Crop Monitoring via Remote Sensing

By

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Dedication

This thesis is dedicated to *my exceptional parents*, whose remarkable love, cooperation and encouragement led me to this wonderful achievement.

Certificate of Originality

I hereby declare that this submission titled "Crop Monitoring Via Remote Sensing" is my own work. To the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics, which has been acknowledged. I also verified the originality of contents through plagiarism software.

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Copyright Notice

Contents

List of Abbreviations

Abbreviations

MLC	Maximum Likelihood Classifier
SVM	Support Vector Machine
ANN	Artificial Neural Network
ML	Machine Learning
RS	Remote Sensing
LightGBM	Light Gradient Boosting Machine
TempCNN	Temporal Convolutional Neural Network
LSTM	Long Short-term Memory
RNN	Recurrent Neural Network
DNN	Deep Neural Network
D1	Dataset 1
D2	Dataset 2
D3	Dataset 3
EO	Earth observation
GBDT	Gradient Boosting Decision Tree
RF	Random Forrest

DL Deep Learning

CNN Convolutional Neural Network

GAN Generative Adversarial Network

OBIA Object Based Image Analysis

AOI Area of Interest

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Abstract

The increasing world population is generating higher food demand that needs effective cultivation methodologies to meet them, especially for the developing countries that have a higher dependence on the agricultural sector. Crop type classification is part of crop monitoring which can help to plan crops effectively and meet the demand-supply chain. Our study had mainly two objectives, acquisition of a dataset for crop type classification and building effective models for Pakistan-specific regions that can have comparatively better outcomes for the region. The dataset was acquired from different regions of Pakistan via local surveys and later on perform post-cleaning to get an optimized model especially for LSTM where data was converted into a time-series dataset which provided us comparatively more accurate results. The dataset had sentinel-2 images ranging from 2016 to 2021 for mainly 5 crops and a no-data class capturing both Kharif and Rabi seasons of the area. We used high temporal and spatial resolution images to train TempCNN, Light GBM, and LSTM where we achieve a model having an accuracy of 94%. The LSTM model on time-series data outperformed where the spatial and temporal pixel of each location was converted to a time dimension. The developed methodology can be used to forecast the supply of different crops as well as the models can be trained on more crop types. The acquired dataset can be used to try different methodologies for developing optimized models.

Keywords: *Dataset Acquisition, LSTM, Light GBM, TempCNN*

Chapter 1

Introduction

1.1 Remote Sensing

Remote sensing (RS) is the process of measuring or acquiring data or information about some object or phenomena by a sensing device that is not in intimate or direct physical contact with the thing or phenomena under study. This acquisition of data or information is not limited to satellites or far away scanners; any data obtained without direct contact with the object is remote sensing. The acquired data can be any input type like temperature, pressure, force, images, or any sensible attribute. However, in a broader sense of the term "remote sensing", things like a sonogram, medical imaging, or even simple x-rays can also be categorized as remote sensing because data and information are gathered without physical contact with objects.

For the scope of this study, we are focusing on the acquisition of data using satellite imagery, commonly known as satellite remote sensing. In satellite remote sensing, we have sensors placed on board satellites that are orbiting the earth. These sensors include multi-spectrum cameras and scanners that continuously scan the planet acquiring images of not only the surface of the planet but also drilling deep down into the surface. RGB images aren't the only type of images that can be acquired from the satellite we chose for our study; instead, this study uses high spatial resolution optical images from the Sentinel-2 satellite. These images had a spatial resolution of 12-bands. These images correspond to rural areas of Pakistan where crop cultivation is one of the primary professions.

For this study, we are mainly focused on classifying the crops grown from time to time in Pakistan. This classification will further yield predictions and thereby contribute to planning the country's total food requirements. Remote sensing provides the benefit of non-reliance on traditional data gathering techniques that are time-consuming, costly, and unreliable.

1.1.1 Active Remote Sensing

When the sensor embodies within itself the source of illumination/energy, for example, we had cameras that used to have a built-in flash on them, so the moment someone clicks the picture, the flash would fire the light and it would get reflected from the object and the camera would record a picture. In this case, the camera is also carrying the source of illumination.

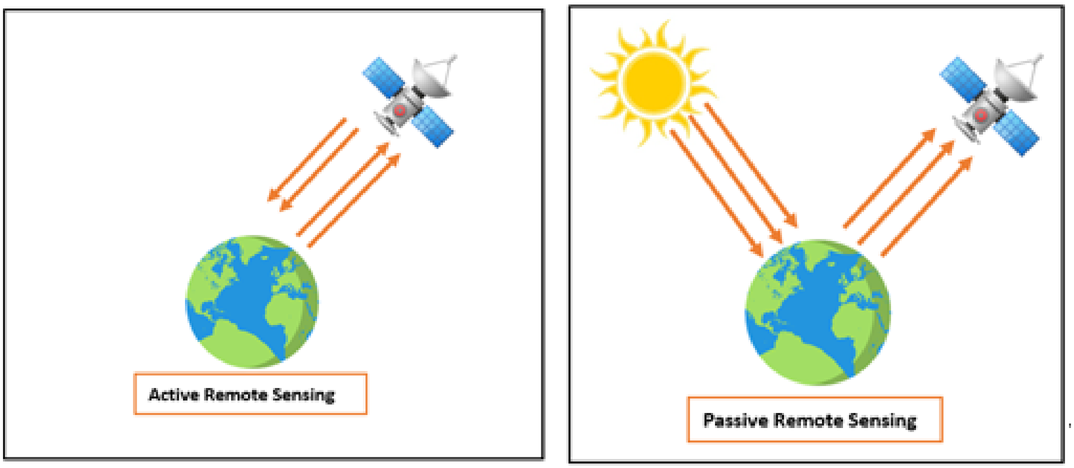

Figure 1.1: Remote Sensing.

Active remote sensing can be understood as in radar because when a satellite is equipped with a radar transponder, it's sending out radar waves or radio waves which bounce off from the earth's surface, the time required for the waves to hit the earth's surface and we recorded by sensors on the satellite is what utilized for making an image, this type of sensing comes under active remote sensing.

1.1.2 Passive Remote Sensing

Passive remote sensing comes into play when the sensor itself does not have a source of illuminating the ground surface or the object which it is imaging and capturing information. Figure 2- Passive Remote Sensing For example, the sun illuminates the earth, and reflectance from the earth's surface is collected by the sensor on the satellite. It is passive because the sensor itself does not carry its own source of energy.

1.2 Satellite Images

Images captured by satellites that are operated by different organizations are used for various purposes including earth observations (EO) which is our primary focus here. From these images, we can forecast the change in atmosphere as they provide us an accurate representation of how the atmosphere is changing. Satellites provide us the accurate data as there are comparatively fewer chances of error in satellite imaging. EO images provide us a representation of what is happening on earth. Generally, we have five types of resolutions in satellite imagery while working with remote sensing i.e spectral, temporal, radiometric, geometric. The spectral resolution is identified by wavelength. Temporal resolution refers to the time interval between the different image collection periods, Radiometric resolutions captures the different level of brightness and the Geometric resolution express the ability of satellite to image a portion of the earth in a single pixel. There are many EO satellites used for earth observation missions however our primary focus is Sentinel-2A and Sentinel-2B. Sentinel-2A captures the high-resolution image of earth from 10 m to 60 m over land having 13 bands (spatial resolution) in short wave infrared, near-infrared and visible part of the spectrum and it revisits the same place every 10 days with the same viewing angle however with revisit time was reduced to 5 days after 2nd launch of the satellite. The aforementioned EO images can be used to observe change on earth, different plant indices can be monitored, observations over soil and other changes can be effective to forecast events.

1.3 Crop Classification

In classification, the dataset is normally categorized into different classes where the input data relates to a specific class. Classification can be performed on both structured and unstructured data and the accuracy of classification depends on model training along with the quality of input data. Once the training of the classifier is completed, the classifier determines the class of new incoming data. The classification is part of supervised learning that have data with class label attached to it and used in model training. The model can be of different types i.e. artificial neural network, convolutional neural network, Recurrent Neural network, decision tree, support vector machine, etc and we select the model with respect to the available dataset. For example, decision trees work well with non-linear data, CNN works better on images, and RNN or LSTM is normally used for time-series datasets.

When it comes to crop classification, the dataset is usually compressed of images extracted from different sources including but not limited to satellite images. In the case of satellite images, we can extract NDVI values, soil moisturizer, and other parameters that can be used as features for modeling. A trained model later can classify any provided crop imaging to its crop type without any extra effort.

1.4 Motivation

According to a published study [3], the demand for the food will be doubled by 2050 and we would have to extract more yield using the existing resources/crop area. The main motivation of the research is to contribute to agriculture in order to meet the extensive demand for food by improving the monitoring process of agricultural land and crops. Computer vision and machine learning models are mature enough to provide high-level insights where the first task is to classify the crops. The contribution to the improvement of crop type classification via remote sensing can lead to the efficient development of different other application i.e. yield prediction and health monitoring of crops.

