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Identifying Crop Types in Agricultural Land Using Deep Learning Techniques

R.Nagendra[1], S. Vasundra[2]

[1]PG Scholar, Department of CSE, Jawaharlal Nehru Technological University College Of Engineering (Autonomous) Anantapuramu

[2] Department of CSE, Jawaharlal Nehru Technological University College Of Engineering (Autonomous) Anantapuramu

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 To construct high-quality in-season crop maps, a Deep Neural Network (DNN) was used Land sat symbolisms. Preparing work processes are made to computerize the repetitive pre-processing, preparing, work methods for testing and post-processing On significant crops such as Maize, soybeans, barley, spring wheat, dry bean sugar beets, and others are among the crops grown in the United States, the hybrid solution was tested on new photographs and yielded reliable findings. In existing system conventional neural network is preferred on perceiving large farm lands the dissipated wetlands and rural area in North Dakota. The trained conventional neural network better It can distinguish important crops in large farms, but it has trouble distinguishing minor crops in damp regions. To improve the performance of the current method, a greater number of high-performance computing platforms must be integrated for training collaboration. Proposed system identify unplanted land or grass land and classifying minor crop type using VGG16 algorithm. The quality of vgg16 map can be A set of post-processes involving data sources have been included to require the correction of misclassified fields. F1 is a performance metric. Using vgg16 might best result in improving the performance.

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

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 The key sensory parts of the neocortex of the human brain use a layered learning process to automatically extract features and abstractions from the underlying data [5]. Deep learning methods are very useful for dealing with large amounts of unsupervised data, and they typically train data representations in a greedy layer-wise fashion [7].The goodness of the data representation has a large impact on the performance of machine learners on the data: a poor data

Even an advanced, complicated machine learner's performance is likely to be harmed by poor data representation, whereas For a relatively simple machine learner, a solid data the right representation can lead to outstanding results. As a result, feature engineering, which focuses on generating features and data representations from raw data, has become increasingly popular [2], is a crucial part of artificial intelligence. As one of the most successful applications of image processing is implemented by Haar cascade algorithm is used detect face features which requires no dataset [1]. Various Learning algorithms are provided for deep learning to implement consecutive Layers. As deep learning provides transformation of layers of deep learning provide a training object and self-learner implementation based on hierarchical inputs and outputs way of data through numerous layers of transformation The first layer receives sensory data (for example, pixels in a picture). As a result, each layer's output is used as input for the following layer. Empirical investigations have shown that combining non-linear characteristic machine extractors (as in Deep Learning) frequently yields facts representations. Better system studying outcomes, advanced class improved quality of generated samples by modelling [9], way of The invariant properties of factual representations [11], as well as generative probabilistic styles [10]. The use of deep learning technologies has resulted in a number of benefits top notch outcomes in different system gaining knowledge of packages, which includes speech reputation [12], pc [7, 8], as well as natural language processing. Section Deep Learning is discussed in further depth in "Deep Learning in Statistics Mining and Machine Learning".

Technological advancement has penetrated agriculture in the present time, proper from small to massive scale farming [2]. The Global Positioning System (GPS) usage allows the farmers to accumulate necessary farming information, which allows self-reliant steering manipulate machine improvement [3]. The main idea behind deep learning algorithms is to automate the Deep learning algorithms frequently extract sophisticated representations (abstractions) from data [5]. From a huge number of unsupervised facts. These algorithms are generally motivated by the synthetic intelligence field, which seeks to mimic the human brain's ability to observe, research, analyse, and make decisions, especially for extremely complex problems. Deep Learning algorithms, which try to imitate the human brain, hierarchical learning strategy, were developed in part to address these complicated challenges. When attempting to extract usable data from big datasets with complex structures and linkages within the entry corpus, models based on shallow learning architectures, such as selection trees, support vector machines, and case-based reasoning, may also fall short. Deep Learning architectures, on the other hand, can generalize in non-local and global manner, resulting in mastering patterns and relationships that go beyond instantaneous buddies in the data [5]. Deep mastery is, In reality, it's an essential step on the way to artificial intelligence. It not only provides complex information representations that are suited for AI tasks, but it also frees computers from human information, which is AI's ultimate goal. It takes unsupervised data and extracts representations statistics without the need for human intervention. Shipped representations of the facts are a key notion behind Deep Learning techniques, in which a huge There are a variety of ways to configure the abstract capabilities of the input facts, allowing for a more compact depiction of each pattern and a deeper generalisation. The number of extracted abstract functions has an exponential relationship with the number of possible configurations. It should be noted that the observed data were 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 [6]. 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 Factors that were learned As a result of deep learning algorithms, abstract representations are produced 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 in In a face recognition mission, an alternative to the face orientation). Such representations, in addition to being invariant, can also separate 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, a picture is made up of various sources of diversity such as light, item forms, and object substances. The summary representations supplied by means of deep gaining knowledge of algorithms can separate the one of a kind asset 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

