Identifying Crop Categories in Agricultural Land Using Deep Learning Techniques

Thejaswi Nandyala Assistant Professor, Department of Computer Applications, Sivananda Sarma Memorial RV College, Bangalore

Puneeth R Assistant Professor, Department of Computer Applications, Sivananda Sarma Memorial RV College, Bangalore

Vandana.G.P. Assistant Professor, Department of Computer Applications, NMKRV College for Women, Bangalore

Getendra Kumar.M Assistant Professor, Department of Computer Applications, Sivananda Sarma Memorial RV College, Bangalore

Abstract

Farming detection for local area has attempted to use the force of man-made brainpower (AI). One significant subject is utilizing AI to make the planning of harvests more exact, programmed, and fast. A group of work process utilizing Deep Neural Network (DNN) to create high-caliber in-season crop maps from Land sat symbolisms. Preparing work processes are made to computerize the repetitive pre-processing, preparing, testing, and post processing work processes. Tested hybrid solution on new images and received accurate results on major crops such as corn, soybean, barley, spring wheat, dry bean sugar beets. In existing system conventional neural network is preferred on perceiving large farmlands the dissipated wetlands and rural area in North Dakota. The trained conventional neural network better recognize major crops in big farms but it struggle in differentiating minor crops in wet lands. The current algorithm is still having flaws need to integrate more high-performance computational platforms to collaborate on training to further improve its performance. Proposed system identify unplanted land or grass land and classifying minor crop type using vgg16 algorithm. The quality of vgg16 map can be enhanced by a series of post processes involving data source to force correct those misclassified field. F1 is a performance metric. Using vgg16 might best result in improving the performance.

Keywords— Deep Learning, Image Classification, Landsat, Deep Neural Network, North Dakota, Artificial Intelligence, Conventional Neural Network, Geo-Processing Workflow, Visual Geometry Group

I. INTRODUCTION

Generally focusing on Machine learning is a method of data analysis that automates analytical model using a set of algorithms which are performed automatically with provided user data. As ML provides generalization on input of data using predefined and learn patterns. As another objective of Artificial Intelligence deep learning concepts provides deep and automated analysis on complex data using a very high level abstract. As various Deep learning algorithms provides various levels of data abstraction, extraction and deep analysis. Deep learning automated extraction mostly used for satellite data analysis. The deep layered learning process motivates the hierarchical learning architecture layered learning process of the primary sensorial areas of the neocortex in the human brain, which automatically extracts features and abstractions from the underlying data [4]-[6]. Deep Learning algorithms are quite beneficial when dealing with learning from large amounts of unsupervised data, and typically learn data representations in a greedy layer-wise fashion [7],[8].

The goodness of the data representation has a large impact on the performance of machine learners on the data: a poor data representation is likely to reduce the performance of even an advanced, complex machine learner, while a good data representation can lead to high performance for a relatively simpler machine learner. Thus, feature engineering, which focuses on constructing features and data representations from raw data [1], is an important element of machine learning. Various Learning algorithms are provided for deep learning to implement consecutive Layers. As deep learning provides transformation of nonlinear inputs and outputs through layers of deep learning providing a object of training and self learn implementation based on hierarchical way of data through multiple transformation layers. The sensory data (for example pixels in an image) is fed to the first layer. Consequently the output of each layer is provided as input to its next layer. The hierarchical Learning knowledge of architecture of Deep Learning algorithms is prompted via synthetic intelligence emulating the deep, Empirical studies have confirmed that facts representations received from stacking up non-linear characteristic extractors (as in Deep Learning) frequently yield better system studying outcomes, e.G., advanced class modeling [9], better quality of generated samples by way of generative probabilistic fashions [10], and the invariant belongings of facts representations [11]. Deep Learning solutions have yielded top notch outcomes in different system gaining knowledge of packages, which includes speech reputation [12]-[16], pc vision [7],[8],[17], and natural language processing [18]-[20]. A greater specified overview of Deep Learning is supplied in Section “Deep gaining knowledge of in statistics mining and gadget learning”

