its output because it allows the network to skip one or more convolutional layers. It shows that the block can learn the residual mapping, which is the difference between the various block's input and output. The block's output can be calculated mathematically as follows:

$$\text{Output} = \text{Activation (Convolution (Input))} + \text{Input}$$

The operations that are performed within the block are represented by the Convolution and Activation. The addition of the Input to the transformed output ensures that the network can learn to adjust the input by adding or subtracting the residual mapping. In deeper networks, specifically, this residual learning is more effective than learning the entire mapping from scratch.

3.5 Classification

Classification, within the realms of machine learning and remote sensing, entails categorizing input data into separate classes or categories based on their distinct attributes. This procedure entails training a model on a dataset that is annotated with labels corresponding to specific classes. Once the model has been trained, it can subsequently predict the class affiliations of new, previously unseen data points. In the context of land cover and crop type classification, this methodology is employed to discern the types of land and crops featured within satellite images. The accuracy of these classifications is determined by assessing their correctness across different geographical regions. The process involves segmenting large-scale satellite images into distinct classes, a step undertaken to facilitate the computation of accuracy.

3.5.1 How is Classification done?

Classification using architectures like ResNet, DenseNet, and EfficientNet involves leveraging their deep and intricate structures. In these models, the input data, often images, are processed through multiple layers that capture increasingly abstract features. Each architecture's unique design, such as ResNet's residual blocks, DenseNet's dense connectivity, and EfficientNet's compound scaling, enhances feature extraction. After processing, global average pooling and fully connected layers produce the final class predictions. During training, these networks learn to differentiate features of different classes, allowing them to classify new data based on learned patterns, resulting in accurate and robust classification outcomes.

CHAPTER 4

4 EXPERIMENTAL PROTOCOL AND EVALUATIONS

The Experimental Protocol and Evaluations chapter includes the outlines of the methodology used to carry out the study, including details about the participants, materials, procedures, and measures used to collect and analyze data. The key elements included in this chapter are as description of the sample size, eligibility criteria, and demographics of the participants involved in the study. The goal of the Experimental Protocol and Evaluations chapter is to provide enough information for other researchers to be able to replicate the study. It is written in clear, concise, and detailed language to ensure that the methods are easily understood.

4.1 Testing data and Methodology

The EuroSat dataset is derived from data captured by the Sentinel-2. Specific images from the Sentinel-2 mission are selected for inclusion in the EuroSat dataset. EuroSat contains 10 different classes named AnnualCrop, Forest, Vegetation, Highway, Industrial, Pasture, PermanentCrop, Residential, River, and SeaLake. All classes encompass the testing data available. In this dataset, we do not have crop classes. EuroSat dataset is appropriate for land cover classification, but crop classification is a challenging task with this dataset. As we know, the EuroSat dataset consists of 10 land cover classes. All classes are purely labeled. We can consider the "Vegetation" category as a parent or SuperCategory. This category represents all types of vegetation land cover, which includes both natural vegetation and cultivated crops. Within the "Vegetation" category, define subclasses or subcategories to represent specific crop types. These subclasses include different types of crops such as wheat, corn, rice, soybeans, potato etc. Assign each image to one of the crop-type subclasses within the "Vegetation" parent category. By doing this, now we have 10 superclasses and 5 subclasses. Now we will compute the accuracy of all classes collectively by applying different models such as DenseNet, ResNet, and Efficient Net. The DenseNet performs outstanding to compute the overall accuracy so we will apply the DenseNet for all the classes [15].

4.2 Accuracy

Accuracy is the number of samples accurately predicted from all the datasets. More precisely, divided by the number of true positives, true negatives, false positives and false negatives, it is known as the number of true positives and true negatives.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

4.2.1 Precision

Precision is a metric used in binary and multiclass classification to evaluate the accuracy of the positive predictions made by a model. It is defined as the ratio of true positive predictions to the total number of instances predicted as positive (sum of true positives and false positives). Precision is expressed by the formula: [6].

$$Precision = \frac{TruePositives}{TruePositive + FalsePositive} \tag{2}$$

4.2.2 F1 Score

The F1 score is a metric used in binary and multiclass classification that combines both precision and recall into a single value. It is the harmonic mean of precision and recall and is particularly useful when there is an uneven class distribution. The formula for the F1 score is:

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{3}$$

4.2.3 Recall

Recall, also known as Sensitivity or True Positive Rate, is a metric used in binary and multiclass classification to evaluate the ability of a model to correctly identify all relevant instances from the total number of actual positive instances. It is defined as the ratio of true positive predictions to the sum of true positives and false negatives. The formula for recall is:

$$Recall = \frac{TruePositive}{TruePositive + FalsePositive} \tag{4}$$

4.3 Confusion Matrix

A confusion matrix is a measurement that is used to solve classification problems. This measurement can be applied for multi-class problems and binary classes. It represents the number of actual values and predicted values. The output of the “TN” shows that a negative number of classes classified as correctly, TN stands for True Negative. Similar to the case of true positive (TP) which indicates the number of classes that are true are classified correctly.