Remote sensing methodology was demonstrated and proven in [4]. Estimation of rice yield was also presented by the author. For this project, the author created a system that used remote sensing data from As inputs, SAR and MODIS are used. This is based on a crop growth model created system generates dimensional explicit rice inputs. Further, the study considered Rice yield estimation in the Red River Delta of Vietnam. The examined considered 8 Provinces producing rice in the area under examination. The TERRA and AQUA time series are combined in this graph sixteen-day Composite Vegetation Indices (VIs) allocated by NASA was used in the MODIS (MOD13Q1 and MYD13Q1 products). The time-lapse photographs that have been taken decided on have been at 250-m resolution. MODIS noted merchandise encompass indices like NDVI and EVI spectral indices. C-band VV and VH, on the other hand, polarisation (SAR facts assigned by ESA) were employed with a 12-day repeat cycle. The spatial resolution was set at 20 metrics. During the pre-processing of the SAR sentinel-1 facts, the Sentinel-1 SLC time-series is turned into terrain-geocoded values. Image calibration and speckle filtering are among the pre-processing stages (time-series), Atmospheric attenuation filtering, radiometric terrain correction and normalising The authors suggested an algorithm for detecting rice crops in this paper. The proposed set of rules became based at the NDFI and EVI spectral indices were collected over time and analyzed. The authors of [4] used Sentinel-1A and 1B satellites' time-series dual polarisation (VV/VH) C-band SAR imagery. For the Crop study, the SAR images acquired from a limited area of substantial North Dakota is evaluated. All Sentinel-1 images (Wide Swath Mode, ascending orbit, Level 1 GRD format) were originally pre-processed on SNAP between April and November 2016.Authors A few pre-processing processes are recommended, including orbit corrections, multi-looking the snap images to 100m pixels, and terrain correction. The authors of the study were all a class set of rules, in which character pixel changed into in comparison with a average crop back scattered response model Taking the version that differs the least from the original, 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 Bierman's (2001) RF algorithm recognized for its robustness and accuracy.