Technological advancement has penetrated agriculture in the present time, proper from small to massive scale farming [1]. Two many years again, the Global Positioning System (GPS) usage allows the farmers to accumulate necessary farming information, which allows self reliant steering manipulate machine improvement [2]. The primary concept in deep leaning algorithms is automating the extraction of representations (abstractions) from the statistics [5],[21],[22]. Deep gaining knowledge of algorithms use a large amount of unsupervised facts to routinely extract complicated representation. These algorithms are largely motivated via the sector of synthetic intelligence, which has the general purpose of emulating the human brain’s ability to observe, examine, analyze, and make choices, mainly for extremely complex issues. Work pertaining to these complex challenges has been a key motivation behind Deep Learning algorithms which attempt to emulate the hierarchical learning approach of the human brain. Models primarily based on shallow getting to know architectures together with selection timber, aid vector machines, and case-primarily based reasoning may additionally fall quick when trying to extract beneficial data from complex structures and relationships inside the enter corpus. In contrast, Deep Learning architectures have the capability to generalize in non-nearby and global approaches, producing mastering patterns and relationships beyond instantaneous buddies within the records [4]. Deep mastering is in truth an crucial step toward synthetic intelligence. It no longer best gives complicated representations of information which are suitable for AI obligations however additionally makes the machines impartial of human information that is the ultimate intention of AI. It extracts representations immediately from unsupervised statistics with out human interference. A key concept underlying Deep Learning strategies is shipped representations of the facts, wherein a large quantity of feasible configurations of the abstract capabilities of the input facts are feasible, allowing for a compact illustration of every pattern and main to a richer generalization. The variety of viable configurations is exponentially associated with the number of extracted abstract functions. Noting that the observed statistics was generated thru interactions of several acknowledged/unknown elements, and for this reason when a facts sample is received thru some configurations of learnt factors, extra (unseen) records patterns can in all likelihood be defined thru new configurations of the learnt factors and styles[5],[21]. Compared to gaining knowledge of primarily based on nearby generalizations, the quantity of patterns that can be obtained the usage of a dispensed illustration scales fast with the quantity of learnt factors. Deep learning algorithms lead to abstract representations due to the fact more summary representations are frequently built based totally on less summary ones. An essential benefit of greater summary representations is they may be invariant to the local adjustments within the enter facts. Learning such invariant functions is an ongoing most important aim in sample reputation (for example getting to know capabilities which can be invariant to the face orientation in a face recognition mission). Beyond being invariant such representations also can disentangle the elements of version in statistics. The actual facts utilized in AI-associated obligations normally get up from complex interactions of many resources. For instance an picture is composed of different sources of variations any such mild, item shapes, and object substances. The summary representations supplied by means of deep gaining knowledge of algorithms can separate the one of a kind assets of variations in information.

Farming detection for local area has attempted to use the force of man-made brain power(AI). One significant subject is utilizing AI to make the planning of harvests more exact, programmed, and fast A group of work process utilizing Deep Neural Network(DNN) to create high-caliber in season crop maps from agricultural Land. Preparing work processes are made to computerize the repetitive pre-processing, preparing, testing, and post processing work processes.