1.5 Objectives

Cultivation practices, soil, weather, and irrigation techniques vary for different areas. A model developed on the Data of the U.S or Ukraine may not provide promising results on Pakistan's agricultural land. The main objective is to gather data from Pakistan and design/develop an effective machine learning model that should be able to perform crop type classification using gathered data from various cities of Pakistan.

1.6 Summary of the contribution

There were mainly two parts of the thesis, one to perform ground surveys to collect data for groud truth which was required for the machine learning / deep learning models where the focus was on Pakistan's agricultural sites. A model trained on Pakistan's data can provide comparatively promising results when compared to a model trained on other country's data. The summary is that the model improvement was the aim of the thesis. The other contribution we aimed was data, that can be used for further research purposes and analysis.

1.7 Thesis organization

The thesis work was divided into 5 parts named in thesis as chapters, where the first chapter introduced the reader to the domain and provide a basic understanding of the remote sensing and crop type classification. The second chapter provides an in-depth and detailed literature review of the domain, previous work, and different methodologies on machine learning, deep learning, and modeling are explained. Chapter 3 is dedicated to the study are where the data gather process and area is explained. That chapter also explains and discus gathered data, issues with the data and how did we handle them. Modeling procedures and developed models are discussed in chapter 4 where the modeling procedures, models themselves, and other related limitations are discussed. Chapter 5 contains the information about how the experiments were performed, what were the results of the models, the performance analysis of the models, and comparisons of the models in terms of accuracy. Last but not least chapter 6 have the crux of the thesis where the thesis was concluded along with future work and recommendations.

Chapter 2

Literature Review

Initially the information about the crops and plants was acquired by statistical sampling and field surveys. With recent technological advancements, remote sensing is also being employed for this data acquisition. Remote sensing is a more efficient way of collecting information about land as it provides up to date large earth surface coverage at once and at relatively low cost [4, 5]. Recently many high-resolution images like Geofeng-1, Sentinel-2, Landsat-8 etc. has become available and being utilized as main source to obtain the information about the crop area [6–11]. Numerous methods and their variants are devised to perform the crop classification. We can divide them into four broad categories: Maximum likelihood classification (MLC), Support Vector Machine (SVM), (RF), Artificial Neural Network (ANN), Deep Learning (DL). Brief description of these is given below:

2.1 Maximum likelihood classification

It is one of the earliest and most commonly used classifiers to perform the classification of remotely sensed data. It is based on Bayes theorem. In this method a pixel is classified into a specific class on the basis of the Maximum Likelihood (ML). The likelihood is the posterior probability of the pixel belonging to some specific class. Murthy et al. [12] proposed a Maximum Likelihood based wheat crop classification method using different strategies.

Multi-temporal data obtained by Indian Remote Sensing satellite (IRS)-1B is used for classification. The strategies include Iterative MLC, MLC with Principal Component

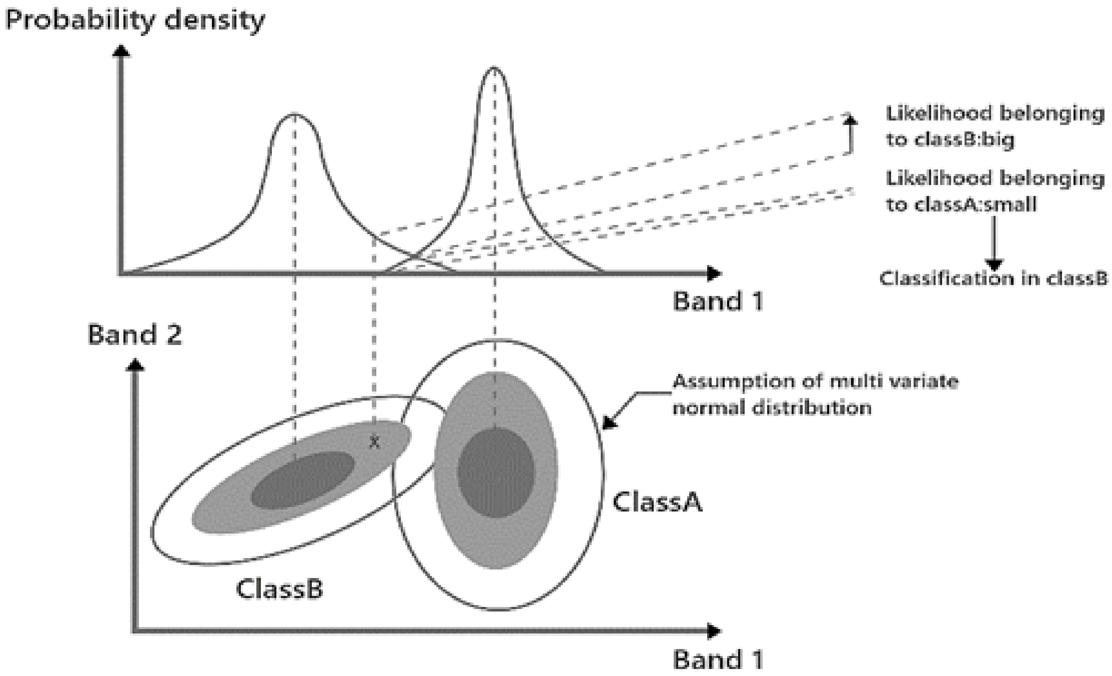

Figure 2.1: Maximum Likelihood Classification. Source [1]

Analysis and sequential MLC. The performance of iterative MLC is better in terms of classifying wheat crop. Asli et al. examines the efficacy of Maximum Likelihood classifier through parcel based and pixel based techniques for crop classification. They used SPOT 5 multispectral images for experimental work.

2.2 Support Vector Machine

It is a supervised predictive analysis data classification, machine learning technique. Support Vector Machine (SVM) model learns from a set of labeled data examples provided against each category and then assigns new elements to one of these labeled categories. It can also be used for regression analysis but mostly it is used for classification problems. Numerous researchers have presented SVM based classification techniques for text, objects and face etc. Likewise, many research works propose the use of SVM for crop type classification. Mingmin et al. [13], proposed a hyperspectral image based alternative implementation method in primal formulation for SVM for land cover classification.

Evaluation of the proposed approached is carried out with the help benchmark datasets. In [14] Chang et al. presented a SVM based library named as LIBSVM. The goal of

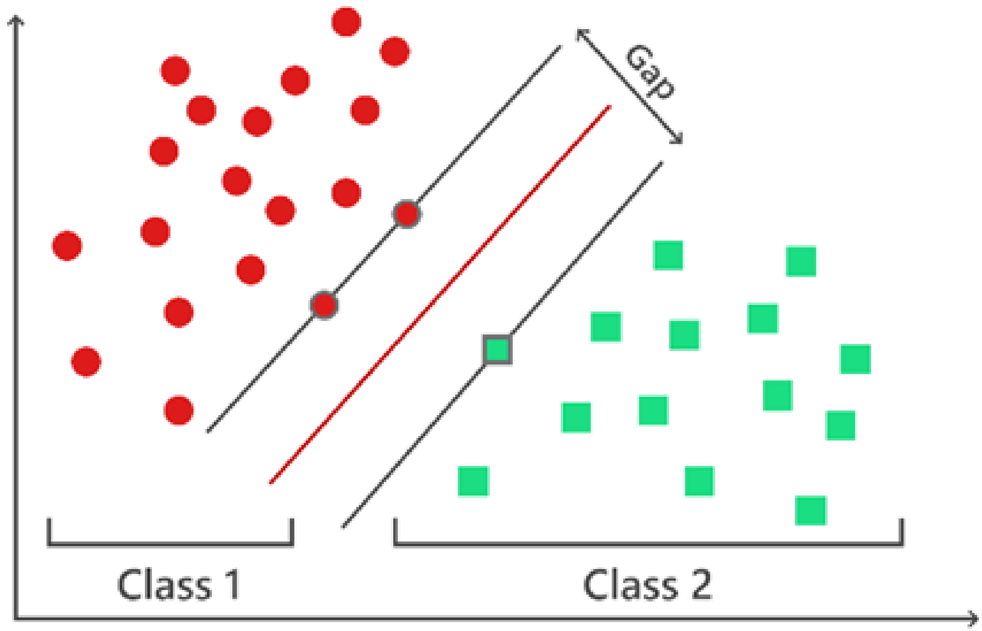

Figure 2.2: Support Vector Machine

this package is easy utilization of SVM. They also presented multiple tasks of classification and regression; this library package supports. Tan et al. [15], proposed a novel hybrid classification approach based on entropy decomposition and SVM. They call it EDSVM. This technique incorporates the features of both methods such as entropy decomposition's desired parameters and the statistical learning approach from SVM, to create optimal boundary line between the different categories of crops in high dimensional space. P. Kumar et al. [16] used SVM for various crop classification and assessed its performance by comparing the accuracies with two other approaches. They used LISS IV satellite data for evaluation and comparison.