The SAR sensor (Sentinel-1) lets in an accurate chronological monitoring the progress of agricultural crops Using a variety of deep learning approaches, the author demonstrates how Sentinel-1 radar imagery may be used to map agricultural land cover. Sentinel-1 is a multi-temporal surveillance satellite fact 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 (randomly selected woodland area, guide vector machines, and K-nearest neighbours) According to the findings of his research, the authors favoured RNN over traditional device learning methodologies. Many academics have used the data from the Sentinel-1 satellite to conduct studies in the field of agriculture, with positive results [4]. The sentinel-1 is a type of sentinel that is used to 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. [4] illustrated the analyses Sentinel-1 photos were processed for the assessment of rice crop acreage. The author advised against pre-processing the Sentinel-1 data 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, Write and correct the terrain. In addition, the designer used ok-way clustering to sample the sphere. The multi-temporal Landsat 8 OLI records from the year 2013 were studied and processed by the authors in [12]. Author downloaded the pics of Northern Italy, Lombardy location, to be taken into consideration for his studies. Overlapped vicinity of cloud cowl much less than 20%, was decided on for the evaluation reason. Multi-temporal The supervised method uses spectral indices (NDFI, RGRI, and EVI) as input. The version of the overall accuracy (kappa Index) turned into from 85% (zero.83) to 92% (0.91) thinking about the pics for precise term (in months). Author favored the medium Landsat data (10-30 m, Landsat) over the low/slight resolution sensor with the normal revisit (300-one thousand m, MODIS), as Landsat provided better effects at local/regional scales, whereas MODIS facts proved to be 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 looked at the performance of the methods indicated above over time (i.e begin of season and stop of the season maps). The study's findings were as follows: established using the referenced facts as noted in [12]. 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 a source of information, without prior verification. ATCOR (Atmospheric/Topographic Correction) is a software tool that corrects atmospheric and topographic data. OLI statistics at-sensor radiance are transformed to floor reflectance using this method.. For this creator applied calibration coefficients available inside the scenes metadata. For atmospheric adjustment, the authors employed the Modena and Ispra Aerosol Optical Depth (AOD) parameters. The location where WRS-2 routes 193 and 194 intersected as a source of information In addition, 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 OLI (2013) dataset was tested. The author summarised the NASS CDL in this article application. Brief creation of the methods and inputs used within the CDL Production changed into described. CDL is a crop data set that is geo-referenced and raster-formatted -unique land cowl map product provided by the USDA's National Agricultural Statistics Service (NASS). 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 as a series of National Land Cover Data enter. Freely to be had country-degree crop vicinity classifications and the Estimates of crop acreage are generated as a result of the choice A tree-supervised class method is used. To the NASS Agricultural Statistic Board, the outcomes were principally based on the CDL and NASS JAS ground reality. 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, guyy upcoming new satellites had been used to capture the imagery, inclusive of Landsat Multi- Landsat Thermatic Mapper (TM) and Landsat Enhanced Thermatic Mapper (ETM+) (as of April 1999), IRS satellite Advanced Wide Field Sensor RESOURCESAT-1 (AWiFS) (by October 2003) In beginning of the 2006, the CDL software undergoes a large reformation and upgrading effort. The new software consisting of The CDL programmed makes use of The See5 decision tree from Relequest Research, ArcGIS from the ERDAS Imaging remote sensing software and the Environmental System Research Institute (ESRI) from ERDAS package, and Statistical Analysis Software (SAS). The CDL programme now uses a new data source that includes data from the Farm Service Agency's 578 Administrative and Common Land Units, as well as RESOURCESAT-1 AWiFS. The authors began their investigation by asking if the United States CDL provided an Land-Use Change has a precise point of reference estimations or not. The author conducted an independent validation of the CDL as part of his research. Because it is located in the climate transition zone, the state of South Dakota was chosen for the study. Based on high-resolution photography, a comparison of CDL and ground-collected data was made.

III. LANDSAT STUDY

LANDSAT

Landsat 8 live imagery is utilised as a model input to read fields on various regional crop maps, with data collected on the ground serving as training labels. Field surveys and roadside photo samples provided the majority of the ground truth data. Crop field boundaries were established using high-resolution photographs digitised from the National Agriculture Imagery Program [6].

Among the data sources include the USDA Farm Service Agency's Common Land Unit, the state government of North Dakota's data portal, and a variety of offline sources. pictures taken from the internet Agriculture sources [6], [7] from Google Earth and the Agriculture Experiment Station at North Dakota State University. These actions for data collecting were overseen by government bodies or institutions and carried out by trained data collectors who followed a set of standards.

The ground data is of excellent quality. As crops are complicated with various crops using their neighbor fields in very By a very high possibility, different stages will occur. The three most essential parameters employed in selecting Landsat sceneries and gathering ground truth are spatial scale, observation date, and greenness. Landsat resolution is suitable for field measurements of dynamics. The duration of each developing stage moves back and forth as the years pass. Landsat was chosen for capturing mature photos at various phases when the crops were ready to harvest. 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 High consistency, geographic coverage, revisit time, and quick data broadcasting are all features of this collection. The main application areas include land monitoring, marine monitoring, agricultural monitoring, and environmental monitoring 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 dependent on the data collection method In imaging mode, the ground swath is illuminated with a continuous stream of pulses.

Level-1 product data is typically accessible and is projected for many of the data users. These goods are available for download from the resources mentioned in Experiential Results Section. The A sequence of algorithms can transform a Level-0 product into a Level-1 product. Next layers of products can be derived from these processed products. The Landsat product folder at the top is named with the convention specified conventional name used in our experimental results as the naming convention is described with

Product Type, Resolution Class, Processing Level, Polarization, Start/Stop Date and Time, and Product Class Mode/Beam Identifier, Mission Identifier Product Type, Resolution Class, Processing Level, Polarization, Start/Stop Date, and Product Class Format Extension, Absolute Product Unique Identifier, Orbit Number, Mission Data Take ID The Landsat data that was pre-processed in this study has the following name: **S2B_2W_GRDDH_2SDV_ 20170221T10032242_ 2017105210042307_ 011012_ 0242DC7_ CDCE57** where all parameters mentioned in naming convention are used.