II LITERATURE SURVEY

In [3], methodology of remote sensing was demonstrated and validated. The author also represented rice yield estimation. For this authors developed a system that considered remote sensing data based on SAR and MODIS data as input. This developed system, based on crop growth model, generates dimensional explicit inputs for rice. Further, the study considered the Red River Delta in Vietnam for rice yield estimationThe examine considered 8 riceproducing provinces of area below consideration. In case of the MODIS (MOD13Q1 and MYD13Q1 products), a mixed time series of the TERRA and AQUA sixteen-day Composite Vegetation Indices (VIs) allotted via the NASA had been used. The time-collection photos that have been decided on have been at 250-m resolution. MODIS noted merchandise encompass indices like NDVI and EVI spectral indices. On the opposite hand, C-band VV and VH polarization (SAR facts allotted via ESA) with a regular repeat cycle of 12-days were used. The spatial resolution of 20-m had been used. Sentinel-1 SLC time-series is converted into terrain-geocoded values within the pre-processing of the SAR sentinel-1 facts. The steps within the pre-processing include image calibration, speckle filtering (time-series), radiometric terrain correction and normalization, filtering of atmospheric attenuation. Here, the authors proposed an algorithm for the Rice Crop detection. The proposed set of rules became based at the analysis of time-collection of NDFI and EVI spectral indices. The authors in [4] utilised time-series dual polarized (VV/VH) C-band SAR imagery from the Sentinel-1A and 1B satellites. The SAR imagery captured from a small vicinity of significant North Dakota become analyzed for the Crop analysis. All the Sentinel-1 pix (Wide Swath Mode, ascending orbit, Level 1 GRD format) captured over a length of April 2016 to November 2016 were first pre-processed on SNAP. Authors advised few steps in the pre-processing, that consists of orbit corrections, followed via multi-looking the snap shots to 100m pixels, and making use of the terrain correction. In the studies, the authors represented a class set of rules, in which character pixel changed into in comparison with a model of average crop backscattered response. Taking the least difference from the version, each and every single pixel turned into classified as the precise crop. Further, the authors analyzed the category accuracy based totally on few parameters. These parameters included the iterations in version constructing, have an effect on of polarization, and wide variety of education fields. The proposed approach carried out general accuracies of above 90%, the use of each VV and VH polarizations independently or in combination. Authors achieved one of a kind styles of evaluation a). Based on twenty schooling subject trails, b). With complete CDL layer (except for training pixels). In the former one, standard accuracy of eighty five%- 96% was completed and within the latter one, it became simplest sixty five%-74%. Thus the former case, regardless of the polarization decided on or count of iterations used, produced extra type accuracy than that of the latter one. The result of the classification set of rules proposed through the author was as compared with the most common, complete time–collection of VH-polarized images, the usage of a RF classifier. This classifier turned into applied the use of Random Tree device in ArcGIS Desktop 10.Five. RF algorithm is a version of the Breiman‟s (2001) RF algorithm recognised for its robustness and accuracy. [16] The SAR sensor (Sentinel-1) lets in an accurate chronological observe-up of agricultural crop growth. Implementing various deep studying techniques, writer highlights the functionality of Sentinel-1 radar imagery for mapping agricultural land cover. Multi-temporal Sentinel-1 facts become stepped forward through applying temporal filtering to decrease noise, though retaining the best systems gift within the photos. As consistent with the analysis and the outcomes proposed via the writer, two deep recurrent neural networks (RNN)-based totally classifiers offers the higher results than that of the machine studying processes (random wooded area, guide vector machines and K-nearest neighbours). The authors preferred RNN over classical gadget getting to know approaches as according to the results retrieved in his research. [17] The sentinel-1 satellite information has already been taken into consideration by way of many researchers for studies inside the place of agricultural with excellent outcomes [3]. The sentinel-1 facts of agricultural fields become processed to evaluate parameters along with form of crop , Green Area Index (GAI), plant peak and flora water content material. [3] illustrated the analyses and processing of the Sentinel-1 images for the estimation of Rice crop acreage. Author cautioned pre-processing of the Sentinel-1 photographs earlier than appearing estimation and correlation within the location of agriculture. To system the SAR pics writer preferred SNAP, earlier than making use of it for a particular motive. Author offered the pre-processing pipeline method illustrated in the SNAP graph as collection of operations Read, Calibration, Speckle Filter, Terrain Correction, and Write. Further, creator performed ok-way clustering for the sampling of the sphere. In [11] authors analyzed and processed the Landsat 8 OLI multi-temporal records of yr 2013. Author downloaded the pics of Northern Italy, Lombardy location, to be taken into consideration for his studies. Overlapped vicinity of the two Landsat WRS-2 paths (193 and 194), cloud cowl much less than 20%, was decided on for the evaluation reason. Multi-temporal spectral indices (NDFI, RGRI, and EVI) used as enter for the supervised algorithm. The version of the overall accuracy (kappa Index) turned into from eighty five% (zero.83) to 92% (0.91) thinking about the pics for precise term (in months). Author favored the medium resolution data (10-30 m, Landsat) over the low/slight resolution sensor with the normal revisit (300-one thousand m, MODIS), as Landsat gave the better effects at local/regional scales, while, MODIS facts turned into apt for accessing inter-annual variability over large, homogeneous areas. Features consisting of spatial and temporal resolutions of the statistics furnished by these satellites make it powerful for use for in-season crop mapping. Medium decision satellites. The authors analyzed the performance of those mentioned algorithms over a time period (i.E begin of season and stop of the season maps). The result of the research was established using the referenced facts as noted in [11]. The important drawback of the CUAA become that the product become now not officially demonstrated, so the information cannot be taken into consideration truthful for use as reference facts, with out earlier verification. Atmospheric/Topographic CORrection (ATCOR) software program [11] become used to convert the OLI statistics at-sensor radiance and converted to floor reflectance. For this creator applied calibration coefficients available inside the scenes metadata. The authors used Aerosol Optical Depth (AOD) parameters: Modena and Ispra for atmospheric correction. The overlapped area of WRS-2 paths 193 & 194 turned into used as input. Further, the MODIS aerosol merchandise have been used, when AERONET information have been no longer to be had. EVI, NDVI, and Red Green Ratio Index (RGRI) had been evaluated for OLI (2013) dataset. [23] Here the author provided the summary of the NASS CDL application. Brief creation of the methods and inputs used within the CDL Production changed into described. CDL is a geo-referenced, raster-formatted, crop-unique, land cowl map product produced via the NASS of the USDA. It takes imagery/information of medium resolution satellite tv for pc and USDA floor fact as enter. It also incorporates different additional information, which include set of the National Land Cover Data as enter. Freely to be had country-degree crop vicinity classifications and the crop acreage estimates are produced as a result of the choice tree-supervised class approach. The consequences have been primarily based upon the CDL and NASS JAS ground reality to the NASS Agricultural Statistic Board. CDL product uses ortho-rectified imagery to identify subject crop sorts exactly and geospatially. CDL product has spatial decision of 56 m. For picture processing and to estimate acreage statistics, the different software‟s consisting of Peditor (primarily based on PASCAL and FORTRAN), Remote Sensing Project (evolved the use of Microsoft Visual FoxPro), over a time period. From 1997 to 2005, June Agriculture Survey (JAS) changed into used by NASS CDL for floor reality series. NASS applied multi-spectral satellite tv for pc imagery in starting of 1970‟s to calculate approximately acreage of big vicinity crops in one of a kind generating states. Latter, guy y upcoming new satellites had been used to capture the imagery, inclusive of Landsat Multi-Spectral Scanner (1987), Landsat Thermatic Mapper (TM) and Landsat Enhanced TM (ETM+) (by means of April, 1999), IRS satellite RESOURCESAT-1 Advanced Wide Field Sensor (AWiFS) (by October 2003) [24]. In beginning of the 2006, the CDL software undergoes a large reformation and upgrading effort. The new software consisting of Relequest Research‟s See5 decision tree, Environmental System Research Institute (ESRI) ArcGIS, ERDAS Imaging remote sensing software program, Statistical Analysis Software (SAS) are used by CDL program. The new data source including 578 Administrative and Common Land Unit data from the Farm Service Agency and RESOURCESAT-1 AWiFS are used by the CDL program. Authors performed research by first raising a query that either the U.S CDL provide an accurate point of reference for Land-Use Change estimates or not. In his research, author performed an autonomous validation of the CDL. The area of the South Dakota was selected for the analysis, as located in the climate transition zone. Comparison of CDL and the ground collected data, based on the high resolution imagery, was done

III. LANDSAT STUDY

LANDSAT

Landsat 8 live imagery is used as model inputs to read fields of various regional crop maps and ground collected datasets are used as training labels. Most of the ground truth data were obtained via field surveys and roadside photo samples. Some crop field boundaries are got by digitalizing the high-resolution images from the National Agriculture Imagery Program [5]. The data sources include the Common Land Unit of USDA Farm Service Agency, the data portal of the state government of North Dakota [54], and also various offline images downloaded from Internet Sources Like google earth, various agriculture sources of North Dakota State University Agriculture Experiment Station [5], [6]. These data programs have been carried out by experienced data collectors following a series of protocols and managed by government departments or universities.