SVM algorithm is an extensively used technique for remote sensing based crop type classification but it is not suitable for large data samples.

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2.3 Random Forest

Random Forest (RF) is a supervised machine learning technique, used for classification and regression. This algorithm uses several decision trees for prediction. At the end, result of all trees are merged and with the help of majority voting final output is predicted. In simple words it is based on ensemble of multiple decision trees.

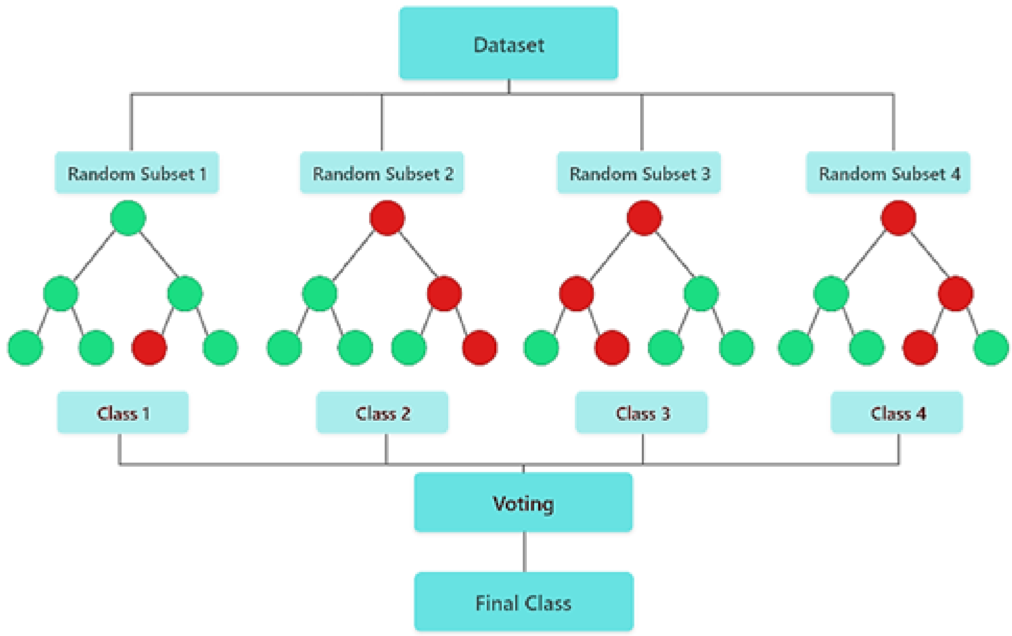

Figure 2.3: Random Forrest.

Several researchers have presented different techniques based on RF for land cover classification. In [17] Rodriguez-Galiano et al. presented the use of random forest for land cover mapping. Landset-5 data is used for experimental work and the efficiency of RF classifier is evaluated on the basis of classification accuracy, effect of sample size and noise in the data. Asli et al. [18], evaluated the performance of random forest for crop classification using parcel based and pixel based techniques. SPOT 5 multi-spectral images are used for experiments. They compared the results with MLC variants but overall, the efficiency of parcel base RF is much better than others. Lebourgeois et al. [19] evaluated and enhanced the efficacy of Random Forest by combining it with OBIA classifier. For experimental work they used Sentinel-2 data combined with DEM, VHRS and HRS data to analyze the significance of each data source and their contribution in classification accuracy. RF based classifier provides an efficient way to measure the significance of each feature on the final output and also it helps in avoiding overfitting.

2.4 Artificial Neural Network

Artificial Neural Network (ANN) is generally known as Neural Network. It a computational model inspired by a biological neural network that is found in human brains. It consists of connected nodes or units simply called artificial neurons. These artificial neurons are connected with each other with the help of a link called edge and this carries signal from one neuron to another and each neuron upon receiving signal, process it and pass it the next connected neuron. These networks learn the features from the data provided in order to minimize the overload of the task relevant and explicit rule-based programming. A generic ANN have an input layer, a hidden layer and an output layer. Input layer takes input/data, hidden layer performs the learning and decision is provided at output layer. ANN is a supervised learning technique that is generally employed in classification and regression tasks.

ANN have been used in domain of agriculture for various purposes such as crop yield prediction [20][21][22] [23] [24], water management [25][26][27] , soil management [28][29][30] , fruit quality assessment [31] [32] [33], and plant disease detection [34] [35] [36] etc.

Similarly, many researchers have used ANN for crop classification as well. P. Murthy et al. [12] present the used of backpropagation Artificial Neural Network for wheat crop classification. For the evaluation of proposed approach, they used multi-temporal data obtained by Indian Remote sensing satellite. They compared the performance of ANN model with different variants of ML classifier and ANN with backpropagation performed well in all cases. Kumar et al. [37] examined the proficiency of artificial neural network for different crop classification by employing various learning parameters. They used Landsat 8 and LISS IV satellite images for classification and evaluation. In[16] Kumar

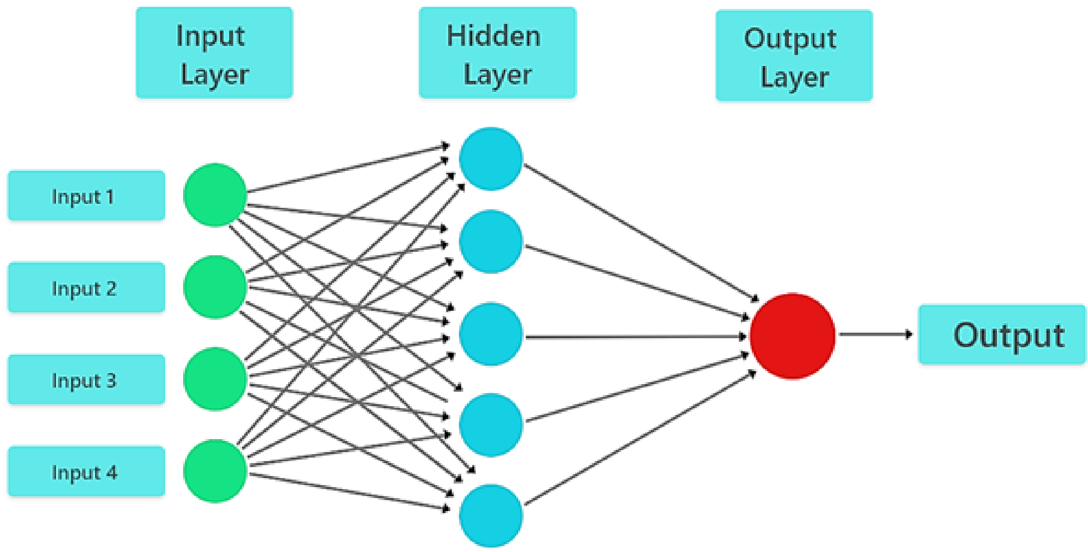

Figure 2.4: Artificial Neural Network.

et al. also used ANN for crop classification and compared its results with two other techniques by using the data captured by resoourcecast-2 satellite. CC Yang et al. [38] proposed the use of ANN with backpropagation for differentiating the corn crop from weeds. They have used a small dataset for training but still achieve accuracy of 80%. In [39] Kumar et al. proposed another ANN based model for crop classification using the C-band RISAT-1temporal satellite images. Madhusmita et al. in [40] proposed a backpropagation based neural network for classifying Iris plant. ANN based methods often suffers from the problem of overfitting and have high computational burden.

2.4.1 Deep Learning

Deep Learning (DL) models are in fact the deeper version of ANNs. They generally consist of more than two hidden layers. The deeper architecture helps model to learn more complex feature representations from input than the features obtained by other means in an end to end manner without human intervention [41]. DL models are able to solve more complex problems in relatively less time due the complex and deeper architecture that leads to more parallelization [42]. Deep learning has been widely studied and applied in image processing domain to perform various tasks such as pattern recognition [43] [44], image restoration [45] [46], image dehazing [47] [48], super resolution [49][50], pansharpening [51][52][53] and image classification [54][55][56] etc. The benefits of DL algorithms have also been examined and applied in the agriculture domain specially for crop classification. Most prominently of these algorithms are Convolutional Neural Network, Recurrent Neural Network and Generative Adversarial Network. Following is the brief description these algorithms along with some prominent work for crop classification using these.

