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Hyperspectral Imagery for Crop yield estimation in Precision Agriculture using Machine Learning Approaches: A review

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Abstract

Crop yield estimation is one of the most significant issues for agricultural management, and one of the areas that precision farming techniques can offer the greatest benefit. Crop yield prediction is an art of forecasting the yield of crop before harvesting. Prediction of crop yield will be very useful for the government to make food policies, market price, import and export policies and proper warehousing well in time. Remote sensing technologies, together with the use machine learning have been shown to be effective in monitoring crop yield, improving land management, and facilitating the implementation of precision farming techniques. The main goals of crop yield estimation of precision agriculture is achieving maximum crop yield at minimum cost with a healthy ecosystem using combination of technologies. In India climatic conditions effected more on crop yield estimation. Other environmental factors also need to concentrate while studying crop yield such as temperature, rainfall, vegetative index, soil type, texture and nutrients. Crop yield prediction and estimation is very important to our government on the aspect of making food policies, crop insurance, market price, import and export policies etc. Use of remote sensing technologies is currently recognized to be the next generation of technical innovations that have the potential to refine the quality of within-field yield mapping technologies. we can implement various machine learning algorithms like ANN and Decision Tree on this research for crop estimation. The performance of ANNs can compare with four conventional modelling methods, namely, Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), Photochemical Reflectance Index (PRI), and Stepwise Multiple Linear Regression (SMLR) models. Principal Component Analysis (PCA) can also use to reduce the dimensionality of the hyperspectral imagery. The prediction can be of two types they are classification or regression. Classification can be to identify in which classes the crop growth falls. For example: Classes such as, well grown, medium grown and under grown. Another type is regression where it will give numerical estimated value. So that value of percentage for the estimated crop yield can be obtained.

Keywords: Precision Agriculture, Remote sensing, Crop yield prediction, Machine learning, Hyperspectral Imagery

1. Introduction

India is at the second number for largest populated country around the world. most of people are depend on agriculture as income source. agriculture is backbone of Indian economy. Cultivation is major problem due to climate changes. Each crop has its unique ability to grow in different weather condition. There can be different factors affecting the production of a crop such as soil condition, pH, nitrogen, phosphate, potassium, organic carbon, calcium, manganese, copper, iron, depth, rainfall, temperature, humidity, price etc. [1]. Precision agriculture also known as smart farming a technology, enabled data-driven sustainable farm management system. It is basically the adoption of modern information technologies, software tools, and smart embedded devices for decision support in agriculture. Precision Agriculture (PA) is a scientific domain that includes combination of technologies, tools, and decision-making systems to improve crop productivity and farm profitability [2]. Precision Agriculture focus on the major area such as crop management, livestock management, water management and soil management. Some application such as crop yield prediction, crop quality, weed detection, disease detection and species recognition categorise under Crop management. due to the rapidly growing population in the world Yield production need to be doubled. Precision agriculture enhance productivity, quality and yield. Crop yield estimation is one of the most significant issues for agricultural management, and one of the areas that precision farming techniques can offer the greatest benefit. Crop yield prediction is an art of forecasting the yield of crop before harvesting [3].

Remote sensing has great potential as a source of information for the prediction of agricultural production, both at the regional and the global scale, because it provides data at a level of consistency, repeatability, timeliness and scalability that is unmatched by any other data source The research and application of remote sensing technology in agriculture started in the late 1960s [4].There are many more Applications of remote sensing in Agriculture include crop condition monitoring, crop identification, change detection, health severity measurement, Land monitoring Crop stress detection Crop Area and production forecast Drought monitoring Soil mapping Pest/disease identification Flood mapping Inland fishery development etc. at 1970s,india started Crop yield estimation under Agricultural Resource Inventory and Survey Experiment (ARISE) using Colour Infrared (CIR) aerial data. in 1988, for the purpose of production estimation of major crops, at district and state level one national program was conducted name as Crop Acreage Production Estimation (CAPE) for the same purpose, in 2007 one of other programs was launched called as FASAL. Hyperspectral and multispectral Satellite images are widely used for agricultural applications due to easy, global and temporal availability. Multiple satellite missions were launched by the National Aeronautics and Space Administration (NASA) and the European Space Agency (ESA), ISRO among others [5].

2 Literature Survey

literature review focus on study of crop yield prediction, remote sensing, and machine learning methods with various case studies and satellite sensors used in agriculture research.