The quality of the ground data is very reliable. As crops are complicated with various crops using their neighbor fields in very different stages by a very high chance. Spatial scale, observation date, and greenness are the three important factors used in choosing Landsat scenes and collecting ground truth. Landsat resolution is suitable for measuring dynamics at the field level. Showing various years, duration of each growing stage shifts back and forth. Selected Landsat for collecting mature images in various stages when the crops have the largest leaf area and the strongest spectral reflectance of crop plants. The capability of the Landsat radar mission is to collect live images data in all weather conditions covering in day-and-night. Landsat provides the imagery at user band requirement. When studying the Features of Landsat collection include high consistency, geographical coverage, its revisit time, and rapid data broadcasting. The main application areas are in the field of land monitoring, marine monitoring, agricultural and emergency services. The LandSat and Offline imagery data acquire from various sources like live images from Landsat, Offline Images from google earth downloaded and images from government of North Dakota, These modes differentiate from each other based on the data acquisition approach. The ground swath is illuminated with an uninterrupted series of pulses, in imaging mode.

Level-1 product data is the product projected for many of the data users and is normally available. These products can be downloaded from the resources mentioned in Experiential Results Section. The Level-0 product can be altered into a Level-1 product by the sequence of algorithms. From these processed products next levels of the products can be derived. The upper-most Landsat product folder is named with the convention specified conventional name used in our experimental results as The naming convention is described with

Mission Identifier,Mode/Beam Identifier, Product Type,Resolution Class, Processing Level, Product Class, Polarisation ,Start/Stop Date and Time,Absolute Orbit Number, Mission Data Take ID, Product Unique Identifier, Product Format Extension. The name of the Landsat data pre-processed in this work is as follows:

S2B_2W_GRDDH_2SDV_20170221T10032242_20171052100423 07_011012_0242DC7_CDCE57

where all parameters mentioned in naming convention are used.

POLARISATION

Distinctive polarisation signatures of the targets on the ground reflect dissimilar polarisations with dissimilar intensities and convert one polarisation into another. As an example, volume scatterers (e.g. forest canopy) have different polarisation properties than surface scatterers (e.g. sea surface). Eigenvector-based, model-based and many other polarimetric target decomposition techniques allow the division of various scattering contributions. These techniques can be used to retrieve facts regarding the scattering methods. Dedicated dual-Pol Imagery classification techniques enable improved classification of specific targets and scattered target areas. The LandSat image of North Dakota in the United States shows the variation in intensities from VH and VV. The combined RGB (color) image on the extreme right side was created using the Sigma0_VV_db band for red, Sigma0_VH_db channel for green and the difference between Sigma0_VH_db and Sigma0_VV_db (Sigma0_VH_db - Sigma0_VV_db) for blue.

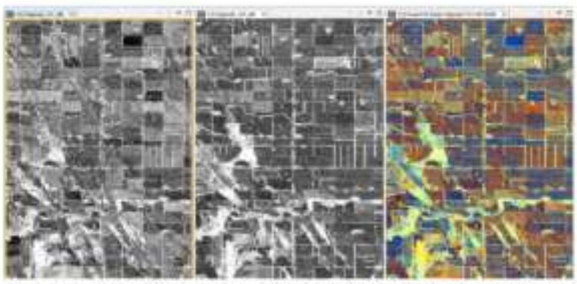

Figure 3.1 Image acquired by the Sentinel-1B on 21st May 2018 over North Dakota with VV intensity image, VH intensity image, and RGB color composite

Figure 1: Imagery Data of crops from Landsat of area coving North Dakota with various Image Composites, Like VV, VH and RGB Intensity images.

III. EXISTING ANALYSIS

In existing system DNN is preferred on perceiving large farmlands over perceiving the dissolve wetlands and rural locations Crop mapping is an image segmentation task and may DNN can be utilized. We use Seg Net as our DNN model because of its demonstrated capability in identifying similar classes street view recognition and we expect it reproduces a similar result in crop mapping. The original version of segNet has four pairs of encode and decode layers..

