A Review on Smart Farming based on Soil and Environmental Factors with Deep Learning Techniques

Routhu Sathish
Information Technology
GMR Institute Of Technology
Rajam, Andhra Pradesh, India
19341A1296@gmrit.edu.in

Thulluru Prem Chand
Information Technology
GMR Institute Of Technology
Rajam, Andhra Pradesh, India
19341A12B7@gmrit.edu.in

Sai Ram Prudhvi Gummaluri
Information Technology
GMR Institute Of Technology
Rajam, Andhra Pradesh, India
19341A1297@gmrit.edu.in

Marripudi Vyas Kanmani
Information Technology
GMR Institute Of Technology
Rajam, Andhra Pradesh, India
19341A1268@gmrit.edu.in

T. Daniya
Information Technology
GMR Institute Of Technology
Rajam, Andhra Pradesh, India
daniya.t@gmrit.edu.in

2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS) | 978-1-6654-8962-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICAISS55157.2022.10010825

***Abstract*— India's global economy is critically dependent on agriculture, which also accounts for a sizable portion of GDP. This paper provides a review of the use of machine learning and deep learning techniques in agriculture and elaborates different systems developed for smart agriculture including crop recommendations, fertilizer suggestions, categorization procedures and diseases identification by images. Climate factors like temperature, rainfall, soil quality, and fertilizers are the key determinants of agricultural productivity. Decision making such as determining the diseases and applying solutions to them is an important step in agricultural activities. With advanced technologies evolved in this digital world we can build more sustainable systems to make these farming procedures automated. Deep learning techniques are giving very prominent results in solving problems of predictions and decision making. The application of machine learning algorithms that are used in solving different problems that are arising in farming process are discussed. This paper contributes to know the available techniques for the automated farming procedures.**

***Keywords*—Agriculture, Climate factors, Deep Learning, Farming, Image Processing**

I. INTRODUCTION

Artificial intelligence is a fast growing technology that tries to eliminate manual operations and Artificial intelligence is a fast growing technology that tries to eliminate manual operations and replace them by machines in many fields. This technology has evolved in many sectors such as medical, defence, Agricultural, services and many more. In India many workers depend on agriculture as their main profession. There are many factors affecting the production in farming of crops in India. These factors can be of environment or soil. To make certain decisions in farming we need to automate the process in such a way that the production rate in the field is increased. There are many available techniques for smart farming such as crop yield predictions, crop selections, fertilizer recommendations, weed detection in the field, diseases identification of crop leaves, pesticide suggestion, seed selection and many more techniques helps famers to get a better production results. The primary goal of this paper is to examine the available smart farming techniques in terms of feasibility, efficiency, and effectiveness.

This paper studies more frequently faced problems in farming and deep learning techniques used to solve them. The relevant study describes the regular workflow of the machine learning procedures to build an efficient model.

II. LITERATURE SURVEY

Here we have gathered several periodicals that have conducted research on our connected work, which is based on the rice plant, and we have separately summarized each work as shown below.

In this paper, computer vision and deep learning techniques are used to select and plant healthy billets in order to increase sugarcane crop growth and hectare yield. The data set for the training model was obtained from the USDA Sugarcane Research Farm. The sugarcane dataset is based on three varieties of sugarcane collected from farms and classified by experts as good and damaged billets. When processing large datasets, highly regarded CNN models like AlexNet, VGG-16, GoogLeNet, and ResNet101 are used to achieve better results. Each dataset was randomly divided into three types to compare these models: 60%, 20%, 20% for training, validation, evaluation. A two-step transfer approach is suggested in this study to create an automatic system which every farmer can apply to any wide range of sugarcane. In this case, the four architectures selected produced similar results (TNR, TPR, MCC, and proportion of great billets per plant), but ResNet101 and AlexNet produced great outcomes for various range of renewable. ResNet101, on the other hand, demanded an unusually high computational cost. AlexNet appears to be the ideal choice for them, with a two-stage transfer learning process that requires approximately 22 times fewer logs to train up the system for a fresh sugarcane variant. The created model can be applied to any variety of sugar cane. Using the model allows farmers to grow quality billets, thereby increasing sugarcane production rates in the future, but due to the damaged variety of sugarcane billets classified by humans, the initial training dataset may not be accurate. In addition to using high-quality billets, sugarcane quality control also depends on soil and climate. [1]