2.4.2 Convolutional Neural Network

Convolutional Neural Network (CNN) is a most prominent DL framework to process the image data in the form of multi-dimensional arrays. The powerful feature of CNN is, efficiently estimating the complex nonlinear relationships. Numerous CNN based crop classification methods have devised so far. In [57] Kussul et al. presented a new CNN based crop classification approach, consisting of two different CNNs, one 2D CNN for learning the spatial details and other 1D CNN for learning spectral details. Empirical processing is then performed to create the final output by combining the learned details of both CNNs. Shunping et al. proposed a first 3D CNN based approach for crop classification [58]. This framework uses spatio-temporal images and fully automatic in terms of feature learning. A special 3D kernel and a fine-tuning step aids model to learn the most discriminative features from the training samples.

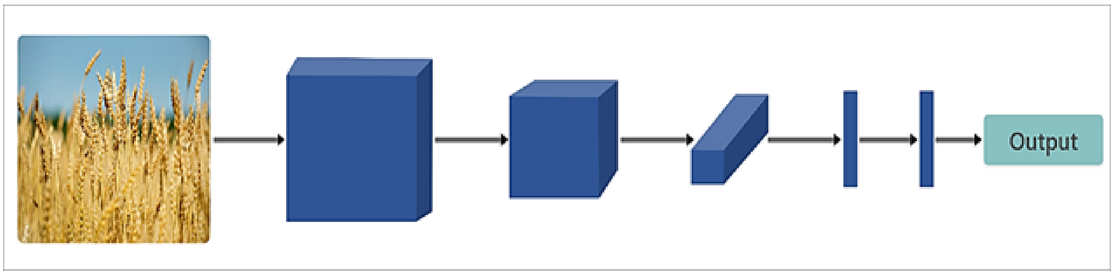

Figure 2.5: Convolutional Neural Network

Kwak et al. proposed another CNN based crop classification model [59] . The presented crop classification approach along CNN takes advantage of Bidirectional LSTM to efficiently extract and combine temporal and spatial features. For spatial features 2D CNN is employed and then extracted features are fed to BLSTM as input for learning the temporal features. Lingjia et al. in [60] presented the use of CNN for crop classification using multi-temporal and multi-source satellite imagery such as Sentinel-1, Sentinel-2 and C-band GF-3. In [61] Bhosle et al. examined the use of CNN for crop classification and compared the accuracy of model with CNN based autoencoder and Deep Neural Network. They have used Indian pines and EO1 hyperion dataset for experimental work. Overall, the performance of CNN is much better than other two models. Krishna et al. also proposed a joint CNN and LSTM based framework for efficient crop classification that exploits the spectral and spatial features at the same time [62].

2.4.3 Recurrent Neural Network

R ecurrent Neural Network (RNN) is another type of Neural Network (NN). RNN have some internal memory to retain information over a period of time and to handle arbitrary sequence input data. Contrasting to CNN, RNN emphasizes on the temporal structure of the image and is appropriate for working with sequential data.

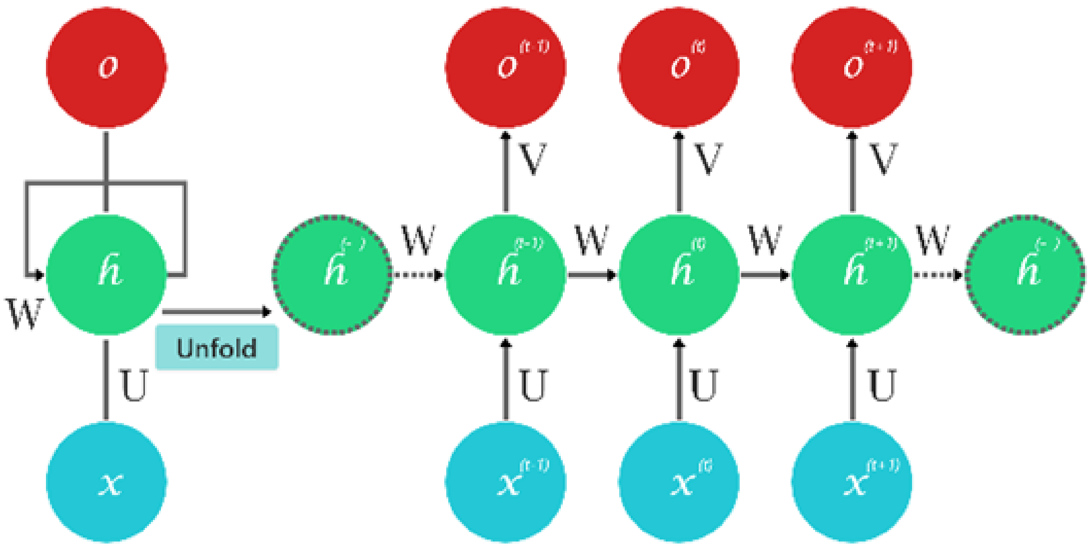

Figure 2.6: Recurrent Neural Network.

These were initially used for text and speech data handling but recently many researchers have presented RNN based crop classification models as well. Mazzia et al. proposed a novel hybrid pixel based deep learning architecture combining the features of RNN and CNN for crop classification using sentinel-2 satellite imagery captured over Italy [63]. The proposed approach is compared with some traditional approaches and it outperformed all of them, providing an efficient way for performing multi-temporal classification over time series data. In [64] Nando et al. proposed the use of RNN for crop classification in combinations with neural ordinary differential equation. This joint venture helps in classifying the image sequences that are irregularly sampled. The proposed approach also performed well in such cases where only few data samples exists due to frequent cloud coverage. Garnot et al. in [65] examined RNN with some other deep learning models to evaluate the importance of temporal and spatial dimensions of time series data. They have used Sentinel-2 dataset for experimental work.

2.4.4 Generative Adversarial Network

Generative Adversarial Network (GAN) is another type of Neural Network having two different networks that compete with each other as an adversarial game to create a new synthetic data sample that is similar to training set. One network is called generator; its task is to generate a data instance close to those in the training data and second network is called discriminator; it compares the generated instance to the real data. The process continues until discriminator gets fooled by the data created by generator, thinking it as a real data sample. GANs have been employed in many image processing applications similarly it is also considered for remote sensing based crop classification. Hamideh et al. in [66] proposed a pixel-based classification approach for multispectral images using GAN to distinguish crop from weed. The have used weedNet dataset for evaluation.

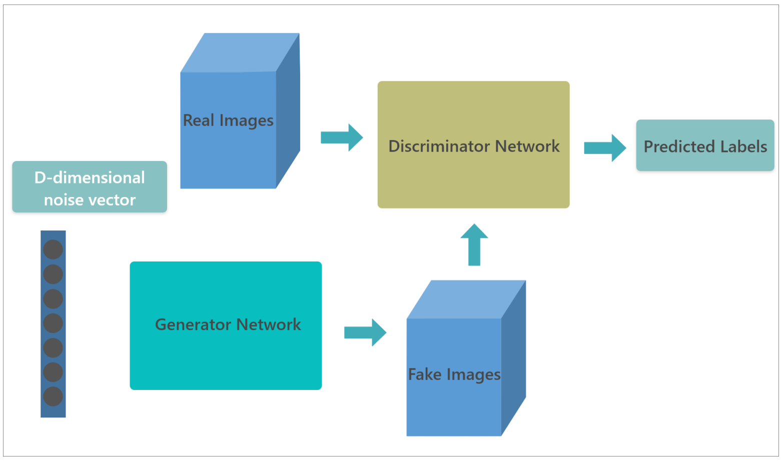

Figure 2.7: Generative Adversarial Network. Source [2]

2.5 Others

Apart from the categories discussed above numerous other models have also been devised for crop classification. Siachalou et al. proposed an approach for crop classification using phenological models along with the theory of Markov chains [67]. In the proposed technique remote sensing images having different resolutions are incorporated to monitor the continuous change in the ecological process. Time series RapidEye and Landsat ETM+ images are used for experimental work. In [68] Gaertner et al. proposed two different approaches using maximum likelihood and Object Based Image Analysis (OBIA) method, to classify Coffea arabica crop. Images of WorldView-2 satellite are used for experimental analysis. Qingting et al. proposed another OBIA based crop classifier using time series enhanced Landsat-MODIS data [69].

Chapter 3

Study Area and Data Acquisition

3.1 Study Area

The area of interest for this case is selected from Pakistan considering agriculture's contribution to Pakistan's GDP which is considerably high. The selected area is from Punjab province where most of the area is used for the purpose and has a developed irrigation system. Furthermore, the districts Bahawalpur, Sahiwal, and Pakpattan were selected. All of the selected areas are one of the highest producers of wheat, cotton, and corn which is the core reason for the selection.