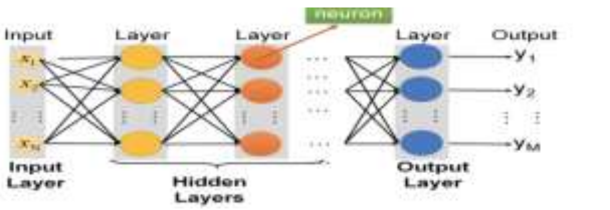

Figure 2: Existing Architecture showing Deep Neural Network

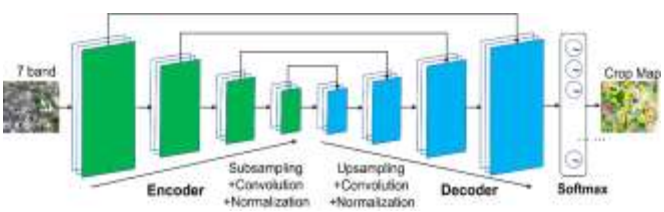

Figure 3: Figure showing detailed steps from Imagery read to Processed and Analyzed Images

Each encoder has a subsampling layer, a dense convolution layer, and a batch normalization layer. The subsampling layer uses a nonoverlapping 2 × 2 or 3 × 3 pooling window Rectified linear unit (ReLU) is the activation in the convolution layer. The batch normalization layer is used to normalize the activations of the previous layer at each batch to accelerate network training by maintaining the mean activation close to zero and the standard deviation close to ones

Drawbacks:

- In this existing system the accuracy is low.
- The current algorithm is still having flaws need to integrate more high performances computational platforms to collaborate on training to further improve its performances.

IV. PROPOSED WORK

In Agriculture sector there is a frequent changes of soil, climate due to geographically changes. If these changes are not noted the result of crops cultivated will vary. So best possible solutions to reduce the susceptibility of farmers and providing better solutions to overcome from risks from extreme weather conditions, pests and diseases outbreaks and the ups and downs of the market that threaten their domestic food and financial gain security is Crop Insurance. As well developed and developing countries requires various faster and accurate analyses of soil, crop and climate in order to provide and improve growth factor in the sector. As many new approaches are coming year to year for overcoming the current scenario changes like natural calamities such as prolonged heat wave, Floods and unexpected crop diseases. For providing better accuracy and overcoming all the challenges like flood and drought warnings, pest management, food security, environmental estimation, food safety, and public wellbeing and safety.

We have taken Crop Monitor data from Landsat satellite and also processed a offline data which is downloaded from ADSV (Alaska Data Search Vertex) and other internet sources on precipitation anomalies, temperature anomalies, soil moisture anomalies, and the evaporative stress index. Proposed system identify grassland and classifying minor crop type using vgg16 algorithm. The quality of vgg16 map can be enhanced by a series of post processes involving data source to force correct those misclassified field. F1 is a performance metric. Using vgg16 might best result in improving the performance

Pre-Processing

To make the training more efficient, the preprocessing of Imagery data needs to take extra steps compared to the conventional classification scheme. Besides the normal preprocessing operation like calibration, atmospheric correction, and spatial enhancement, Landsat and cropland map products must be prepared into input batches and output masks respectively. andsat images (downloaded via Google Earth Explorer) is used for crop analysis based on Table 1 Crops. As per our survey, the main aim of the pre-processing is to perform calibration, speckle filtering and terrain correction on the selected subset image. The following section briefly describes the steps involved in the pre-processing of the Imagery data from variu sources and also shows the imagery activities performed for reading, calibration, speckle filter, and terrain correction of Collected data on various crops.

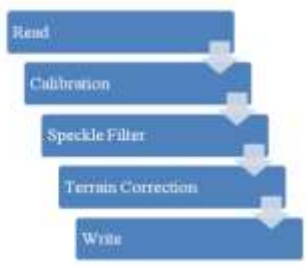

Fig 2: Image showing the architecture activity in our pre processing stages

The very first step involves in the pre-processing after reading of images from internet sources and live landsat data is that the data should be calibrated. The purpose of the calibration is to produce imagery within which the pixel values can be directly associated with the radar backscatter of the scene. It is necessar y to perform this step, so that the values of the pixel truly represent the radar backscatter of the reflecting surface [13]. For qualitative use of Imagery data, un-calibrated imagery data is enough and for quantitative use of LandSat data, calibrated images are essential. Corrections that get applied during calibration are mission-specific. Software will automatically determine the type/kind of input you have. The product metadata is required to determine what type of the correction need to be applied. Calibration is necessary for quantitative use of data [26] [13]. The target product will be the new file and may be stored in the same directory as that of source file or to the new directory. By default, all real and imaginary (i,q) bands were selected for the calibration operator. In order to ensure that the operator will produce single naught band for real and imaginary pair, uncheck Save in Complex option. To perform the polarimetric processing, data is to be kept as complex values. Land Sat products are used radiometric corrected by default. This step is required for the comparison of Landsat images based on the different combination of parameters such as sensor, modes, time.

V. EXPERIMENTAL RESULTS

As a part of our execution we have studied offline and online images of North Dakota, United States Imagery for North Dakota (part of the United States‟ Midwestern area) was captured. As our study was done in various seasons in a year covering winter and spring with various crops like wheat, corn, soybeans as a staple crops which are mostly grown in North Dakota. In selected area various other crops like sunflowers, dry beans, Durum wheat, peas, barley, sugar beets are also seen as per statistics provided CropScape-CDL, 2018 CDL statistics for North Dakota and the statistical data giving that the total acreage area is 45246913.1 of acres used for cultivation.