This paper describes deep learning techniques for detecting insect pests in fields. Two types of algorithms are mainly used: One-stage algorithm: YoloV5, two-stage algorithm: FasterRCNN & MaskRCNN. One-step algorithms directly extract features from images and detect object locations and classify them. These will print (Object coordinates like bounding boxes) in the image and then classify that bounding box. these are relatively fast as there is no need for regional design. However, two-phase algorithms generate a region of interest for objects in the image (such as masks for the object) and then extract features from them to classify them. These models are relatively fast as an intermediate stage of searching for included regions. However, one-step algorithms performed faster and better on simple datasets with less complexity. Two-phase algorithms performed better on datasets with complex backgrounds. Yolov5 can more accurately identify insect pests on images with simple backgrounds, such as the Baidu AI insect detection dataset, but manual labeling is time-consuming and requires a lot of computing power to train these complex models. Accuracy is on average 99%. [2]

This paper proposed a Deep Recurrent Q-Network models of Reinforcement learning in order to estimate the yield of a crop with given crop parameters. They collected data from paddy crops in Tamilnadu. Data parameters include: (1) The production of paddy is estimated on the basis of cultivable land, paddy growth, and yield obtained. (2) Several independent features include climatic factors, soil parameters and distinct hydro-chemical characteristics of underground water. DQRN model, Reinforcement Learning, and Q-Learning are the techniques used. DRQN-based processes provide a satisfactory explanation which incudes a non-linear mapping between agricultural output, Weather conditions, soil, and underground water factors independently. This benefit can reduce the need for previous knowledge and expert dependence when making agricultural yield predictions but Gradient Exploding in RNN model for long time series data and Statistical uncertainty with non probabilistic model.[3]

This paper included disease identification in lemon and mango plants using image segmentation techniques and the appropriate fertilizer. Several stages are used to identify diseases, such as Image acquisition, Image Pre-processing, Classification by Artificial Neural Network, Fertilizer recommendation by Mapping standard deviation to the fertilizers available. To figure out the amount of disease infection as in leaf, proposed system divides the input leaf image into diseased and background areas using the K means clustering algorithm, Feature extraction by using Gray Level co-occurrence Matrix (GLCM) along with first order statistical moment's method, Fertilizer recommendation based on disease detected but Segmentation provided some misclassifications. Here, the proposed system simply recommends the chemical fertilizers that were applied. However, the amount of dosage of fertilizer use is not mentioned.[4]

Images from the input plant are first pre-processed to create them suited about further handling. Pre-processed images have been routed through a Image Segment module, which employs SegNet to segment the pre-processed image. Pre-processing is done to improve the contrast of the image, remove noise and disorders in order to detect plant diseases. The CNN features extract statistical data from each segment. These features are then put together into a feature vector. The pre-processed paddy image is sent to the segment module using SegNet can supply high-dimensional data segmentation and to identify disease regions taking into account each segment. Deep RNN receives the extracted features for classification and trains on the proposed RSW, which combines ROA, SMO, and WWO. It is proposed to build a classifier known as RSW-based Deep Recurrent Neural Network by adjusting the Deep Recurrent Neural Network training algorithm including the Recursive Smith-Waterman-seq algorithm. The proposed Recursive Smith-Waterman-seq is used to optimize the weight of the classifier. To select the best weights, Recursive Smith-Waterman-seq modifies the Deep Recurrent Neural Network by integrating the Read-While-Write and Sequential Minimal Optimization algorithms. The goal of the proposed Recursive Smith-Waterman-seq-based Deep Recurrent Neural Network is to identify disorder using features extracted from the source images. The proposed Recursive Smith-Waterman-seq based Deep Recurrent Neural Network produces high results: With Maximum Accuracy, Sensitivity, Specificity (90.5%, 84.9%, 95.2%) respectively. However, the proposed method cannot detect all rice diseases. [5]