The false positive term is used when the negative class is classified as positive. While performing classification this is one of the most commonly used metrics. The following formula is used to compute the accuracy of the model (through the confusion matrix).

$$Dice = \frac{TN + TP}{TN + FP + FN + TP} \tag{5}$$

4.3.1 Tensorflow

Tensorflow is a free and open-source framework that is used to solve supervised, and unsupervised reinforcement learning problems. This library is used for machine learning, NLP, and deep learning such as neural network and LSTM[18]. This library is based on tensor computation. It is one of the popular libraries that is written in C++, Python, and Cuda.

4.3.2 Keras

Keras is one of the open-source libraries that is run above the tensorflow and theano. It is written in Python language. Keras is used for fast experimental computations and analysis of deep learning models.

4.3.3 Numpy

It is an open-source library for Python programming. It is used to manipulate Multidimensional arrays and matrices along with mathematical operations to operate on arrays.

4.3.4 Pandas

The Pandas is a library of Python used for data manipulating data and analysis. It is also written in Python and C language in practice it is mostly used for DS and time series.

4.3.5 Matplotlib

Matplotlib is a library of Python that is used to create a graphical representation as a 2D graph. It contains the module pyplot which makes things easy to plot by giving the feature, it also controls the style, font properties, and formatting.

4.3.6 Sklearn

Sklearn is a library that is used for statistical analysis including regression clustering, classification, and dimensionality reduction in Python. Basically, it is open-source software and is also used for the ML models to predict accuracy, loss, precision, and f1-score and recall.

4.4 DenseNet

In the following experiment, we perform preprocessing on the dataset because the dataset has (64*64) image size, we convert it into (224*224*3) before any analysis. Then converting an image to an array for training a model based on the features of an image. For training and testing the model we use a dataset named "EuroSat v1.0". This dataset has 10 classes containing the Land Cover and Crop images. The dataset is divided into 70% training, 15% validation, and 15% test sets to compute the accuracy of the model. This division allows for model training, hyperparameter tuning, and performance evaluation. We used different models to compute the accuracy as a whole like DenseNet, ResNet and Efficient Net. For computing the accuracy of the model, we trained the model on 70% dataset, and the accuracy was found 79% in the case of ResNet and 82% in the case of Efficient Net. But when we run the DenseNet model for the same data we get 84% to 87% accuracy. After checking performance, we apply Dense for all the classes as results shown in Confusion Matrix in fig.11.