Value	Category	Count	Acreage
1	Corn	13429329	2986610.9
5	Soybeans	32268840	7176417.3
6	Sunflowers	1724734	383571.6
21	Barley	1251706	278372.7
22	Durum Wheat	4480913	996531.1
23	Spring Wheat	30584621	6801856
24	Winter Wheat	238268	52989.5
31	Canola	6773745	1506444.6
41	Sugarbeets	878139	195293.4
42	Dry Beans	2471532	549655.5
53	Peas	1558254	346547.3

Table 1 CDL statistics for North Dakota showing various categories of crops with count and acreage
(Source: https://nassgeodata.gmu.edu/CropScape/)

```
# Read in our image and ROI image
img_ds = gdal.Open('/content/gdrive/MyDrive/Mtechproject/DATASET/Crop_type/20170306.tiff',
gdal.GA_ReadOnly)
roi_ds = gdal.Open('/content/gdrive/MyDrive/Mtechproject/DATASET/Crop_type/cdl2017.tiff',
gdal.GA_ReadOnly)

img = np.zeros((img_ds.RasterYSize, img_ds.RasterXSize, img_ds.RasterCount),
           gdal_array.GDALTypeCodeToNumericTypeCode(img_ds.GetRasterBand(1).DataType))

for b in range(img.shape[2]):
   img[:, :, b] = img_ds.GetRasterBand(b + 1).ReadAsArray()

roi = roi_ds.GetRasterBand(1).ReadAsArray().astype(np.uint8)

# Display them
plt.subplot(121)
plt.imshow(img[:, :, 1])#, cmap=plt.cm.Spectral)
plt.title('Satellite Image')

plt.subplot(122)
plt.imshow(roi)#, cmap=plt.cm.Spectral)
plt.title('CDL Image')
plt.show()
```

Coding 1: Code showing reading image and ROI images, coding showing online and offline image reading

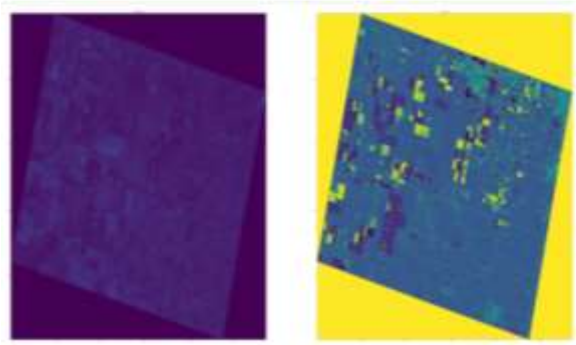

Figure 5: Figure showing various crops read from Live Satellites

Coding 2: Code showing reading crop images Online and Offline Line

Preprocessing

At the principal level stage, the dataset is first cleaned and processed using preprocessing techniques using panda's package. The counterplot of various crops and target attributes group is shown in Table 2. After that, using the data visualization procedure, the data frame attributes are shown in Figure 5.

```
from sklearn.utils import resample
# Separate majority and minority classes
df_majority = df[df['target']== 1]
df_minority = df[df['target']== 0]
 # Downsample majority class and upsample the minority class
df_minority_upsampled = resample(df_minority, replace=True,n_samples=
500,random_state=123)
df_majority_downsampled = resample(df_majority,
replace=True,n_samples=500,random_state=123)
 # Combine minority class with downsampled majority class
df_upsampled = pd.concat([df_minority_upsampled,
df_majority_downsampled])

# Display new class counts
df_upsampled['target'].value_counts()
```

Coding 3: Code showing reading image and ROI images, coding showing online and offline image reading

Above algorithm separates majority and minority classes with sample of majority and sample miniority classes using combination technique of minority and majority classes.

	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Reading Values

Table 2: Table showing various Imagery values which are read from Live Satellite

```
# plot the loss plot
from matplotlib.pyplot import figure

figure(figsize=(8, 6), dpi=80)
plt.plot(history.history['loss'][::-1], 'r')
plt.plot(history.history['val_loss'][::-1], 'b')
plt.legend({'Train Loss': 'r', 'Test Loss':'b'})
plt.show()
```

Coding 4: Code showing the implementation of Train and Test Loss activity

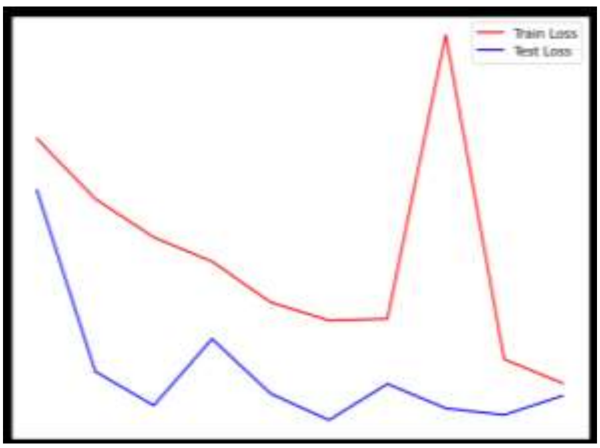

Chart 1: Chart showing Train and Test Activity

```
# plot the accuracy plot
figure(figsize=(8, 6), dpi=80)
plt.plot(history.history['accuracy'][::-1], 'r')
plt.plot(history.history['val_accuracy'][::-1], 'b')
plt.legend({'Train accuracy': 'r', 'Test accuracy':'b'})
plt.show()
```