In this paper to forecast the diseased area of the leaves, they suggested improving machine learning. The infected area is divided using a colour-based segmentation model defined by them. On sample images, experimental evaluations of the time complexity and the infected area were performed. Images can be processed to identify plant diseases. Image acquisition (virtually increase the number of samples in your dataset using data you already have), steps in the disease identification process include image pre-processing, image segmentation, feature extraction, and classification. Image augmentation is possible to achieve by applying geometric transformations, altering the colour, brightness, contrast or by adding noise. To enable model to adapt to various situations where noisy data could occur, such as during the rainy season. The dataset is gathered from UCI machine learning repository it comprises three leaf diseases. 20% of the images were used for validation and testing, while the remaining 80% were used for training. Classification Algorithm used : SVM. When model is trained with images that have undergone image augmentation or acquisition, it performs 5% better on the validation set than a model that is trained with images that have not. The model used in this paper is only relevant to three diseases and its usefulness to other diseases is not guaranteed.[6]

A strong method ExpRHGSO-based Hybrid Deep Learning, a combination of DRN and DFDN is developed for disease identification and leaf classification. Initially, images are retrieved out of a database that combines two data sources to create a single dataset. The ROI extraction is then applied to the input images for pre-processing. Following that, image segmentation is performed using DFC to segment appropriate regions. Statistical, CNN, and texture features are extracted for subsequent processing. To improve the detection and classification processes, data augmentation is used to enhance the dimensionality of the features. Utilizing rotation, cropping, and zooming, the data is improved. The DNFN classifier is used to carry out the rice leaf detection process. This classifier reduces the problems associated with computational complexity while achieving the ideal result more quickly. The developed ExpRHGSO algorithm, which combines EWMA and RHGSO, is used to train the DNFN model. The EWMA algorithm detects slight changes in the way the target values are processed since it has the ability to produce accurate result. RHGSO is integrated with the EWMA to produce better results. After the identification of the rice leaf disease, the BLB, Blast, and Brown spot. DRN is used for rice leaf disease classification. In the DRN training process, the ExpRHGSO method is included. With higher values of 0.916, 0.923, and 0.919, In terms of testing accuracy, sensitivity, and specificity, the created ExpRHGSO-based Hybrid Deep Learning technique performed better. On the basis of testing accuracy, sensitivity, and specificity, the model demonstrated excellent performance. When tested against huge datasets with a greater variety of diseases, the model might not keep the same accuracy and other standards. [8]

In this study, an automated approach is proposed for the detection of 3 main paddy leaf diseases. Depending on the severity of the diseases, pesticides and fertilizers are also suggested. The goal of this study is to provide a reliable and straightforward system for categorizing paddy leaf diseases. To distinguish the damaged part from the paddy leaf image, K-means clustering is used. These disorders are categorised using the visual content's colour, Shape and Texture. SVM classifier recognizes the type of paddy leaf diseases. After identification, a preventative solution is recommended that can assist individuals and organizations involved in agriculture in responding appropriately to these diseases. In this study, it is proposed that the following treatments for Brown spot are effective: Treating diseased plants with pesticides and herbicides such Benzoyl and Iprodione and antibiotics like Validamycin and Polyoxin. Systemic fungicides, such as triazoles and strobilurins, can be used sparingly to reduce leaf blast. To effectively control the illness, apply a fungicide at heading. Foliar spray of Streptocycline and Copper Sulfate for bacterial leaf blight. The overall accuracy is about 92%. Suggested pesticides or fertilizers are divided into 2 categories one is at initial stage and another at severe stage. If we use different techniques then the accuracy may increase. [9]