POLARISATION

Targets on the ground have distinct polarisation fingerprints that reflect different polarisations with different intensities and convert one polarisation into another. Volume scatters, for example, have different polarisation qualities than surface scatters (e.g., a forest canopy) (e.g. sea surface). The division of multiple scattering contributions is possible using eigenvector-based, model-based, and other polarimetric target decomposition techniques. These approaches can be used to get information on scattering methods. Improved classification of specific targets and scattered target regions is possible thanks to dedicated dual-Pol Imagery classification algorithms. The change in intensities from VH and VV can be seen in this Landsat image North Dakota is a state in the United States. The composite RGB (colour) image on the far right side was The Sigma0 VV db band was used for red, Sigma0 VH db channel for green, and Sigma0 VH db channel for blue for blue.

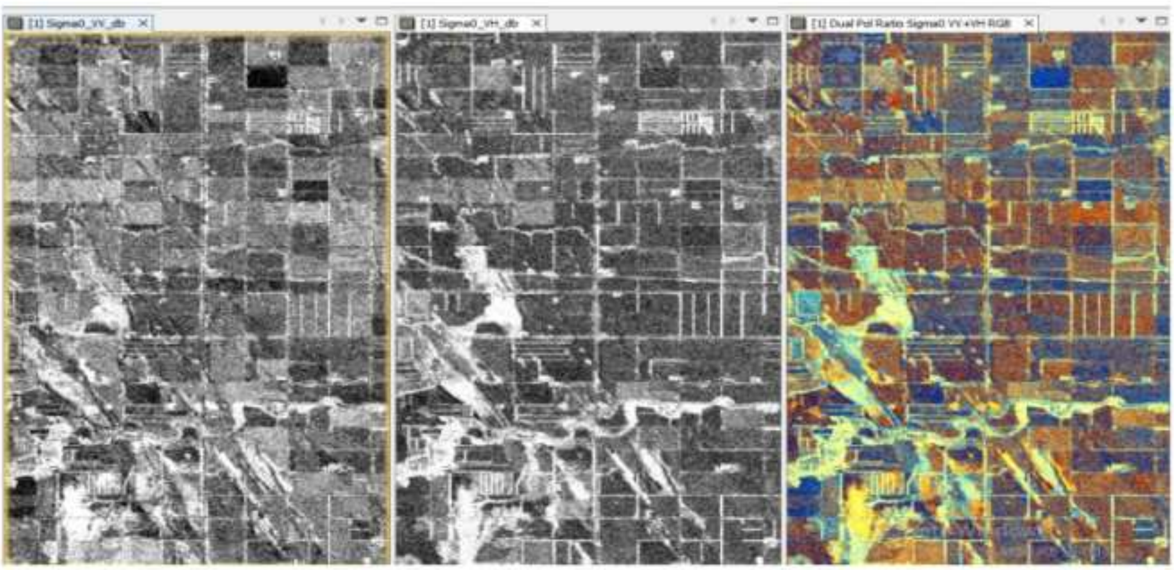


Figure 1: Imagery Data of crops from Landsat of area coving North Dakota with various Image Composites, Like VV, VH and RGB Intensity images.

III. EXISTING ANALYSIS

In existing system DNN is preferred on perceiving large farmlands over-perceiving the disappearance of wetlands and rural areas Crop mapping is an image segmentation problem that can benefit from DNN. We chose SegNet as our DNN model since it has been shown to be capable of detecting comparable classes in We expect crop mapping to function similarly to street view recognition. SegNet features four pairs of encode and decode layers in its original form.