Figure 3.1: Study Area

3.2 Data Acquisition

Ground surveys were conducted to acquire the ground truth's data from the study area. An android application was developed to extract the coordinates of the polygons. Another application named

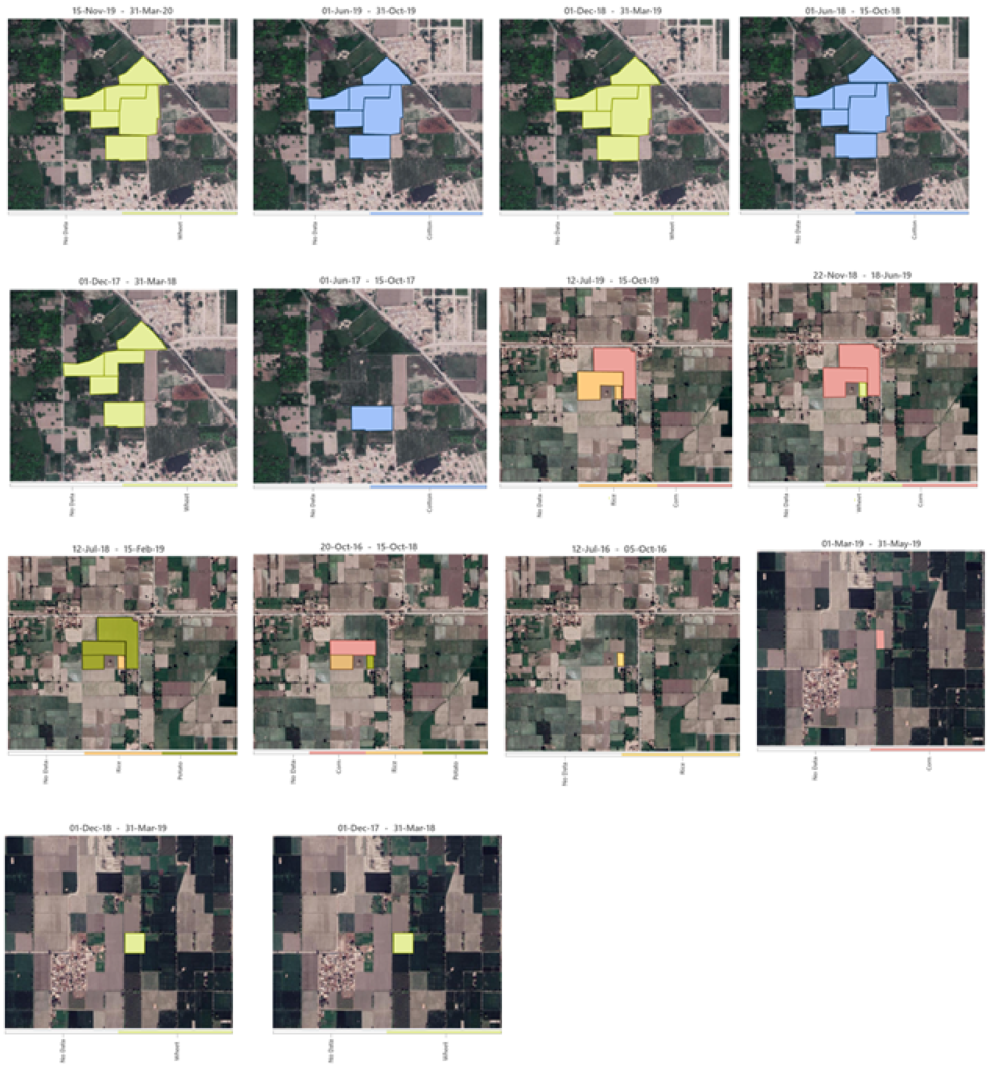

Figure 3.2: Polygons of AoI

as "GPS Logger" was also used to record the coordinates of polygons which provides comparatively better and accurate results. The main workflow for the data acquisition included visits agricultural sites of the study area and then acquire coordinates for AOI (Area of Interest) and then the farmer provides the information about crops, i.e. crop type, sowing data, and harvesting dates. The ground survey includes the information associated with each polygon, as sample data is shown in the table. Total 9.52M square feet area was captured with crop type label where 3.4M belongs to wheat, 3.1M to cotton and remaining data have corn, potatoes, and rice crop.

Crop Name	Sowing	Harvest	Area (Sq. m)	District	Season
Cotton	01/06/2017	01/06/2017	696960	Bahawalpur	Kharif
Cotton	01/06/2018	01/06/2018	43560	Bahawalpur	Kharif
Cotton	01/06/2018	01/06/2018	43560	Bahawalpur	Kharif
Cotton	01/06/2018	01/06/2018	43560	Bahawalpur	Kharif

Table 3.1: Ground Survey Data

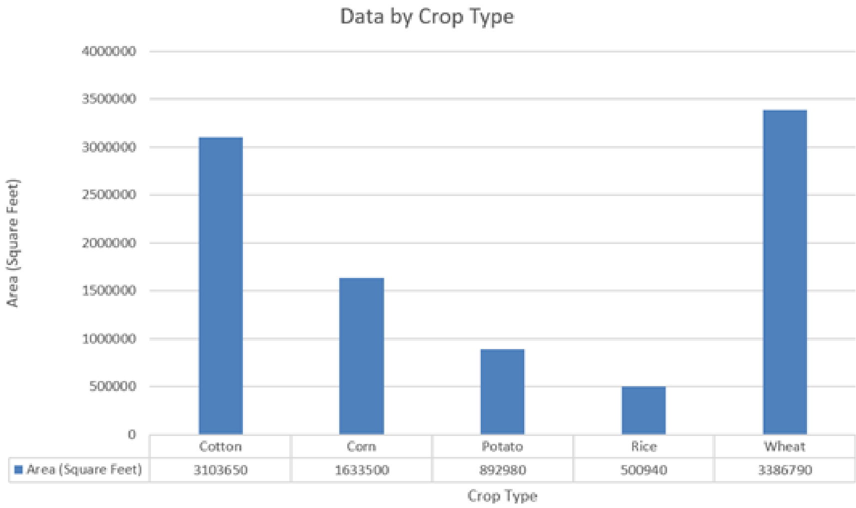

Figure 3.3: Data by Crop Type

In the selected study area, there are two seasons in agriculture refer by Kharif and Rabi. The Kharif season begins with sowing in the April of each year and then harvest in October that can last to December. The second principal crop season is known as Rabi that usually starts with the sowing of the crop in the Month of November to December of each year and ends with the harvesting between April-May each year. The track of season is available in the gathered data for analysis and modeling.

The distribution of the data over seasons can be seen in the figure 10; where 55% of the gathered data belongs to Kharif season and remaining 45% is of Rabi. While the distribution of the data over city can be seen in the figure 11; where about 67% of the data was gathered from Bahawalpur region, 32% from Sahiwal and only 1% is from Pakpattan.

Sentinal-hub was used to extract Sentinal images after creating an account and gen-

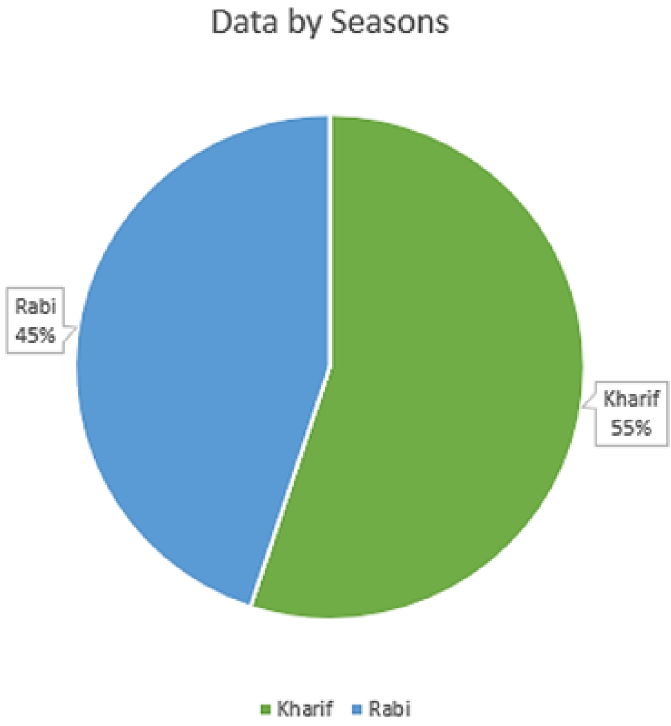

Figure 3.4: Data by Seasons

erating API tokens, where each image had a spatial resolution of 10 and a temporal resolution of 15. Sub grids of 3x3 were further extracted from the images and assigned corresponding crop lables where each grid had 3x3x10 size and single samples had 15 temporal resolutions ending up with 15x3x3x10 dimensions. The original dataset had 165, 313, 90, 49, 339 samples of Corn, Cotton, Potato, Rice, and Wheat respectively.