2.1 Remote Sensing Systems in Precision Agriculture

Remote sensing is a technique of getting information of objects without direct contact. Remote sensing has great potential as a source of information for the prediction of agricultural production, both at the regional and the global scale, because it provides data at a level of consistency, repeatability, timeliness and scalability that is unmatched by any other data source. Remote sensing using drones, satellites and sensors in fields has revolutionized agriculture around the world, making it possible to understand what is happening to crops day-by-day and year-on-year [11]. Table 1 consist some application of remote sensing satellite sensor in precision agriculture.

Table 1: Applications of satellite sensors used for precision agricultural

Application	sensors	Duration	Spatial Resolution	Temporal Resolution	Author
Crop growth [2-6]	SkySat-1	2013–present	MS (1 m)	daily	Ferguson, Richard 2018 [12]
	SkySat-2	2014–present	MS (1 m)	daily	Zhang, Chongyuan 2020 [13]
	RadarSAT (1995–2013)	1995–2013	C-band SAR (30 m)	1–6 days	Caturegli, Lisa, et al (2015) [14]
	WorldView-2	2009–present	MS (1.4 m)	1.1 days	Tian, Jinyan, et al (2017) [15]
	Pleiades-1A Pleiades-1B	2011–present	MS (2 m)	1 day	Kokhan, Svitlana 2020 [16]
	KOMPSAT	2012–present	MS (2.8 m)	1.4 days	Ahn, Ho-yong, et al 2020 [17]
	Sentinel-1	2014–present	C-band SAR (5–40 m)	1–3 days	Meroni, Michele, et al (2021) [18]
	TripleSat	2015–present	MS (3.2 m)	1 day	Chua, Randy 2020 [19]
Water management	SPOT 1 and SPOT-2	1990–2009	MS (20 m)	2–6 days	[Baraldi, Andrea, et al (2009)[20]
	IRS 1A	1988–1996	MS (72 m)	22 days	Choubey, V. K. (1994) [21]
	Terra-ASTER	2000–present	MS (15 m)	16 days	Hasab,Hashim Ali, et al. (2020) [22].
nutrient management	IKONOS	1999–2015	MS (3.2 m)	3 days	Goetz, Scott J., et al (2003) [23]
	GeoEye-1	2008–present	MS (1.65 m)	2–8days	Caturegli, L (2015) [24]
	Sentinel-2	2015–present	MS (10 m)	2–5 days	Sharifi, Alireza.(2020) [25]
Crop yield	IKONOS	1999–2015	MS (3.2 m)	3 days	Yang (2018) [26]
	Terra/Aqua MODIS	1999–present	MS(250–1000 m)	1–2 days	Maselli, Fabio, et al (2020) [27]
	Spot-5	2002–2015	MS (V, NIR–10 m, SWIR–20 m)	2–3 days	Aicha, et al(2018) [28]
	KOMPSAT-2	2006–present	MS (4 m)	5 days	Denis, Antoine, et al (2021) [29]
soil moisture	SMAP	2015–present	L-band SAR (1–3 km)	2–3 days	Vibhute, Amol D., et al. (2020) [30]
Crop Disease Detection	Spot-6 / Spot-7	2012–present	MS (6 m)	1-day	Yang, (2020) [31]
weed management	Worldview-3	2014–present	SS (1.24 m)	1-day	Sidike, Paheding, et al (2019)[32]

2.1.1 Hyperspectral Imaging

Hyperspectral imaging is the one of best informative source of remote sensing. It plays vital role in many domains like military and space use, industries, medical field, security and safety, agriculture and many more. It can capture the entire, continuous electromagnetic spectrum of colour and light [33]. There are lots of application of hyperspectral imaging in agriculture like Crop nutrition and fertilization, including macro and micronutrients (P, K, Mg, Mn, Cu, Mn, Zn), Early disease detection and stresses, Biophysical indicators for high throughput phenotyping to support plant breeding experiments. Analysis of biophysical properties, Analysis of biochemical properties (e.g., Anthocyanins, Carotenoids, Chlorophyll) etc. hyperspectral imaging in agriculture are use ground-based or space-based platforms [34]. Ground-based systems are typically used to make measurements requiring extremely high spectral resolution, such as measurements of spectral signature or bidirectional reflection distribution function [35].