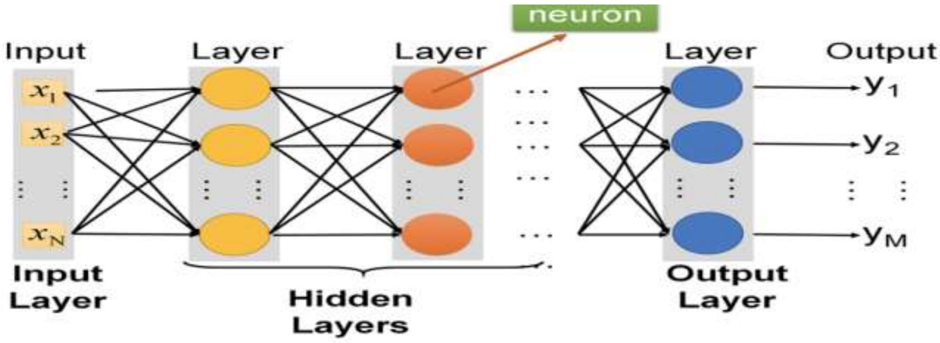


Figure 2: Existing Architecture showing Deep Neural Network

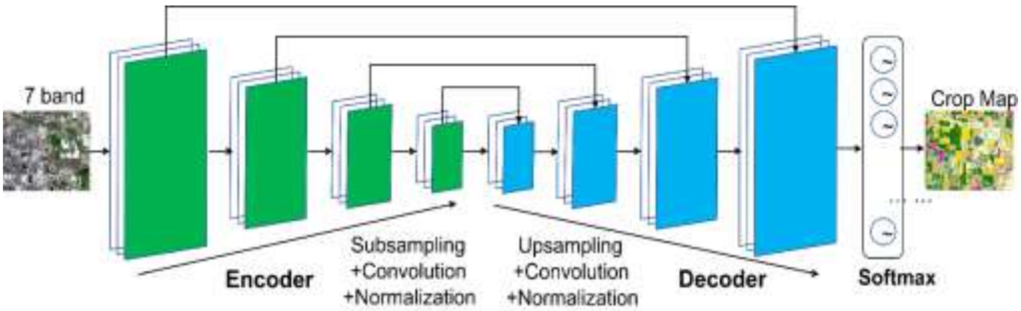


Figure 3: Figure showing detailed steps from Imagery read to Processed and Analyzed Images

A subsampling layer, a dense convolution layer, and a batch normalising layer are all present in each encoder. A nonoverlapping 2x2 or 3x3 pooling window is used in the subsampling layer. The activation in the convolution layer is the Rectified linear unit (ReLU). The batch normalisation layer keeps the mean activation near zero and the standard deviation around one to speed up network training by normalising the activations of the preceding layer at each batch.

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 Crop insurance protects farmers from risks such as extreme weather, insect and disease breakouts, and market swings that put their domestic food and financial security at jeopardy. 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 an offline data which is downloaded from ADSV (Alaska Data Search Vertex) and other internet sources on evaporative stress index, precipitation anomalies, temperature anomalies, soil moisture anomalies. 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

Preprocessing Imagery data requires more stages than the traditional classification technique to make the training more efficient. Landsat and Input batches and output masks must be produced for cropland map products, respectively, in addition to standard preprocessing operations such as calibration, atmospheric correction, and spatial augmentation. As well as satellite pictures (downloaded via Google Earth Explorer) is used for crop analysis based on Table 1 Crops. The major goal of pre-processing, according to our research, on the selected subset image, do calibration, speckle filtering, and terrain correction. The stages involved in pre-processing imagery data from various sources are briefly described in the following section, which also includes examples. The imagery activities performed for reading, calibration, speckle filter, and terrain correction of Collected data on various crops.

Fig 4: Image showing the architecture activity in our pre -processing stages

After reading photos from the internet and live Landsat data, the data must be calibrated as the first stage in the pre-processing procedure. The goal of the calibration is to provide pictures in which the pixel values are directly related to the scene's radar backscatter. This step must be completed in order for the pixel values to accurately represent the radar backscatter of the reflecting surface [14]. Imagery data should be used qualitatively, Uncalibrated imaging data is sufficient, but calibrated images are required for quantitative Landsat data application. Mission-specific corrections are applied during calibration. The type/kind of input you have will be automatically determined by the software. To identify what type of adjustment should be done, the product metadata is required. For quantitative data utilization, calibration is required [14]. The new file will be the target product, and it can be saved in the same directory as the source file or in a different directory. For the calibration operator, everything, both real and imagined bands were picked by default. Uncheck the Save in Complex option to make certain that the operator is produces a single naught band for the real and imaginary pairs. Data must be preserved as complex numbers in order to execute polarimetric processing. By default, Land Sat products are radiometric corrected. This phase is necessary for comparing Landsat images using various combinations of factors such as sensor, modes, and 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 crop 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 Crop Scape-CDL supplied information for 2018 CDL statistics for North Dakota and the statistical data giving that the total acreage area is 45246913.1 of acres used for cultivation.

Table 1 CDL statistics for North Dakota showing various categories of crops with count and acreage

(Source: https://nassgeodata.gmu.edu/CropScape/)

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

```
# 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()
```

Online and offline image reading

In order to meet this requirement, input photographs will need to be cropped, warped, or paddinged. As seen in figure 5, these additional treatments frequently change image composition, diminish image resolution, or cause additional image distortion, reducing the aesthetics of the original photographs due to the probable loss of fine grained features and holistic image arrangement. Fine-grained features and overall image arrangement, on the other hand, are crucial for image quality assessment.