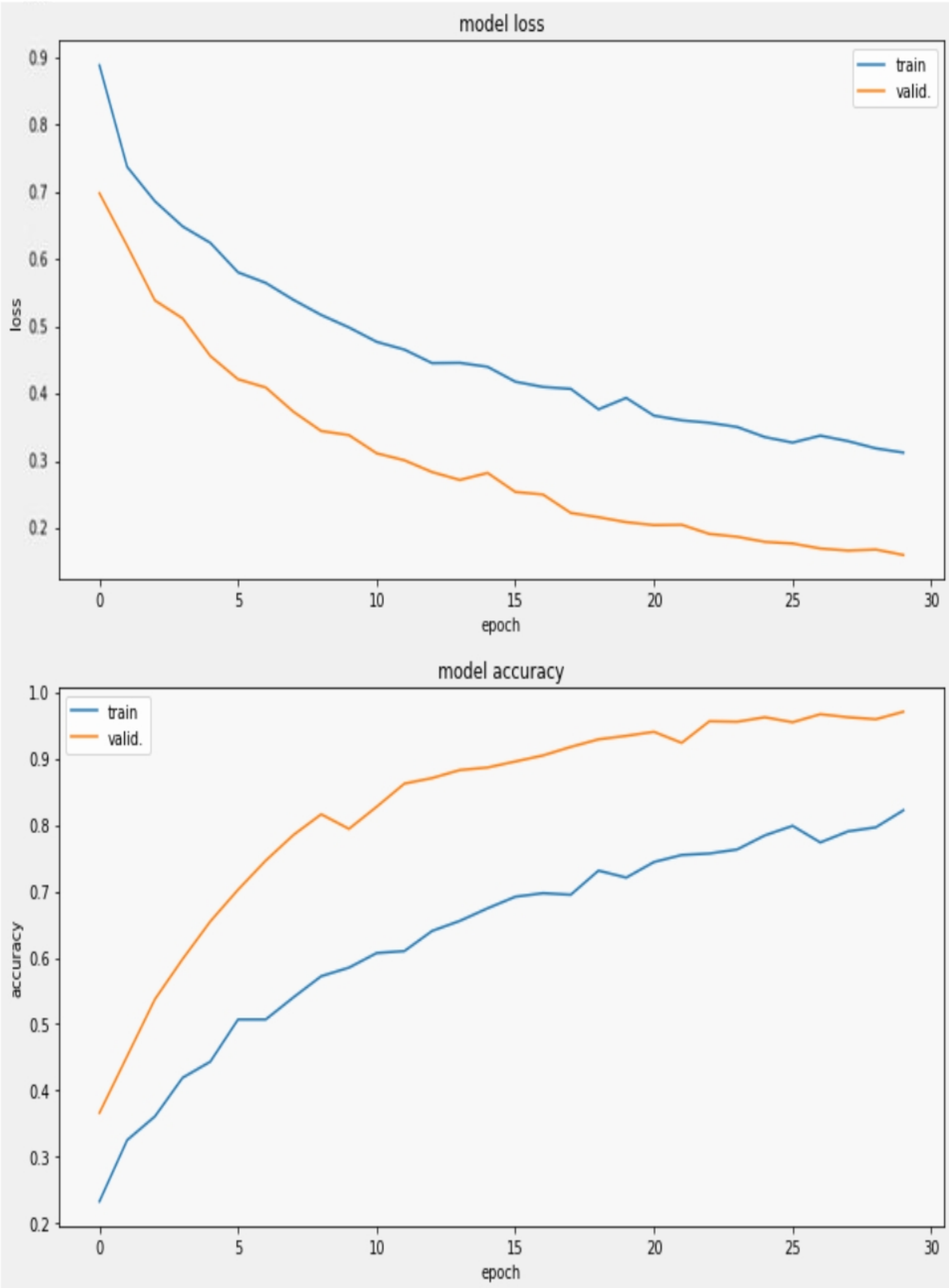

Figure 7: "Dense-Net Model accuracy and loss graph"