Class	Sqr ft	Sqr m	Pixels	Samples (3x3)
Corn	1633500	151755.85	1515	165
Cotton	3103650	288336.12	2877	313
Potato	892980	82959.87	828	90
Rice	500940	46538.46	463	49
Wheat	3386790	314640.47	3137	339
No Data	2613600	242809.36	2428	269
Total	12131460	1127040.134	11248	1225

Table 3.2: Original Data set

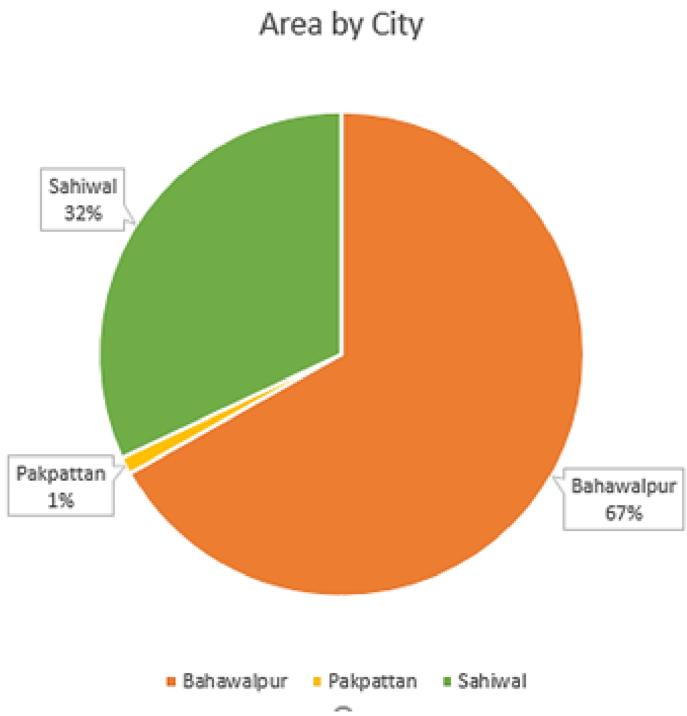

Figure 3.5: Area by City

Another dataset was extracted for multiple crops and random areas including residential areas without any label to cater to no-data class during the classification process. The primary objective behind the no-data class was this, if we provide data of any crop that does not belong to the training set, the model should be able to assign it a no-class label which means given data do not belong to any class from data on which it was orignally trained. A total of 2.6 million square feet area was captured for no-class data that ended up creating 269 samples of 3x3 grids.

Chapter 4

Crop Type Classification Modeling

4.1 Dataset Partition

The gathered data sets had high variation in terms of the number of samples among crop types which could lead to biases and overfitting models on certain types of classes where the dataset had a higher number of training samples. In order to normalize the data, a split was performed on the dataset. Cotton and Corn was combined into one dataset and named as Dataset-1. On the other hand, remaining crops were into another dataset named as Dataset-2. Crops in dataset 1 had a greater number of samples so we perform an 80-20 split to generated training and test sets. We had a total 313 number of training samples for cotton and a total 339 number of samples for wheat, after an 80-20 split, the training data had a total 521 number of samples and 131 samples were left for testing purposes. Dataset 2 had crops where the number of samples is less as well as the variation is high. Potatoes had almost double samples than Rice and Corn is approximately double than Potatoes. Considering this variation and to normalize the training, the 80-20 split was not performed on this dataset, rather an equal number of training samples (40 from each class) were selected for training, and the remaining were put to the test set.

Another dataset was developed from the original data where each sample grid was converted into 9 samples points. as a single-pixel had a spatial resolution of 10 and a temporal resolution of 15, each pixel from spatial dimensions was converted into series

Crop Type	Samples	Training (80%)	Test (20%)
Cotton	313	250	63
Wheat	339	271	68
No Data	269	219	50

Table 4.1: Dataset 1

Crop Type	Samples	Training (80%)	Test (20%)
Corn	165	40	63
Potato	90	40	50
Rice	49	40	9
No Data	60	40	20

Table 4.2: Dataset 2

and appended temporal set to form a time series dataset. After conversion, each sample point had 150 points in series (10 spatial *15 temporal) along with an increased number of training points. The final dataset consisted of Cotton, Wheat, Corn, Potato, Rice, and No Data having 2817, 3051, 1485, 810, 441, 2421 samples respectively. The complete samples space was divided into training and testing sets using an 80-20 split.

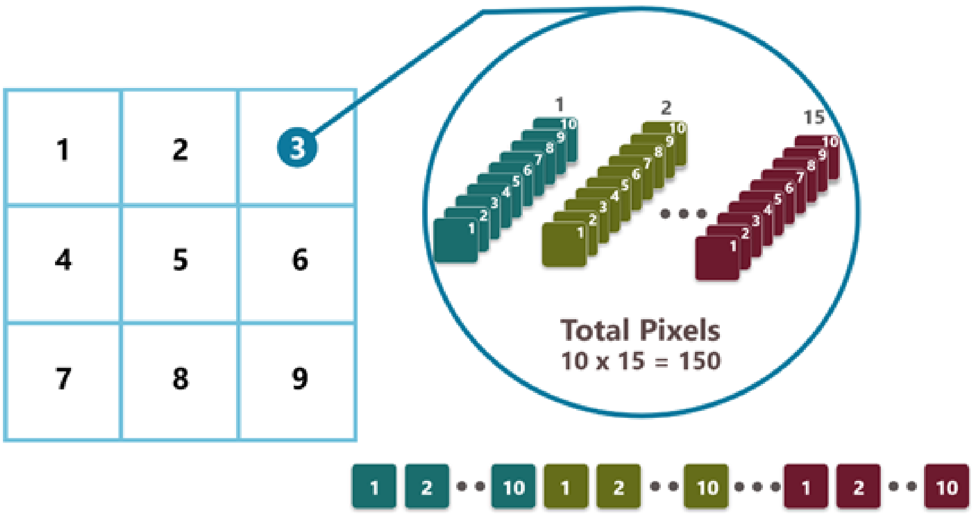

Figure 4.1: Area by City

Crop Type	Samples	Samples Series	Training	Test
Cotton	313	2817	2250	567
Wheat	339	3051	2439	612
Corn	165	1485	1188	297
Potato	90	810	648	162
Rice	49	441	360	81
No Data	269	2421	1971	450
Total	1225	11025	8856	2169

Table 4.3: Dataset 3

4.2 Light Gradient Boosting Machine (LightGBM)

LightGBM is a variant of GBM which is faster, efficient at distributing and leveraging the resources along with high performance backed by decision tree algorithm similar to XGBoost or even random forest. LightGBM is based on a concept to split the tree on the basis of leaf rather than tree wise or level wise. The overfitting problem in the LightGBM can be handled by appropriately defining the depth of splitting. Light Gradient Boosting Machine took the inspiration from Extra Boosting Machine where we have more or less the same algorithm with few improvements. Normally decision trees work very well with nonlinear data but the problem is that a single decision tree can very easily overfit provided data set and if we built a deep decision tree it's very prone to outlying observations so usually people deal with this problem by building ensembles and also by using multiple trees one of the ensembles is gradient boosting. In naïve gradient boosting, we take the data and feed weak learners like a shallow decision tree which ends up with a model having some error call them residuals, after that we take another model and fit to the residuals, and it's repeated many times but in the gradient boosting on decision trees, we usually do not use entropy instead use particular gain for the modeling. Light GBM is the library that comes from Microsoft that aims to make the Gradient boosting on decision trees faster and they achieve that by checking all of the splits while you basically want to create new leaves, it check only some of them so before they are built a tree, so before they built a tree they sort all of the attributes and then bucket the observations they create bins here and when they want to split a leaf in the tree they do not iterate over all of the leaves but overall of the buckets so there is a much smaller number of splits considered each time. it's actually called histogram implementation by the authors you can very easily improve your optimization techniques. In our case, we select multical model having mostly default parameters where the number of leaves was 31, the optimization metric was multi_logloss, boosting was GBDT (Gradient Boosting Decision Tree) with a 0.1 learning rate and 100 iterations.

4.3 Temporal Convolutional Neural Network (TempCNN)

Artificial Neural networks (ANN) lies under the umbrella of machine learning. ANN contain node layers, having input layer, one or more hidden layer and an output layer where each node has a connection with other nodes and has weights and thresholds. There are different types of neural networks like RNN, ANN, etc. but CNN is widely used in image classification and computer vision-based tasks. Before CNN, traditional feature extraction methods were used which were very time-consuming. CNN is like a multi-layer perceptron having hidden layers called convolutional layers. Convolutional layers get the input, detect edges and transform that input after that it outputs the transformed input to the next layer. Convolutional layers detect patterns for example shapes, circles, etc. and we specify the number of filters for a specific layer. If a filter detects a pattern of edges, then this filter is called an edge detector. Some filters may detect corners some filters may detect circles or shaps. The deeper the network builds, the more sophisticated these filters become so in later layers. For example in later stages, our filter may be able to detect specific objects, and even deeper layers the filters can detect even more sophisticated objects.