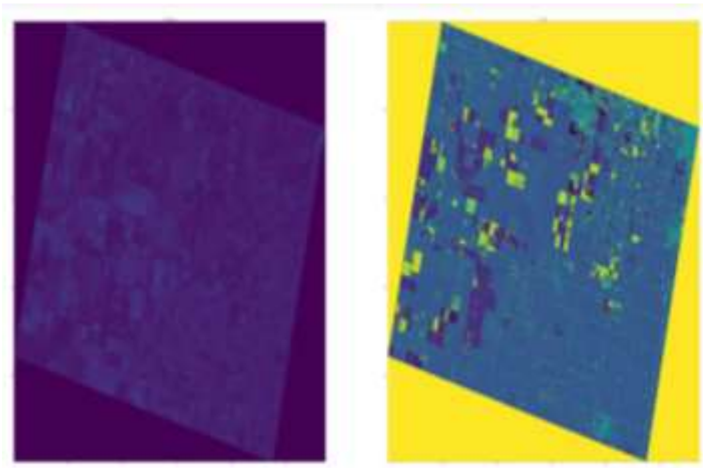


Figure 5: various crops read from Live Satellites

crop images Online and Offline Line

Preprocessing

At the principal level, the dataset is cleaned and treated using panda's package's pre-processing approaches. Table 2 shows the counterplot of several crops and target characteristics groups. The data frame properties are then displayed in Figure 5 using the data visualisation process.

```
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()
```

online and offline image reading

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

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

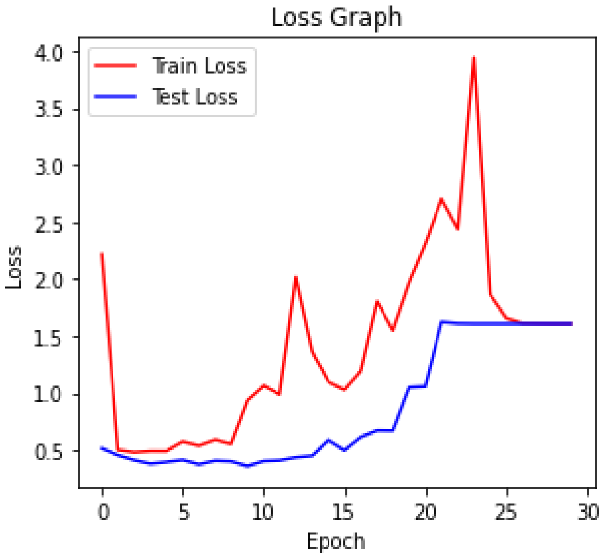
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3
0	3700.0	3499.0	1859.0	3715.0	9762.0	6498.0	6048.0	5944.0	5329.0	5083.0	7161.0	6806.0	6546.0	5917.0	5913.0	6006.0	5177.0	3689.0	4264.0
1	5329.0	5193.0	5062.0	4471.0	4618.0	5713.0	4860.0	4269.0	4286.0	4254.0	5914.0	5327.0	4644.0	5401.0	8509.0	5442.0	4466.0	2969.0	3668.0
2	3257.0	2791.0	1490.0	2676.0	8878.0	6992.0	6513.0	6277.0	5783.0	5753.0	9508.0	9693.0	8742.0	8003.0	8239.0	5541.0	4198.0	2671.0	3231.0
3	4756.0	4574.0	4157.0	3844.0	3728.0	6015.0	5611.0	5455.0	5111.0	5347.0	4615.0	4165.0	2962.0	4215.0	7993.0	5268.0	3919.0	2436.0	2855.0
4	3851.0	3466.0	2485.0	3259.0	4969.0	5547.0	4778.0	4422.0	4172.0	4214.0	4389.0	3238.0	2235.0	2799.0	6907.0	5676.0	4906.0	3457.0	3815.0

Reading Values

implementation of Train and Test Loss activity

```
# 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()
```