2.1.2 Spectral signature of vegetation

A plant leaf does not absorb aIl wavelengths so it consists of biochemical and chemical substances with different absorption peaks. It is documented those various pigments - such as chlorophyll-a and b, anthocyanin, a and ~-carotenoids, lutein, violaxanthin - the physical structure of leaves and their spectral signature [36][37]. Remote sensing provides information about vegetation species over huge areas at a low cost. The hyperspectral sensors have the potential to divide the electromagnetic (EM) spectrum range in various narrow contiguous bands for detection of signatures. These sensors record the energy (emitted and reflected) and also used for processing, analysing the data which will be used for further analysis [3].

2.2 Use of remote sensing for crop yield estimation

2.2.1 Satellite Sensors

There are several officially announced hyperspectral earth observation satellite sensors on orbit, including PROBA-CHRIS, EO-1 HYPERION, HysIS, HISUI as described in table2. The first Indian Hyperspectral Imaging Satellite (HysIS) from Srihari Kota on 29 November 2018 launched by The Indian Space Research Organisation (ISRO). The information provide by satellite is useful in research study of agriculture, environmental, coastal zones, geolog, forestry etc [39].In 2019, Ministry of Economy, Japan developed space borne hyperspectral earth imaging system known as Hyperspectral Image Suiter (HISUI). It has 3 years of activity duration. HISUI will be terminated in 2021-2022. It has high spatial resolution with 185 spectral bands, spectral range to 0.4 to 2.4 μm and spectral resolution is 10nm and 12. nm for VNIR region and SWIR regions respectively [40].

Table 2: specifications of hyperspectral Sensor

Sensor	Sensor Agency	Band	Spectral range	Spatial Resolution(m)	Status/year	Revisit time
Hyperion EO1 [41]	NASA, USA	242		30 m	Mission Terminated 2000-2015	200 days
HysPIRId [42]	NASA	217	400-2500	60 m	2022	19 days
CHRIS PROBA[43]	UK Space Agency	37	415–1050	17/34 m	2001	3 days
AVIRIS 4 [44]	USA	224	400–2500	4-20 m	Data available on user request	-
HysIS [39]	ISRO, India	32	60/256	30 m	2019-2026	5/19 days
HyMap [45]	Australia	128	10-20	2-10 m	Data available on user request	Airborne
HISUI [40]	Japan	185	0.4μm-2.5μm	20-30m	2019-2021	Airborne
MODIS [46]	NASA	36	400–1400	5-10 nm	2002 -2007	2 day
PRISMA[47]	Italy	210	400-2500	12 nm	launched in 2012, -2016	Airborne
CASI [48]	Canada	288	0.2-1.5		user demand	Airborne
AISA [49]	Finland	84	8-12	100nm	user demand	Airborne
GaoFen-5[50]	NASA	330	400-2500	30 m	Launched in 2018/ 15 year plan	7 day

2.2.2 Satellite Platforms

For gathering the data many types of sensor and platforms are used in crop yield estimation and yield mapping in precision agriculture such as satellites, airplanes, helicopters, UAVs and close-range etc. as shown in Table 3. [51][52].

2.3 crop yield estimation and predictions

For developing agriculture domain crop yield estimation and predictions is essential by reliable time to time and correct information of crop area, crop growth and condition to plan various polices.
Chu and Yu [2020] developed rice prediction model which predicts summer and winter rice crops in the eighty-one countries of the Guangxi Zhuang Autonomous Region, China. This module was categorised in to three stages in first stage is pre-processed original area and meteorology data later that in second stage BPNN and RNN learns deep spatial and temporal features from the input data of first stage .at last stage BPNN learns the summer and winter rice crop deep feature relationship. The final result of this BBI model was present lowest error values with MAE and RMSE of 0.0044 and 0.0057 for summer rice prediction and 0.0074 and 0.0192 for winter rice within 100 iterations [53].
A case study in Western Australia, Patrick Filippi et al (2019) built Random Forest models to predict crop yield of wheat, barley and canola using data from national and global datasets, such as rainfall and MODIS between 2013 to 2015.to explore the crop yield ability three modules was created, depend on the pre sowing, mid-season and late season crop conditions.[54]. One another similar approach on under varying environment condition. Author studied difference between predicted and actual yields [55].