Coding 5: Code showing Implementation of Train and Test Accuracy

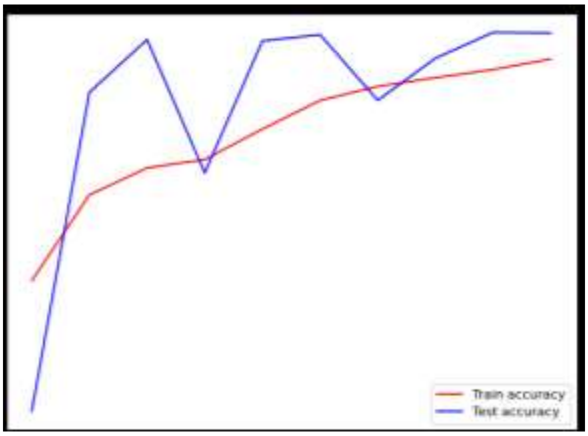

Chart 2: Chart showing Train and Test Accuracy

Applying CNN AND ANN MO0DELS

```
# Set the CNN model

model = Sequential()

model.add(Conv1D(filters = 32, kernel_size = (5),padding = 'Same', activation ='relu',
input_shape = (50, 1)))

model.add(Conv1D(filters = 32, kernel_size = (5),padding = 'Same', activation ='relu'))
model.add(MaxPool1D(pool_size=(2)))
model.add(Dropout(0.2))

model.add(Conv1D(filters = 64, kernel_size = (3),padding = 'Same', activation ='relu'))
model.add(Conv1D(filters = 64, kernel_size = (3),padding = 'same', activation ='relu'))
model.add(MaxPool1D(pool_size=(2), strides=(2)))
model.add(Dropout(0.3))

model.add(Conv1D(filters = 128, kernel_size = (3),padding = 'Same', activation ='relu'))
model.add(Conv1D(filters = 128, kernel_size = (3),padding = 'Same', activation ='relu'))
model.add(MaxPool1D(pool_size=(2), strides=(2)))
model.add(Dropout(0.4))

model.add(GlobalMaxPooling1D())
model.add(Dense(256, activation = "relu"))
model.add(Dropout(0.5))
model.add(Dense(5, activation = "softmax"))
model.summary()
```

Coding 6: Code showing Implementation of CNN Model

```
#print the test accuracy
score_1 = model.evaluate(x_test, y_test, verbose=0)
print('Test accuracy:', score_1[1])
```

```
Test accuracy: 0.9098799824714661
```

```
#classification_report
from sklearn.metrics import classification_report
pred = model.predict(x_test)
pred = np.argmax(pred, axis=1)
out = np.argmax(y_test, axis=1)
matrix = classification_report(pred, out)
print('Classification report : \n',matrix)
```

```
Classification report :
               precision    recall  f1-score   support

           0       0.93      0.98      0.95     28598
           1       0.83      0.87      0.85     28710
           2       0.96      0.89      0.93     32313
           3       0.85      0.83      0.84     30727
           4       0.98      0.99      0.98     29652

    accuracy                           0.91    150000
   macro avg       0.91      0.91      0.91    150000
weighted avg       0.91      0.91      0.91    150000
```

Table 3: Classification Report with accuracy in Macro and Weighted Average

ANN MODEL

```
# ANN model
from keras.layers import BatchNormalization
from keras.layers import Dropout


model_2 = Sequential()
model_2.add(Dense(580, activation='relu', input_shape=(50,)))
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

model_2.add(Dense(325, activation='relu' ))
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

model_2.add(Dense(125, activation='relu' ))
model_2.add(BatchNormalization())
model_2.add(Dropout(0.5))

model_2.add(Dense(5, activation='softmax'))

model_2.summary()
```

Coding 7: Code showing Implementation of ANN Model

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_2 (Dense)	(None, 580)	29580
batch_normalization (BatchNo	(None, 580)	2320
dropout_4 (Dropout)	(None, 580)	0
dense_3 (Dense)	(None, 325)	188825
batch_normalization_1 (Batch	(None, 325)	1300
dropout_5 (Dropout)	(None, 325)	0
dense_4 (Dense)	(None, 125)	40750
batch_normalization_2 (Batch	(None, 125)	500
dropout_6 (Dropout)	(None, 125)	0
dense_5 (Dense)	(None, 5)	630

Total params: 263,905
Trainable params: 261,845
Non-trainable params: 2,060

Table 4: Table showing Sequential Model implementation with various params and shaping process for trainable and Non trainable params

```
# plot the loss plot
figure(figsize=(8, 6), dpi=80)
plt.plot(history_1.history['loss'], 'r')
plt.plot(history_1.history['val_loss'], 'b')
plt.legend({'Train Loss': 'r', 'Test Loss':'b'})
plt.show()
```