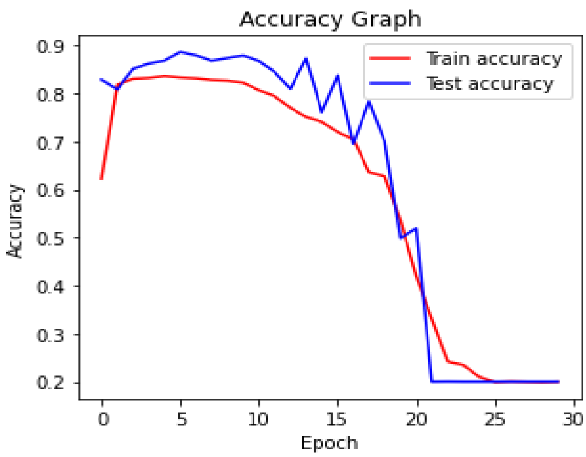
Train and Test loss of model



Implementation of Train and Test Accuracy

```
# 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()
```

Train and Test Accuracy of model



Applying CNN AND ANN MO0DELS

Implementation of CNN Model

```
# 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()
```

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

```
#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

ANN MODEL

Implementation of ANN Model

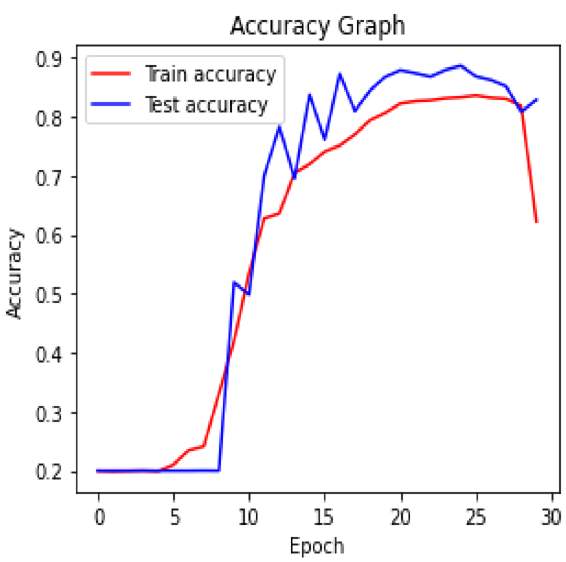
```
# ANN model
from keras.layers import BatchNormalization
from keras.layers import Dropout


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()
```

```
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
```

Perform Train and Test Loss

```
# 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()
```

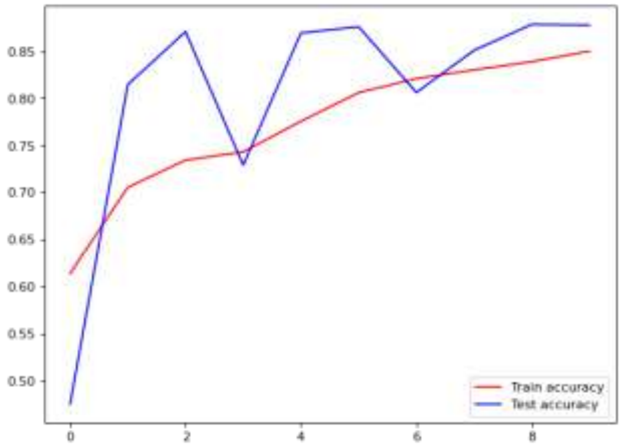
Train and Test Loss of model



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()
```

Train and Test Accuracy of model



Epoch

RBF SVM FOR ACCURACY

various online offline images with plot confusion matrix

```
#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,   200, 29633]])
```

Table 4: Table Showing Classification report with accuracy, macro and weighted average under various categories

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

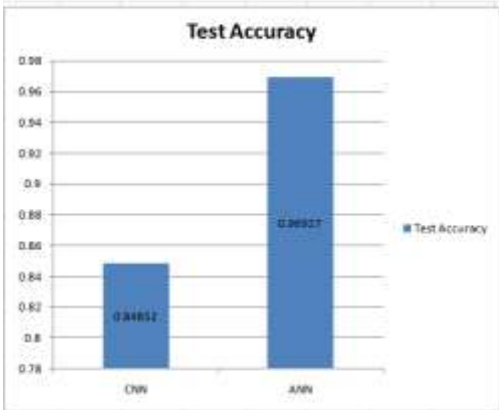
Table 5: Performance Table showing test accuracy of CNN and ANN models

Performance Table

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

	model	Test-Accuracy
0	CNN	0.84852
1	ANN	0.906927

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



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 North Dakota data will be retrieved from Satellite Facility of the ADSV (Alaska Data Search Vertex) and preprocessed as described in this article. The images have already been pre-processed. 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 distinct dates, ideally separated by two or three months. As different dates data to be studied for Variation analysis Over time, a great deal of research in various fields is required. Following that, rudimentary image pre-processing scripts in Python will be created for further processing and classification. Our calculated results are utilized to determine the test accuracy and acreage of various crops.