2.4 Machine Learning in Precision Agriculture

2.4.1 Machine Learning Approach

Table 3: Hyperspectral Imaging Platforms [51][52]

Attribute	**Satellites**	**Airplanes**	**Helicopters**	**Fixed-Wing UAVs**	**Multi-Rotor UAVs**	**Close-Range Platforms**
Operational Altitudes	400–700 km	1–20 km	100 m–2 km	<150 m	<150 m	<10 m
Spatial Coverage	Very large	Medium—large (~100 km)	Medium Small (~10 km)	Medium Small (~5 km)	Small (~0 .5km)	Very small (~0 .005km)
Spatial Resolution	20–60 m	1–20 m	0.1–1 m	0.01–0.5 m	0.01–0.5 m	0.0001–0.01 m
Operational Complexity	low	medium	medium	High	High	High
Image Acquisition Cost	Low to medium	High	High	High	High	High
Flexibility	Low	medium	medium	High	High	High
Temporal Resolution	Days to weeks	Depends on flight operations				

Machine learning is the branch of computer science which is used to build algorithms which exhibit self-learning property means that machine learns itself so it known as Machine Learning. The ML consist three types supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the model is created with known labelled data with previous knowledge.[56]. For research purpose many different algorithms are studied by researchers. Some of them are listed as follows
Support Vector Machine (SVM) is a classification and regression algorithm that builds multi-dimensional boundaries between data points in the feature space. The output of the SVM is predicted based on the classes divided using the training data.[57]. A decision tree is one of the simplest and intuitive machine learning method with tree structure by splitting label data to its node [58].
K Nearest Neighbour KNN is a neighbourhood-based classifier where a data point is classified based on the classification of 'k' closest points. KNN does not require training and is not prone to overfitting.[59]. Convolutional Neural Network CNN is a deep learning method with convolutional, pooling and fully connected layers. Convolutional and pooling layers do the feature extraction while fully connected layers do the classification. CNN is very efficient in extracting mid-level

and high-level features especially with image data. They are generally successful in capturing spatial and temporal characteristics in data.[60]. Instance-based learning is a memory-based model that learns based on the comparison, i.e., examples are compared with instances from the training datasets Prominent algorithms in Instance-based learning includes learning vector quantization, k-nearest neighbour (KNN), and locally weighted learning.[61].

2.4.2 ML Algorithms for Agriculture Application

ML algorithms are mainly used to solve complex problems where human expertise fails such as weather prediction, spam filtering, disease identification in plants, pattern recognition. Here, Table 4 listed and discussed some innovative ML algorithms which play vital role in solving diverse set of problems in the field of precision agriculture.

Table 4: Machine Learning algorithms used for precision agricultural application

1	irrigation management	ANN	Seyedzadeh, Amin, et al. (2020) [62], Navinkumar,. (2020) [63], Al-Naji, Ali, et al. (2021) [64], D'Emilio, Alessandro, et al (2018) [65]
		SVM	Ifriza .(2021) [66] Liu, Dong, et al. (2020) [67]
		Deep learning	Chen, Huazhou, et al.(2020) [68], Chen, Huazhou, et al.(2020) [69], Pan, Jinqiu, et al. (2018) [70]
		Decision tree	Patil, Chinmay, et al. (2021) [71], Brédy, Jhemson, et al. (2020) [72],
		Regression	García–Nieto, Paulino J., et al. (2020) [73], Kumar, Anusha, et al.. (2017) [74]
2	crop yield prediction	ANN	Aghighi, Hossein, et al. (2018) [75], Gandge, Yogesh(2018) [76],
		Bayesian network	Ma, Yuchi, et al. (2021) [78] Cao, Juan, et al. (2021) [79] van Klompenburg(2020) [80] Shetty, Supreetha A., et al (2021)[81].
		Deep learning	Shetty, Supreetha A. (2021) [82], et al. Elavarasan (2020) [83], Mehra et al. (2018) [84]
		Decision tree	Bhanumathi, S(2019) [85] Chlingaryan et al. (2018) [86]
		Instance-based learning	Feng, Luwei, et al. (2020) [87],
		Ensemble learning	Keerthana, Mummaleti, et al (2021) [88],
		SVM	Keerthana, Mummaleti, et al (2021) [89] Reshma, R., et al. (2020) [90]
3	disease detection	ANN	Nihar, Fatema, et al. (2021) [91], Saeed, Farah, et al. (2021) [92],
		Bayesian deep learning	Zheng, Rui, et al. (2021) [93], Hernández, S., (2021) [94],
		Deep learning	Wani, Javaid Ahmad, et al. (2021) [95], Ashok, Surampalli, et al. (2020) [96], Tiwari, Divyansh, et al. (2020) [97].
		Regression	Saeed, Farah, et al. (2021) [98].
		SVM	Patil, Asha (2021) [99], Abdullah, Dakhaz (2021) [100].
4	weeds detection.	ANN	Panda, Bikramaditya, et al. (2021) [101],
		Decision tree	Wang, Bo (2020) [102],
		KNN	Khurana, Gurpreet (2021) [103],
		SVM	Badhan, Siddhesh, et al. (2021) [104],
		CNN	Veeragandham (2021) [105],
		Deep learning	Knoll, Florian J., et al. (2019) [106],
5	nutrient management.	ANN	Peng, Qiu, and Weihong Xu. (2021) [107], Leelavathy. (2021) [108],