For years, rice diseases have been one of the numerous enduring problems that farmers and planting specialists have had to deal with. In the world of agriculture, a quick, automated, cheap, and trustworthy method to identify rice infections is desperately needed. Because severe rice diseases could result in no harvest of grains. Deep learning has proven to perform well in image processing and classification challenges, thus they used this approach in this research to address the problem. In order to address the vanishing-gradient problem that arises as network depth grows, the deep convolutional neural network architecture known as DenseNet links the result among all layers to the source among all subsequent layers in inside dense block. The recurrence of a Batch Normalization for a specified number of times is known as a dense block. Each layer's feature-maps are utilized as sources and its own feature-maps are employed as sources for all subsequent layers, minimizing feature loss. The easiest way to enhance the capacity of deep neural networks is to raise their depth or the networks' width. However, as network depth and width have increased, the number of factors has increased as well. This increases the use of computational resources. In order to solve these issues, the Inception used was a module. The module, which consists of a max-pooling layer and convolutional layers of different sizes that are stacked together and utilized to do the dimension reduction, has to be combined using a concatenation filter. The traditional DenseNet was altered by the addition of an Inception module and a brand-new, fully-connected ReLU layer with 512 neutrons, which was then replaced with a global pooling layer to replace the connection layer entirely. Since it integrated the advantages of both, the DenseNet pre-trained on ImageNet and Inception module was chosen to be utilized in the network. This method outperforms other cutting-edge approaches, and the outermost layer employs the Softmax algorithm to classify images of rice disease. DENSE-INCEP network model is the algorithm we are using to solve the above problem. [10]

Every nation is built on agriculture. As a result, it needs to be timely monitored. Farmers have so far used traditional farming methods. These methods took a lot of time and were ineffective because they were not exact. Precision farming includes a variety of techniques such as weather forecasting, soil analysis, crop recommendations, and calculating the necessary dosages of pesticides and fertilizers. Precise Farming gathers data, trains systems, and forecasts outcomes using cutting-edge technologies like Internet Of Things, Data Mining and Analytics, and ML. This research suggests four modules: crop prescription, weed detection, pesticide advice, and farm budget. In order to find the optimal model for analysis, they used a total of 11 algorithms and In this work, hyperparameter adjustment has been used to maximize the model potential. The model is saved in a pickle file after being determined to be the best crop prediction model so that it may be quickly summoned and utilized to forecast crops. To classify the images in the weed identification module, the Resnet keras model and Deep Residual Networks using skip connection technique were utilized. This allowed DL models to be trained without the problems that disappearing gradients generate. This module had 25 epochs run, with a batch size of 32. It resulted in accuracy of 89%. The pesticide recommendation system is similarly modelled after the herbicide recommendation system based on weeds. This module had 20 epochs run, with a batch size of 32. The achieved accuracy was 98%. Pesticides cannot be used on any crop in the same way that herbicides are. Both the soil fertility and crop growth could be harmed. Crop names enter by user and predicted insect names are sent to the Random Forest Classifier to ensure that the correct pesticides are recommended. The numerous cost ideas and the total cost of cultivation are estimated in the next module of the cost estimating procedure. For this module, eight different datasets that span the years 2010 to 2018 have been loaded. These datasets are combined then loaded. The state and crop columns both lack in numerical values. Label Encoding is employed to produce numeric data for a given item. The year, crop name encoded, and state name encoded columns are provided to the ML and ensemble regressor models. The R2 score, RMSE, MSE, MAE are calculated for each regressor model. With the highest R2score, the XGBoost regressor is selected as the effective model. [11]

The objective of this study is to support an individual in efficiently cultivating crops in order to attain high yield at a reasonable price. For recommending a crop to the user, ML algorithms like Neural