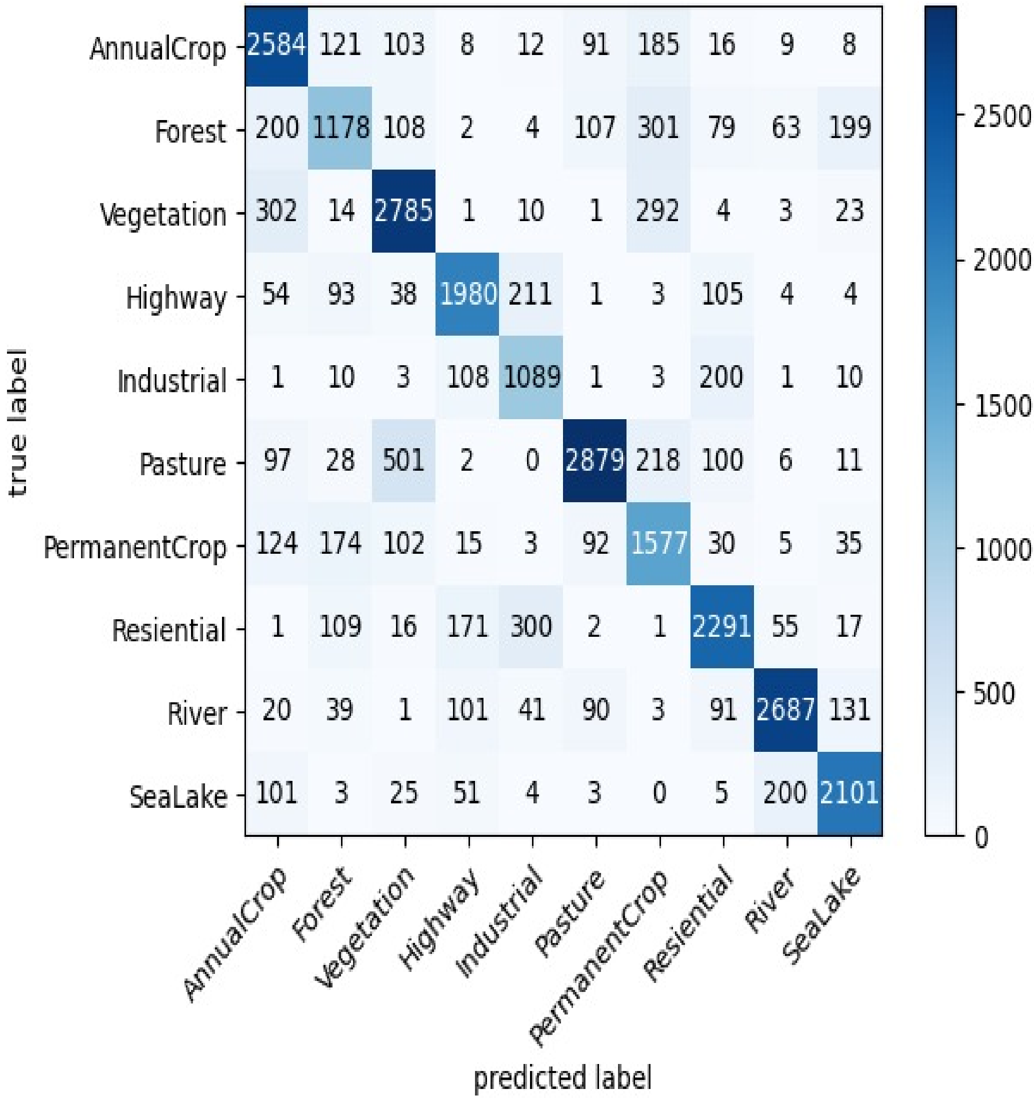

Figure 8: Confussion Matrix for all Land Cover Classes from 1 to 10

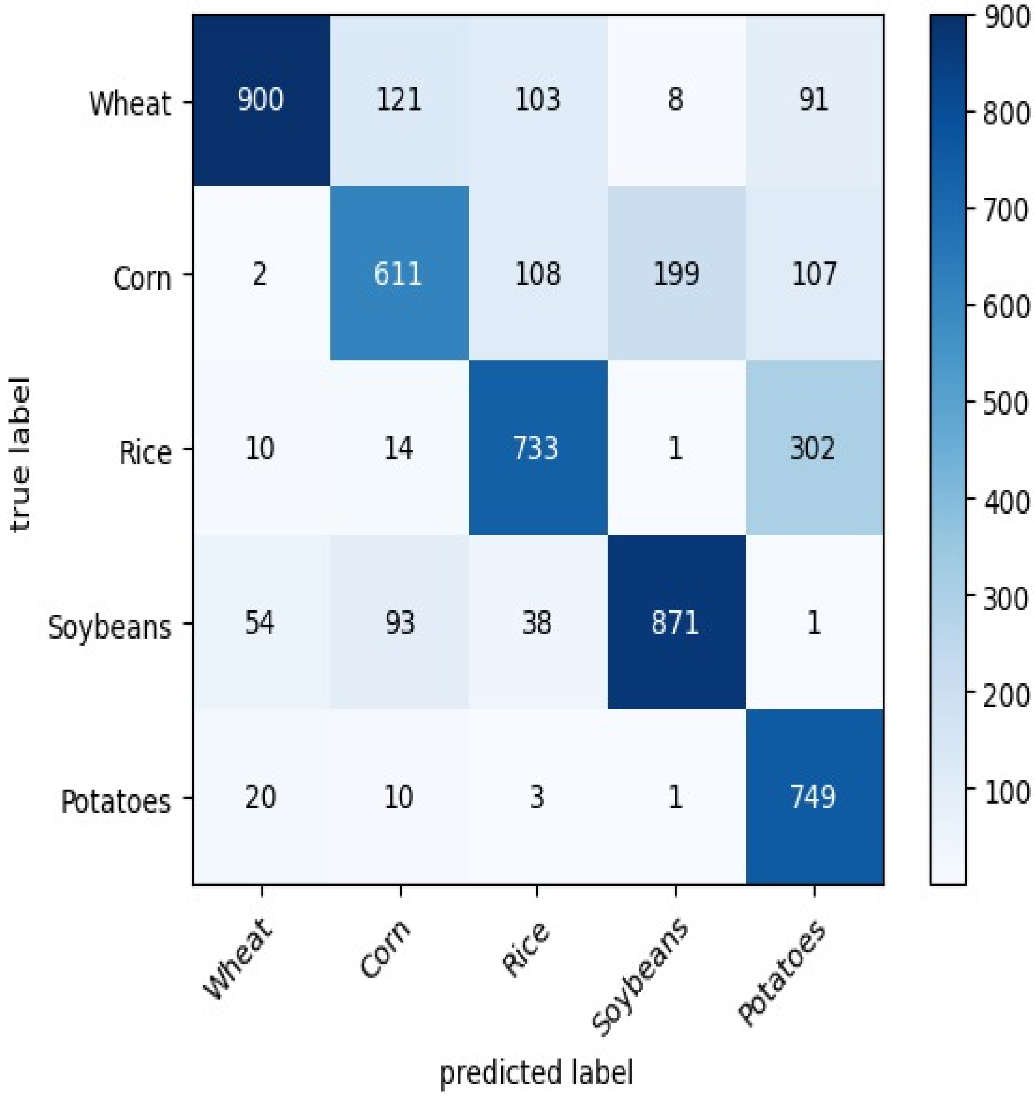