Coding 8: Code showing to Perform Train and Test Loss

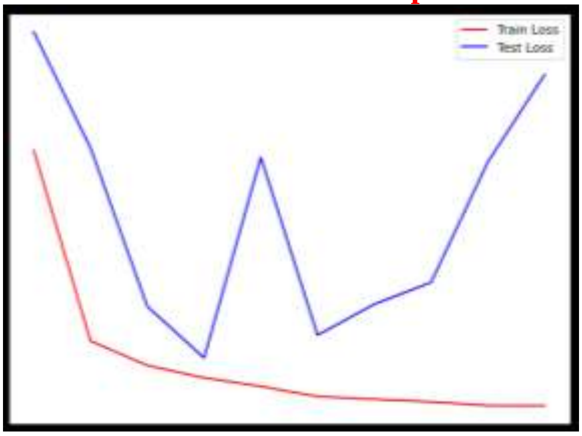

Chart 3: Chart Showing Train and Test Loss

Applying Accuracy

```
# plot the accuracy plot
figure(figsize=(8, 6), dpi=80)
plt.plot(history_1.history['accuracy'], 'r')
plt.plot(history_1.history['val_accuracy'], 'b')
plt.legend({'Train accuracy': 'r', 'Test accuracy':'b'})
plt.show()
```

Coding 9: Code showing Train and Test Accuracy

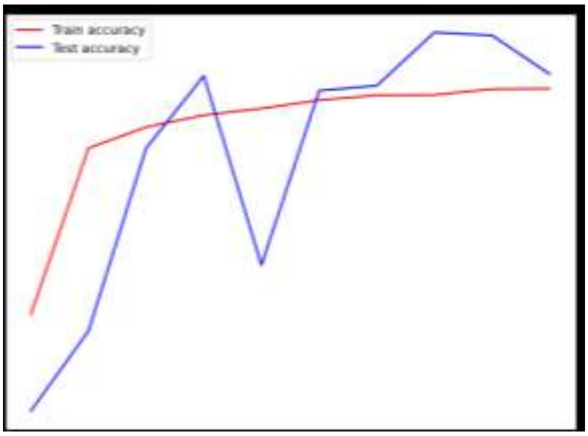

Chart 4: Chart showing Train and Test Accuracy

RBF SVM FOR ACCURACY

```
#plot confusion matrix
#from sklearn.metrics import confusion_matrix
#class_names = enc.classes_
#df_heatmap = pd.DataFrame(confusion_matrix(model_2.predict_classes(X_test),np.argmax(y_test,axis=1)))
#heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")
from sklearn.metrics import classification_report
from sklearn.metrics import plot_confusion_matrix
pred = model_2.predict(X_test)
pred = np.argmax(pred, axis=1)
out = np.argmax(y_test, axis=1)
confusion_matrix(pred, out)
```

```
array([[27587,   155,    76,    48,    14],
       [  785, 24114,   323,  1391,     1],
       [  801,   668, 27619,   648,    17],
       [  618,  5058,  1923, 27704,   335],
       [  209,     5,    59,   209, 29633]])
```

Coding 10: Code showing reading various online offline images with plot confusion matrix

Classification report :

	precision	recall	f1-score	support
0	0.92	0.99	0.95	27880
1	0.80	0.91	0.85	26614
2	0.92	0.93	0.92	29753
3	0.92	0.78	0.84	35638
4	0.99	0.98	0.99	30115
accuracy			0.91	150000
macro avg	0.91	0.92	0.91	150000
weighted avg	0.91	0.91	0.91	150000

Table 5: Table Showing Classification report with accuracy, macro and weighted average under various categories

Performance Table

```
[ ] print(tabulate(results, headers='keys', tablefmt='psql'))
```

	model	Test-Accuracy
0	CNN	0.84852
1	ANN	0.986927

Table 6: Performance Table showing test accuracy of CNN and ANN models

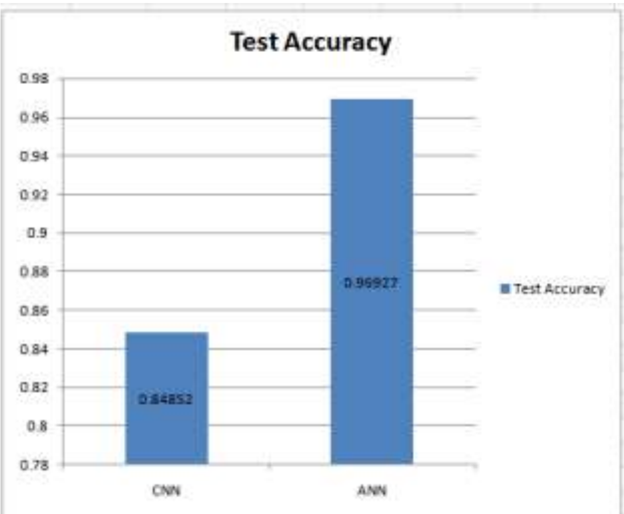

Chart 5: Chart Showing Test Accuracy of Crops Using CNN and ANN Models

VI. CONCLUSION AND FUTURE SCOPE

The offline and online Imagery data of North Dakota, United States Imagery for North Dakota, as our study taken Live Landsat and Offline data for the North Dakota, United States will be downloaded from ADSV Satellite Facility (Alaska Data Search Vertex) and pre-processed as per the steps mentioned in this article. The pre-processing of the imagery data from Landsat and Offline images can be performed using Batch Processing. As project achieved a good test accuracy using CNN and ANN methods. Further, we need to study pre-processed images of the same polarization with different dates preferably at a gap of say two or three months. As different dates data to be studied for Variation analysis over time considerably over different areas needs to be studied. After, initial Imagery pre-processing scripts will be built using python for further processing and classification. As our designed calculations are used to know the test accuracy and acreage of various crops calculation.

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