In our dataset, we have a high spatial and temporal resolution of the images. Single samples have images at 15 different time-stamps from sowing to harvesting and are recognized as temporal resolution. We use that temporal resolution for building temp CNN which applies filters on temporal pixels to detect the change over time. Overall three Conv layers were used each having kernel size of 5, filters parameter to 15 along with relu activation function and 0.5 dropouts. As the dense layers have relu activation functions and the last layer had softmax activation. The adam optimizer was used, we passed the data in batches instead of all of the training data at once having 32 batch size and trainined in 50 epochs.

4.4 Long Short-Term Memory (LSTM)

Conventional RNN face the difficulty to learn and preserve information over many time steps especially when working on larger datasets thus causing a higher risk of vanishing gradient issue. While training the stacked neural network certain activation functions (e.g.: gradient or derivatives) are added to neural network, the gradient decreases significantly, causing the network hard to train and is referred to as vanishing gradient problem. The problem is, in few cases, the gradients become smaller and smaller, functionally stopping the gradient to change its value. In the worst case/ it may completely cause the network from stop learning and no real learning is done. The vanishing gradient problem is a common issue in deep neural networking, so to overcome this issue long short-term memory is used.

The magnitude of gradients are effected by two things, the weights and the derivatives through which the gradients passes, while LSTMs help to solve this issue by storing the processed information of longer dataset.

Chapter 5

Experiments and Results

5.1 Light GBM

LightGBM was trained on both datasets where it gives 83.98 accuracies on dataset 1. The F1 score, recall, and precision for the no-data class were higher than other classes for the dataset. The F1 score, Recall, and precision for no-data class in D1 were 87.76, 86, and 89.58 respectively, on the other hand, cotton had 82.81 F1 Score, 84.13 recall, 81.57 precision, and Wheat had 82.35 F1 scores, 82.35 recall, and 82.35 precision. When we look at the confusion matrix, false-negative values are 12 for the wheat class where 9 of them were misclassified as cotton, and 3 were wrongly predicted as no-data. The cotton class was second in terms of false-negative with 10 containing 8 misclassified as Wheat and 2 misclassified as no-data. The no-data class had comparatively lower false-negative cases where 3 of no-data samples were predicted as cotton and 4 of them were wrongly predicted as Wheat.

LightGBM had lower accuracy when comparing the result to D1 where it had 83.98 percent accuracy. To further drill down the performance, F1 score, recall and precision were calculated which gives better results on corn where we had a higher number of test sets. The F1, recall, and precision for corn was 82.05, 76.8, and 88.07 respectively. For the remaining dataset, the potato had 74.29 F1, 78 recall which is more than corn, 70.91 precision, rice had lowes F1 score of 38.71, lowest recall 66.67, and lowest precision 27.27, and at the last no-data class had 73.17 F1, 75 recall, and 71.43 precision. The confusion matrix showed that corn had a higher number of misclassified samples which are 29 having 14 misclassified to potato, 10 to rice, and 5 samples were wrongly assigned

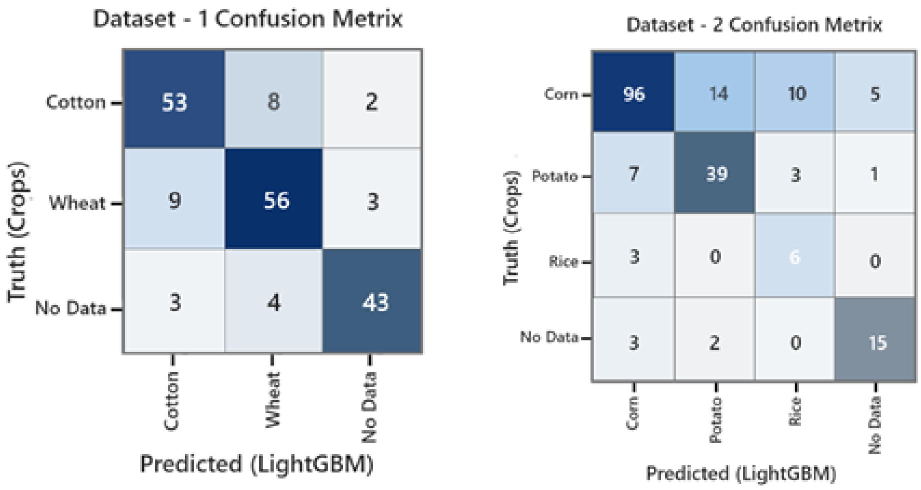

Figure 5.1: D1 - Confusion matrix

GBM D1:

Class	F1	Recall	Precision
* Cotton	82.81	84.13	81.54
* Wheat	82.35	82.35	82.35
* No Data	87.76	86.0	89.58

GBM D2:

Class	F1	Recall	Precision
* Corn	82.05	76.8	88.07
* Potato	74.29	78.0	70.91
* Rice	38.71	66.67	27.27
* No Data	73.17	75.0	71.43

Light GBM	
Dataset	Accuracy
D1	83.98
D2	76.47

Figure 5.2: Performance of Models on D1

to the no-data class. The corn class had a comparatively high number of test samples which is the main reason. Potato class had 11 misclassification where 7 of them belongs to potato, 3 to rice, and 1 to no-data class. The rice class had lowes test samples due to which it had the lowest misclassification which is 3 and all belong to the corn class and show a bit resemblance to the corn class. The last no-data class had a total of 5 false-negative samples, 3 were predicted to cron and 2 of them were misclassified to potato class. The overall performance of LightGBM on dataset 2 was not good enough and the results are comparatively low when compare to the performance of same model on dataset 1. The main reason behind this is the lower number of training samples for these classes which were not enough to accutate optimize the model and converge. Increasing number of samples might help to improve the performance of the same model.

5.2 TempCNN

The tempCNN was used to train both dataset 1 (D1) and dataset 2 (D2) for cop type classification which gives overall better performance than LightGBM. The first data had 2 crops and 1 no-data class which were trained by the tempCNN model. The mode provided overall 87.29 percent accuracy which is higher than both of LightGBM models. In further performance analysis, the model showed 86.36 F1 scores, 90.48 recall, and 82.61 precision for the cotton class. The F1 score, Recall, and precision were 84.88, 85.29, 90.63 respectively for the Wheat class. The no-data class had an 87.76 F1 score, 86 recall, and 89.58 precision. The confusion matrix of the actual and predicted results shows that the wheat class had a higher number of false-positive values that is 10 where 7 belongs to cotton and 3 to no-data class. Cotton had the lowest 6 misclassifications where 4 were classified to Wheat and 2 categorized to no-data class. The final no-data class had 7 misclassifications out of them 5 were cotton and 2 belong to the Wheat class. The results showed that cotton and wheat had a slightly higher correlation compare to no-data.

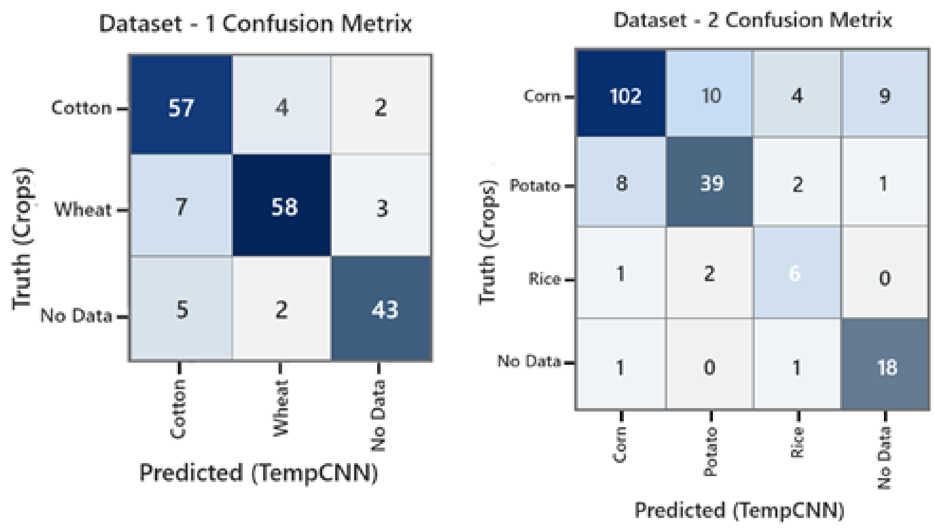

Figure 5.3: D2 - Confusion matrix

Temp CNN was also trained on dataset 2 (D2) where it showed 80.88 percent accuracy which is lower than tempCNN's accuracy on D1 however it is higher than the LightGBM's performance on the same dataset. The confusion matrix shows corn had the highest number of misclassification due to the higher number of test samples where 10

TempCNN D1:

Class	F1	Recall	Precision
* Cotton	86.36	90.48	82.61
* Wheat	87.88	85.29	90.63
* No Data	87.76	86.0	89.58

TempCNN D2:

Class	F1	Recall	Precision
* Corn	86.08	81.6	91.07
* Potato	77.23	78.0	76.47
* Rice	54.55	66.67	46.15
* No Data	75.0	90.0	64.29

TempCNN	
Dataset	Accuracy
D1	87.29
D2	80.88

Figure 5.4: Performance of Models on D2

were misclassified to potato, 4 to rice, and 9 to no-data class. The potato class had 11 false-negative values, out of them, 8 were misclassified to corn, 2 to rice and one samples point was wrongly predicted to no-data class. 3 of the rice class test records were false-negative out of them, 1 was predicted as corn, and 2 to potato class as the rice class had a total of 9 test records. Last but not least no-data class seems to fit comparatively better as we had only 2 misclassifications one for corn and the other one predicted as rice. The performance of the model was also analyzed by F1, recall, and precision values where corn had 86.08, 81.6, 91.07 scores respectively. Potato class had 77.23 F1 scores, 78 recall, 76.47 precision, rice had 54.55 F1, 66.67 recall, 46.15 precision, and the no-data class had 75 F1 scores, 90 recall, and 64.29 precision. The overall performance was lower than TempCNN's performance on the D1 dataset.