Figure 9: Confussion Matrix for all Crop Type Classes from 1 to 5

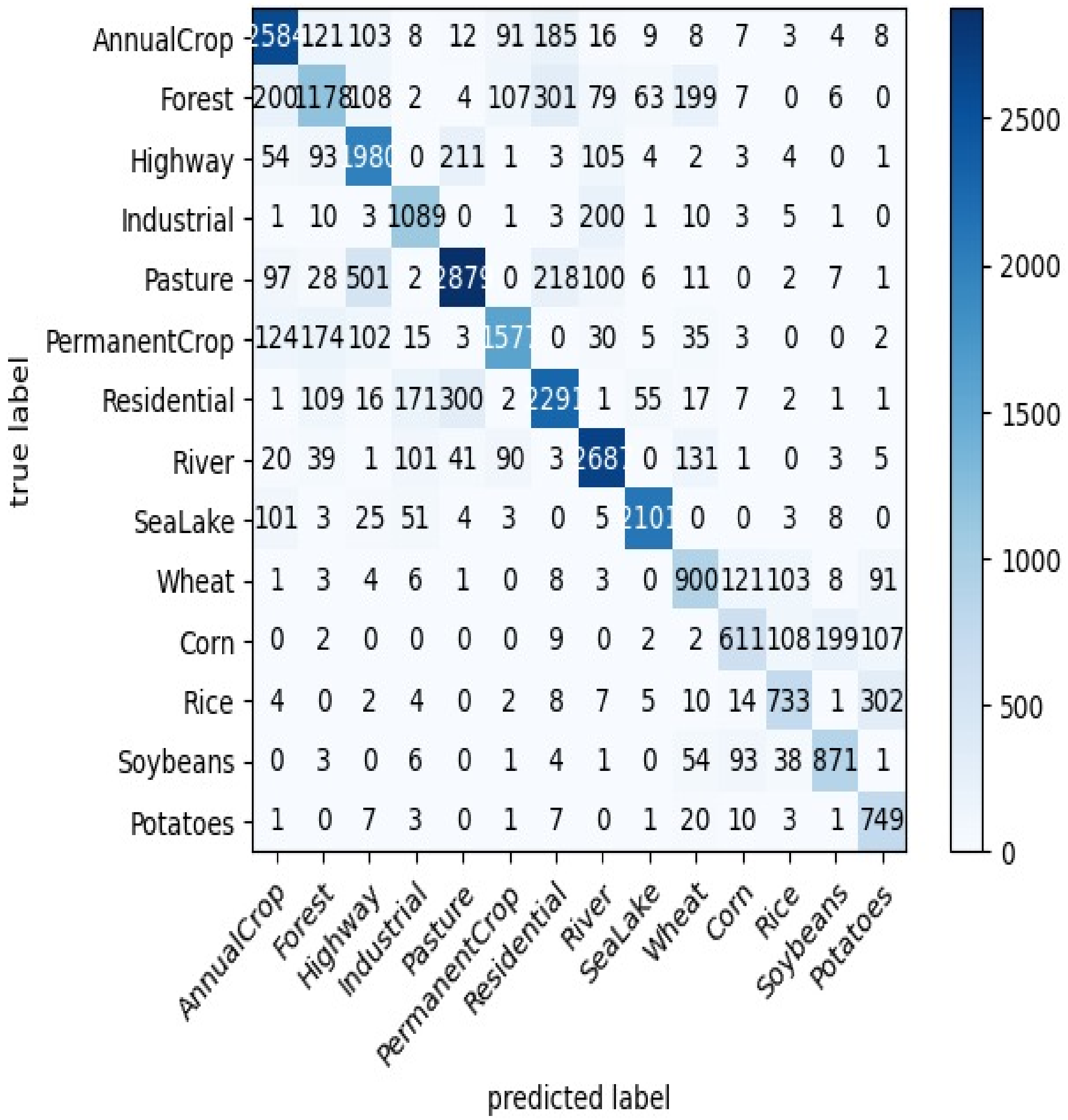

Figure 10: Confussion Matrix for all the Land Cover and Crop Type Classes from 1 to 14