			Zheng, Caiwang(2021) [109],
		Clustering	Zhang (2021) [110], Gokulnath (2021) [111],
		Decision tree	Jahan (2021) [112], Amirruddin, Amiratul Diyana, et al. (2021) [113]
		Ensemble learning	Bai, Xueyuan, et al. (2021) [114]
		Deep learning	Nandhini. (2021) [115]
		Regression	Peng, Junxiang, et al. (2021) [116]
6	prediction of soil properties	Naïve Bayes algorithm	Malik. (2021) [117]
		Clustering	Gao, Hongju. (2021) [118]
		CNN	Das. (2021) [119]
		Regression	Ou, Depin, et al. (2021) [120]

2.4.3 Machine learning for crop yield prediction and Estimation

Paudel (2021), predicted early season or end of season prediction for the large-scale crop yield with crop modelling and machine learning approach by using database from s the European Commission's MARS Crop Yield Forecasting System (MCYFS). five crops soft wheat, spring barley, sunflower, sugar beet, potatoes from three countries the Netherlands, Germany and France Tested for his developed workflow. Ridge Regression, K-nearest Neighbours Regression, Support Vector Machines Regression and Gradient Boosted Decision Trees Regression these four algorithms are used for accuracy tested on different 13 case studies [121].

Kamir et al. (2020) predicted wheat production and identified yield gap hotspot with the help of nine machine learning algorithms as SVR, RF, Gaussian Process, k-NN, Cubist, Multivariate Adaptive Regression Splines, MLP and KNN. Data was collected from three sources, one from NDVI at 250 m resolution from the MODIS i.e., MOD13Q1 data set from 2009 to 2015, second rainfall and temperature data from SILO (Scientific Information for Land Owners) at Australia and third one from maps of observed grain yield were collected using harvesting machines. The result of SVMr algorithm performs best with showing high accuracy with an RMSE value of 0.545 t ha^{-1} and an R2 of 0.77 at the pixel level, and an R2 using cross validation [122].

Hossein Aghighi (2018) Introduce crop monitoring and yield estimation technique of Maize crop using remote sensing at NorthWest of Iran. NDVI dataset of Landsat 8 OLI satellite was used for investigate research study. In this study comparison of performance of Boosted Regression Tree, Random Forest Regression, Support Vector Regression, and Gaussian Process Regression algorithms are done by conventional regression method. on the basis of 2013-2014 trained dataset, model predict the crop yield of Maize in 2015 as R value was higher than 0.87 on 13 [123].

At county-level soybean yield prediction by using remote sensing data in the U. S was done by Jiaxuan You (2017), to extract feature from raw data he used CNN and LSTM algorithms. He proposed dimensionality reduction approach by Deep Gaussian Process framework to integrate the spatio-temporal information from the data. The better result of this models with 30% reduction of RMSE from the best competing methods.[124].

Table 5 summarizes the previous research and case studies of yield prediction using Machine learning approach

Table 5 previous research and case studies of yield prediction using Machine learning approach