Conclusion to the results is that TempCNN can provide more promising results on a bigger dataset where we could be able to train the model for a long run as the D1 had a higher number of training samples which ultimately provided better accuracy and other performance indicators. The higher variation in the test samples for dataset 2 provides a higher variation in the F1 score, recall, and precision.

5.3 LSTM

A time-series model LSTM was trained on dataset 3 where we have converted spatial and temporal pixels of the samples in a series and 3x3 grid was converted to 9 samples points that increased the training and test set which was helpful especially for those classes where we were facing low samples set issue i.e. rice class. The other major reason was to build a dataset having sequential data in order to train the models. LSTM outperformed all of the previously trained models having an accuracy of 94.08 percent that is pretty good for deployment in real-time.

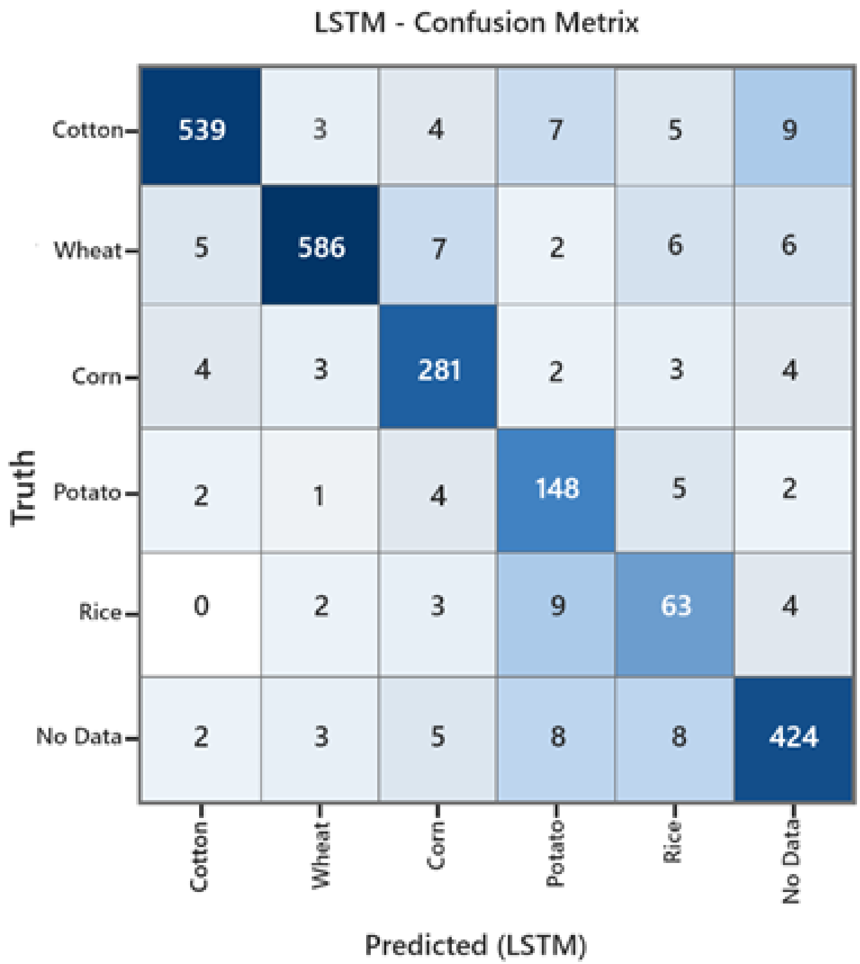

Figure 5.5: D3 - LSTM Confusion matrix

There were 8856 time-series-based training samples for LSTM and the model was tested on 2169 test samples. The Cotton, Wheat, corn, potato, rice, and no-data class had 96.34, 96.86, 93.51, 87.57, 73.68, 94.33 F1 score respectively. The recall for cotton was 95.06, Wheat had 95.75, 94.61 for potato, 77.78 for rice, and 94.22 for no-data class. The Precision was 97.64, 97.99, 92.43, 84.09, 70, 94.43 for Cotton, Wheat, Corn, Potato, Rice, and no-data class. When we look at the confusion matrix for the model, cotton had 539 true-positive, 13 false-positive, 28 false-negative, Wheat had 586 true-positive, 12 false-positive, 26 false-negatives, Corn had 281 true-positive, 23 false-positive, 16 false-negatives, the potato had 148 true positives, 28 false-positive, 14 false-negative, rice had 63 true positives, 27 false-positive, 18 false-negative, and no-data class had 424

LSTM:

Class	F1	Recall	Precision
* Cotton	96.34	95.06	97.64
* Wheat	96.86	95.75	97.99
* Corn	93.51	94.61	92.43
* Potato	87.57	91.36	84.09
* Rice	73.68	77.78	70.0
* No Data	94.33	94.22	94.43

LSTM	
Dataset	Accuracy
D3	94.08

Figure 5.6: LSTM Performance on D3

true positives, 25 false-positive, 26 false-negative. F1, recall, and precision was above 90 for almost all of the classes except rice where we had significantly lower training samples but overall results were pretty good.

Chapter 6

Conclusion

In this research, we gathered data from agricultural sites of Pakistan and designed mainly three models for the data. The original data was divided into three datasets, Dataset 1 had samples of only two crops that had a higher number of samples and the remaining crops were placed in dataset 2. Another dataset for no-class was collected and placed in both datasets where the purpose was to classify those samples which do not belong to any of the crops.

The collected data did not have an equal number of samples instead there was a very high variance between the number of samples of each class which could lead to overfitting of models on a certain class. Originally two models were developed LightGBM and TempCNN for the classification task and we provide both datasets to the aforementioned models. TempCNN gives better performance compared to LightGBM on both datasets, however, the accuracy on dataset 2 was reasonably low because of low training samples. To analyze the performance of models, accuracy was not the only measure, F1 score, recall, and precision was also included. Then we build a slightly different dataset in order to increase the performance for which dataset 3 was developed where we bring time-series data in real terms. The dataset was developed to train a model which could perform better on the sequential dataset. A variant of RNN named LSTM was used for this purpose. After some feature engineering steps, the overall training samples were increased on which LSTM was trained. The final model LSTM outperformed LightGBM and TempCNN. LSTM performed comparatively better even on those datasets where we had fewer number of training samples. The overall accuracy for the LSTM was 94.08% and other performance indicators also provide promising results. This research provides a comparison of models along with the comparison of results for different types of datasets. The key to improving the performance of a model is not only model design but the dataset's transformation and feature engineering play a significant role.

6.1 Future Work

The research we carried out had a broader future requirement and opens to multiple branches of research. Taking the example of the dataset, we had few crops where the number of training samples was fewer compared to others and the results also show that the increased number of training samples can lead to mode effective training of existing models. Apart from that, data can also capture from more diverse agricultural sites. A higher number of samples from different areas can have more prominent features for training and classification. The number of cop types can also increase by gathering data of targeted crops. When it comes to modeling on existing captured datasets, we do have a wider room for research as we can try different modeling techniques. The temporal data can be used to train other variants of RNN and compare results to the existing ones. There are other features that can be used for modeling i.e. plasma content, soil moisturizer by extracting data a few days prior to sowing or in early days of sowing, greens effect and other vegetation-related feature along with these existing attributes can help to optimize the modeling strategy.

Apart from that, this research can help to extract estimated land cover by particular crop in the given country where the planning of planation can help to increase the production of more value and required crops. There is room for yield prediction along with this study which ultimately gives us an idea of possible yield estimation of a crop in a given time. This technique can also help us to identify areas with high yield and low yield. The practices from high yield areas can be communicated to low yield sites in order to increase the overall outcomes. Areas with comparatively better outcomes on certain crops can be identified that can help to grow the right crop on the right agricultural site.

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