4.5 Results Discussion

The misclassification between the "Vegetation" and "Pasture" classes in the confusion matrix can be attributed to the inherent visual similarity between these land cover types. Both classes involve green, vegetated areas, and distinguishing them may be challenging due to subtle differences in the composition of the vegetation. "Industrial" and "Residential" classes also give us high similarity value shown in Figure :9. Industrial areas and residential zones often exhibit comparable man-made structures, infrastructure, and built-up features, making it challenging for deep learning models to distinguish between them accurately. The high misclassification between the "PermanentCrop" and "Forest" classes in Figure :9 can be attributed to the visual similarity and spectral overlap between these land cover types. Both permanent crops and forests may exhibit similar patterns in satellite imagery due to their vegetation characteristics, which can include dense and structured canopies.

High misclassification between different classes in a confusion matrix often occurs due to the inherent complexities and similarities in the spectral patterns of distinct land cover types. For example, classes with similar visual characteristics, such as "PermanentCrop" and "Forest," might share common features like dense vegetation, making it challenging for algorithms to distinguish between them accurately. Environmental factors, such as seasonal changes and varying growth stages, can further contribute to the spectral ambiguity. Additionally, limitations in the resolution and quality of satellite imagery may impact the ability to capture fine-grained details essential for precise classification.

The model is trained on labeled data, using classes that represent different land cover types, including potato fields. The training process involves optimizing model parameters to enhance accuracy. Once trained, the model is validated and tested on separate datasets to assess its generalization capabilities. Applicability in the context of a potato chip company involves deploying the trained model for real-world scenarios. The model can be integrated into monitoring systems to identify potato crops, predict yields, assess crop health, and detect potential issues early on. This information empowers the company to make informed decisions in sourcing, quality control, and supply chain management, ultimately contributing to more efficient and sustainable potato chip production.