Previous Studies	**Crop /location /dataset**	**algo**	**Research Focuses on models**	**Summery and accuracy measure**
SA Shetty(2021) [125]	major crops grown in the Karnataka ,India	Random forest	A Multi-Layer Perceptron neural network model and Random forest regression models	Web based application is developed using python to crop prediction. Multi-Layer Perceptron network and Random forest regression obtained the Mean absolute error of 12.3% and 12.4%, mean square error of 3.4% and 2.9%, root mean square error of 18.55% and 17.12% respectively.
B Darwin(2021)[126]	grapes, apples, citrus, tomatoes and vegetables	convolutionneural network (CNN) SVM	Theautomation in image analysis with computer vision and deep learning models used	provided a better accuracy for smart farming The deep learning models outperform the other conventional image processing techniques with an average accuracy of 92.51% in diverse agricultural applications.
Raí A. Schwalbert (2020)[127]	Soybean/southern Brazil	linear regression, random forest and LSTM	forecasting soybean yield using NDVI, EVI, land surface temperature and precipitation as independent variables	This research portrays the benefits of integrating statistical techniques, remote sensing, weather to field survey data in order to perform more reliable in-season soybean yield forecasts with MAE increasing from 0.24 Mg ha−1 to 0.42 Mg ha−1
Wei Marcelo Chan Fu et al.(2020)[128]	Carrot/ Uberaba state of Minas Gerais, Brazil	andom forest (RF) regression algorithm	Georeferencedcarrot yield sampling was carried out and satellite imagery was obtained during crop development. The Gini index was used to find the fivemost important predictor variables of the model.	The five most important predictor variables were the near-infrared spectralband at 92 and 79 days after sowing (DAS), green spectral band at 50 DAS and blue spectral band at92 and 81 DAS. The RF algorithm applied to the entire dataset presented R2, RMSE and MAE valuesof 0.82, 2.64 Mg ha−1and 1.74 Mg ha−1, respectively. The method based on RF regression applied to adatabase composed of spectral bands proved to be accurate and suitable to predict carrot yield
Stas, M (2016) [129]	wheat crop	Boosted Regression Tree (BRT), SVM	Three types of NDVI-related predictors have been used Single NDVI, Incremental NDVI were used for analysis. The results revealed that BRT performs better than SVM	When a limited number of training samples is available, ML techniques used here are better able to cope with large set of predictors (compared to MLR The results of comparison, which are based on a cross-validation error (RMSE), showed that BRT model consistently outperforms SVM
Sushila Shidna (2019)[130]	Healthy leaf of crop	Convolutional Neural Networks (CNN)	two tired machine learning models are used with neural networks and k-means clustering method is used	Research observed deficiency identification of leaf to predict yield pre-diction. The accuracy of prediction wasn 76 to 77%
X.E. Pantazi(2016)[131]	wheat crop/ Bedfordshire, UK	unsupervised learning algorithm	Counter-propagation Artificial Neural	Thepresented approach incorporates the yield limiting factors in a multi-layer fusion

			Network (CPANN), Supervised Kohonen Network (SKN) and XY-fusion network(XYF), based on Supervised Learning	mode SKN network for the predic-tion of the low category of wheat yield with a correct classificationreached 91.3% for both cross validation and independent valida-tion.
Chen et al. (2019)[108]	Strawberry/ Florida in Citra, Florida, USA	Faster Region-based Convolutional Neural Networks (Faster R-CNN)	deep neural network model, used to detect and counting flowers, mature strawberries, and immature strawberries, ResNet-50 architecture and transfer learning from ImageNet, to detect 10objects	accuracy to be 84.1%, with an average occlusion of 13.5%
Shah et al. (2018)[132]	corn yield	Support vector machine, random forest	multivariate polynomial regression, support vector machine regression and random forest models	SVM regression finds the minimum 5.48, 3.57and 1.58 RMSE, MAE and median absolute error value respectively square value was 0.968.
Zeel Doshi (2018) [133]	jowar, bajra, maize wheat, rice	Decision Tree, K Nearest, Random Forest and Neural Network	Developed system based on models of combination of Big Data Analytics and Machine Learning algorithms	four machine learning algorithms have different accuracies Decision Tree 90.20, K-NN 89.78, Random Forest 90.43 and Neural Network 91.00

3 Conclusions

This review paper gives information about Role of Remote Sensing Systems and machine learning in Precision Agriculture. Here we categorise remote sensing application for precision agriculture as Crop growth, Water management, nutrient management, Crop yield, weed management, Crop Disease Detection, soil moisture. For the crop yield prediction and estimation hyperspectral satellite sensor are used. The review consists of two main parts first is on crop yield prediction and estimation using hyperspectral remote sensing and another part on machine learning algorithms. the first part describes the previous case studies of precision agriculture with details of remote sensing and various sensors used in agriculture research. In second part focus on Machine Learning Approach with different algorithms like convolutional neural network (CNN) SVM, Random Forest, Decision Tree, K Nearest, Random Forest and Neural Network etc with case studies.

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