REFERENCE

[1] Vasavi Ravuri, S.Vasundra, A.Aryan, Somula Ramasubbareddy, K.Govinda. “Face Recognition Using Cascade Algorithm” International Journal of Recent Technology and Engineering (Volume-8 Issue-2S4, July 2019)

[2] Y. Bengio and Y. LeCun: AI Scaling Learning Algorithms. Kernel Machines on a Large Scale Bottou L, Chapelle O, DeCoste D, Weston J. Bottou L, Chapelle O, DeCoste D, Weston J. Bottou L, Chapelle O, DeCoste D, Weston J. Bottou L, Chapelle O, DeCoste D, Weston J. Bottou L, Chapelle O,

http://www.iro.umontreal.ca/~lisa/pointeurs/bengio+lecun chapter2007.pdf

[3] The Y-W: A rapid learning algorithm for deep belief nets, Hinton GE, Osindero S. 10.1162/neco.2006.18.7.1527 Neural Computer, 18(7), 1527–1554. MATH MathSciNet

[4] P Domingos (2012) There are a few things you should know about machine learning. Commun 55th ACM (10)

[5]Y. Bengio and Y. LeCun: Scaling learning methods for AI. Kernel Machines on a Large Scale Bottou L, Chapelle O, DeCoste D, Weston J. Bottou L, Chapelle O, DeCoste D, Weston J. Bottou L, Chapelle O, DeCoste D, Weston J. Bottou L, Chapelle O, DeCoste D, Weston J. Bottou L, Chapelle O,

http://www.iro.umontreal.ca/~lisa/pointeurs/bengio+lecun chapter2007.pdf

[6] R. Salakhutdinov and G.E. Hinton (2009) Bolzmann machines with a lot of depth. 448–455 in JMLR.org's International Conference on Artificial Intelligence and Statistics.

[7] R. Azar, P. Villa, D. Stroppiana, A. Crema, M. Boschetti, and P. A. Brivio, "Assessing inseason crop classification performance using satellite data: A test case in Northern Italy,"

[8] Dahl G, Ranzato M, Mohamed A-R, Hinton GE (2010) Phone recognition with the mean-covariance restricted boltzmann machine. In: Advances in Neural Information Processing Systems. Curran Associates, Inc. pp 469–477

[9] Bengio Y, Lamblin P, Popovici D, Larochelle H2007. Greedy layer-wise training of deep networks, Vol. 19. Bengio Y, Lamblin P, Popovici D, Larochelle H2007. Greedy layer-wise training of deep networks, Vol. 19.

[10] Dalal N, Triggs B (2005) Histograms of oriented gradients for human detection. In: Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference On. IEEE Vol. 1. pp 886–893

[11] NDSU. Archive - Ag News From NDSU. (2020). [Online].Available: https://www.ag.ndsu.edu/news/topics/

[12] T. D. Setiyono et al., "Spatial Rice Yield Estimation Based on MODIS and Sentinel-1 SAR Data and ORYZA Crop Growth Model," Remote Sensing, vol. 10, no. 2, pp. 1–20, 2018.

[13] Dahl G, Ranzato M, Mohamed A-R, Hinton GE (2010) Phone recognition with the mean-covariance restricted boltzmann machine. In: Advances in Neural Information Processing Systems. Curran Associates, Inc. pp 469–477

[14] Hinton G, Deng L, Yu D, Mohamed A-R, Jaitly N, Senior A, Vanhoucke V, Nguyen P, Sainath T, Dahl G, Kingsbury B: Deep neural networks for acoustic modelling in speech recognition: Four research groups' shared perspectives IEEE Signal Process Mag, vol. 29, no. 6, pp. 82–97, doi:10.1109/MSP.2012.2205597

[15] Conversational voice transcription utilising context-dependent deep neural networks, Seide F, Li G, Yu D. 437–440 in INTERSPEECH. ISCA.

[16] Mohamed A-R, Dahl GE, and Hinton G: Deep belief networks for acoustic modelling. Audio Speech Language Translation 10.1109/TASL.2011.2109382. IEEE Trans 2012, 20(1), 14–22