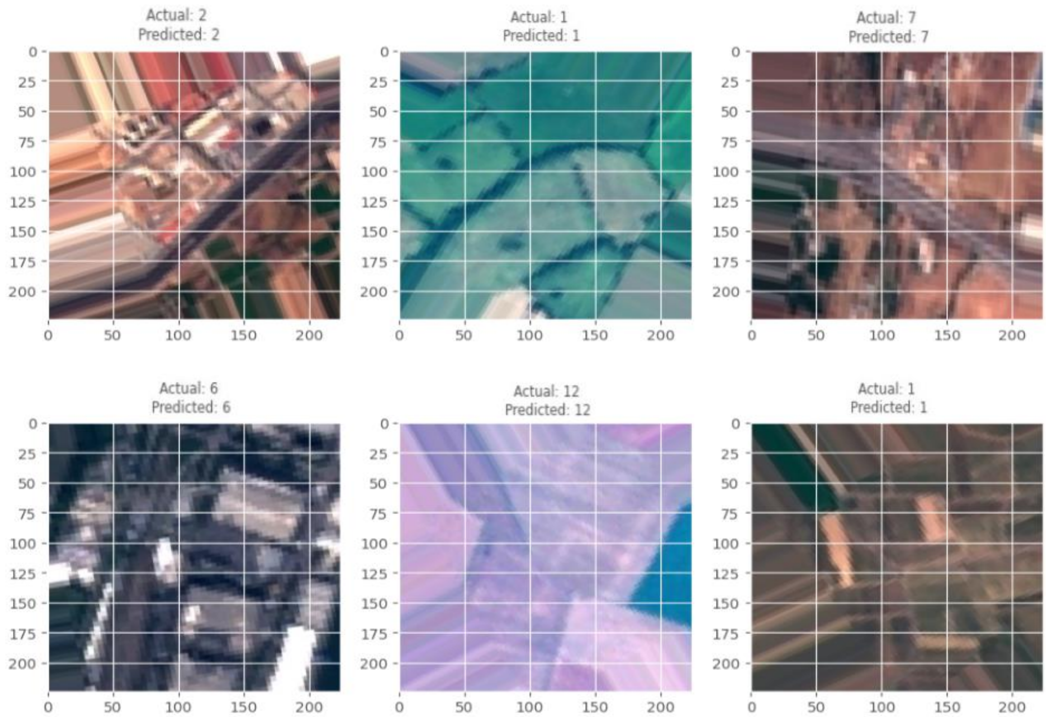

Figure 11: Class Prediction

4.6 Results Comparison

For image classification, there are three most popular deep learning models DenseNet, EfficientNet, and ResNet. Each of these models has its own unique architecture and training methodology resulting in varying accuracy and computational efficiency. If we consider in terms of accuracy DenseNet has been found to outperform both EfficientNet and ResNet on our case Land Cover and Crop classification dataset. The EfficientNet gives 82% and ResNet 79% accuracy. However, the DenseNet performed well and gave 85% to 89.9% accuracy. Then we apply the DenseNet for all the classes and compute the results as shown in the confusion matrix in Fig. 9. ResNet has been found to be more computationally efficient than DenseNet and EfficientNet, especially in terms of memory usage. ResNet achieves this by using skip connections that allow for deeper networks without causing vanishing gradients, resulting in faster training and less memory usage. The training and validation results of the model are shown in fig-9 which tells us how well the model will perform during training. The objective is to minimize both the training and validation losses simultaneously to create a model that can accurately generalize the data.

In summary, the enhancement of land cover and crop classification accuracy is achievable through several key factors. These include access to high-resolution multispectral satellite data, the adoption of advanced deep-learning models, and the incorporation of temporal data for ongoing monitoring. The combined influence of these factors serves to elevate the precision and dependability of classification results, rendering them indispensable tools in diverse applications spanning agriculture, environmental monitoring, and urban planning. However, ongoing research is focused on developing new techniques and methods to improve the accuracy of Land Cover and Crop classification using satellite images.

CHAPTER 5

5 CONCLUSIONS AND FEATURE WORK

In this paper, we work on Land Cover and Crop Classification. Types of land on the Earth's surface is known as Land Cover (LC), and identifying the different crops planted in a specific area using satellite images is known as crop classification. Land cover and crop type classification is a challenging task due to the vast diversity of land cover types, requiring high spatial and spectral resolution satellite imagery, the presence of mixed land cover and crop types in a single image, Limited Labeled data availability, etc. In this work, we use the "EuroSat v1.0" dataset, which consists of 10 different land cover classes. We consider the "Vegetation" category as a parent and wheat, corn, rice, potatoes, and soybeans as subclasses. At first, we trained and tested the model by using the complete dataset as it is but, the results were not efficient for crop types. Then we train the model on an expanded dataset that contains 10 superclasses and 4 subclasses. We compute the results using different models such as EfficientNet, ResNet, and DenseNet. The DenseNet performed well rather to other models. The EfficientNet gives 82% and ResNet 79% accuracy. However, the DenseNet performed well and gave 84% to 87% accuracy. Then we apply the DenseNet for all the classes and compute the results as shown in the confusion matrix in fig.11.

The EuroSat dataset which is used in this work is good for Land Cover but If we get more data for crop types then the results can be improved. AI-driven data augmentation methods tailored specifically for land cover and crop type classification can help mitigate the challenges of limited labeled data and enhance model generalization.

6 References

[1] Cristina Gomez, Joanne C. White and Michael A. Wulderl, "Optical remotely sensed time series data for land cover classification: A review", ISPRS Journal of Photogrammetry and Remote Sensing, vol. 116, pp. 55-72, 2016.
[2]. You, N.; Dong, J. Examining earliest identifiable timing of crops using all available sentinel 1/2 imagery and google earth engine. ISPRS J. Photogramm. Remote Sens. 2020, 161, 109–123.
[3]. Cai, Y.; Guan, K.; Peng, J.; Wang, S.; Seifert, C.; Wardlow, B.; Li, Z. A high-performance and in-season classification system of field-level crop types using time-series landsat data and a machine learning approach. Remote Sens. Environ. 2018, 210, 35–47.
[4]. Zhong, L.; Hu, L.; Zhou, H. Deep learning based multi-temporal crop classification. Remote Sens. Environ. 2019, 221, 430–443.
[5]. V. a. K. A. a. C. M. Mazzia, "Improvement in Land Cover and Crop Classification based on Temporal Features Learning from Sentinel-2 Data Using Recurrent-Convolutional Neural Network (R-CNN)," Applied Sciences, p. 238, 2019.
[6]. Z. Yi, L. Jia, and Q. Chen, "Crop Classification Using Multi-Temporal Sentinel-2 Data in the Shiyang River Basin of China," Remote Sensing, vol. 12, no. 24, p. 4052, Dec. 2020 [7]. H. Zhao, S. Duan, J. Liu, L. Sun, and L. Reymondin, "Evaluation of Five Deep Learning Models for Crop Type Mapping Using Sentinel-2 Time Series Images with Missing Information," Remote Sensing, vol. 13, no. 14, p. 2790, Jul. 2021
[8]. M. Debella-Gilo and A. K. Gjertsen, "Mapping Seasonal Agricultural Land Use Types Using Deep Learning on Sentinel-2 Image Time Series," Remote Sensing, vol. 13, no. 2, p. 289, Jan. 2021
[9]. N. Teimouri, M. Dyrmann, and R. N. Jørgensen, "A Novel Spatio-Temporal FCN-LSTM Network for Recognizing Various Crop Types Using Multi-Temporal Radar Images," Remote Sensing, vol. 11, no. 8, p. 990, Apr. 2019
[10]. European Space Agency's (ESA) Sentinel Scientific Data Hub, [online] Available: https://scihub.copernicus.eu/.
[11] H. Fahmi and W. P. Sari, "Analysis of deep learning architecture for patch-based land cover classification," 2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), Yogyakarta, Indonesia, 2022, pp. 1-5.
[12] Debella-Gilo M, Gjertsen AK. Mapping Seasonal Agricultural Land Use Types Using Deep Learning on Sentinel-2 Image Time Series. Remote Sensing. 2021.
[13] Mazzia V, Khaliq A, Chiaberge M. Improvement in Land Cover and

Crop Classification based on Temporal Features Learning from Sentinel-2 Data Using Recurrent-Convolutional Neural Network (R-CNN). Applied Sciences. 2020; 10(1):238. https://doi.org/10.3390/app10010238
[14] J. Pan et al., "Land Cover Classification Using ICESat-2 Photon Counting Data and Landsat 8 OLI Data: A Case Study in Yunnan Province, China," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 2507405, doi: 10.1109/LGRS.2022.3209725.
[15] Y. Cao et al., "A Two-Step Ensemble-Based Genetic Algorithm for Land Cover Classification," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 409-418, 2023, doi: 10.1109/JSTARS.2022.3225665.
[16] Yi Z, Jia L, Chen Q. Crop Classification Using Multi-Temporal Sentinel-2 Data in the Shiyang River Basin of China. Remote Sensing. 2020; 12(24):4052. https://doi.org/10.3390/rs12244052
[17] Zhao H, Duan S, Liu J, Sun L, Reymondin L. Evaluation of Five Deep Learning Models for Crop Type Mapping Using Sentinel-2 Time Series Images with Missing Information. Remote Sensing. 2021; 13(14):2790.
[18] Teimouri N, Dyrmann M, Jørgensen RN. A Novel Spatio-Temporal FCN-LSTM Network for Recognizing Various Crop Types Using Multi-Temporal Radar Images. Remote Sensing. 2019; 11(8):990.
[19] K. Kenduiywo, D. Bargiel and U. Soergel, "Higher Order Dynamic Conditional Random Fields Ensemble for Crop Type Classification in Radar Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 8, pp. 4638-4654, Aug. 2017, doi: 10.1109/TGRS.2017.2695326.
[20] H. Wang et al., "CC-SSL: A Self-Supervised Learning Framework for Crop Classification with Few Labeled Samples," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 8704-8718, 2022, doi: 10.1109/JSTARS.2022.3211994.
[21] M. Debella-Gilo and A. K. Gjertsen, "Mapping Seasonal Agricultural Land Use Types Using Deep Learning on Sentinel-2 Image Time Series," Remote Sensing, vol. 13, no. 2, p. 289, Jan. 2021
[22] Christiansen, M.P.; Laursen, M.S.; Mikkelsen, B.F.; Teimouri, N.; Jørgensen, R.N.; Sørensen, C.A.G. Current potentials and challenges using Sentinel-1 for broadacre field remote sensing. arXiv 2018, arXiv:1809.01652.
[23] Long, J.; Shelhamer, E.; Darrell, T. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 8–10 June 2015; pp. 3431–3440.
[24] Romero, A.; Gatta, C.; Camps-Valls, G. Unsupervised deep feature extraction for remote sensing image classification. IEEE Trans. Geosci. Remote Sens. 2016, 54, 1349–1362.

[25] Hoberg, T.; Rottensteiner, F.; Feitosa, R.Q.; Heipke, C. Conditional random fields for multitemporal and multiscale classification of optical satellite imagery. IEEE Trans. Geosci. Remote Sens. 2015, 53, 659–673

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PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

PAGE 17

PAGE 18

PAGE 19

PAGE 20

PAGE 21

PAGE 22

PAGE 23

PAGE 24

PAGE 25

PAGE 26

PAGE 27

PAGE 28

PAGE 29

PAGE 30

PAGE 31

PAGE 32

PAGE 33

PAGE 34

PAGE 35

PAGE 36

PAGE 37