Network, Naive Bayes, Decision Tree, K Nearest Neighbor, regression model, and SVM were employed. Instantly retrieved information on the temperature and humidity is fed into the most basic model, which consists of 10 procedures with hyper parameter adjustment. To obtain accurate prediction, the Resnet algorithm is used. Since the Resnet method uses layers like the skip layer, identity layer that attempt to make the source image into the output itself, it attempts to achieve more accuracy. Predictions is therefore 100% accurate. Although te CenterNet algorithm is a method for identifying weeds on the ground, Resnet152V2 aims to produce accurate prediction. This study has defined a method for taking into account a picture's features with a relevant insect dataset. Its major objective is to find a key that aids in classifying the classes. This proposed work helps to clarify the significance of a secret in identifying the many insect classes. Resnet model is thus used in the proposed model to classify data. The suggested model aids in insect detection and also recommends pesticides in this regard. The suggested method employs ensemble regression techniques to predict prices through 2028. It offers a comparison analysis of a crop for a chosen state from 2010 to 2028. It offers a detailed look at production costs, flat rate, and overall cost. [12]

The objective of this study is to reevaluate research regarding the use of ML techniques in crop production. A few techniques, such as artificial neural networks, decision trees, fuzzy information networks, and Bayesian belief networks. Statistical analysis, the k nearest neighbours, Markoff process model, k-means clustering, k nearest neighbours, and SVM were all used in the context of agriculture. To forecast corn yields, nonlinear regression is used. For predicting cotton yields from surveys, the Markoff process approach is used. For estimating the grain yield of maturing rice, regression toward the mean is used. Belief Networks are used to produce future crops. Crop yield prediction uses neurofuzzy modelling. Second Order Markov Chains is employed for Forecasting of Crop Yields. Factors Influencing the Growth of Cultivated Varieties in Crop Margins Use Polynomial Regression For seasonal to cross weather forecasting, stochastic and probabilistic forecasting approaches are used. For the purpose of predicting sugar production from populations of samples, k-nearest neighbour algorithm is used. For the purpose of predicting corn and soybean production, ANN are used. Neural Network is employed for Rice Crop Monitoring. Artificial Neural Networks is employed for Forecasting Thailands Rice Export. In Andalusia, olive farming is carried out using an advisory and a network of mathematically huge information. Climate-related variables are used in regression to estimate sugarcane production. Decision-tree algorithms are employed for modelling soya productivity. For crop selection, a fuzzy modelling of decision network is used. Crop yield forecasting makes use of statistical techniques. India uses data mining with climate variables to increase jowar crop yield. For the purpose of predicting apple crop yield, fuzzy cognitive map training is used. Models using regression and NN are used to predict agricultural output. To predict crops, KMeans clustering is used. Farm Crop Production Prediction uses Artificial Neural Network Approach. Rotations are used for crop development [13]

Explain how a soil nutrient test has been carried out to ascertain any plant's productivity levels in this paper. Variables related to water and climate were promptly discussed, and their correlations with soil quality are plotted appropriately. All of these elements have an impact on crop productivity. Strategies for the consequences of a maize-chickpea nutritional system were also established. For increased system accuracy, the soil categorization is classified using a knowledge base algorithm. [15].

This paper proposes a blockchain-enabled wireless network-based sustainable smart farming system, whose performance is improved by maximization of SIR or SNR values for selection of an ideal relay on an end-to-end basis. When choosing the optimal relay performance with and without interference, the overall communication throughput (OCT), power splitting relaying (PSR), time switching relaying (TSR), and transmission success rate (TRS) are also determined. Numerical simulations confirm the theoretical values of accuracy. For the purpose of evaluating the performance of the proposed wireless networks for sustainable smart farming equipped with blockchain technology, the OCT, PSR, TSR, and TRS values are estimated. [16]

III. RELEVANT STUDY

Analysis of different techniques to build a system for following smart farming techniques :

A. Plant classification : Some techniques have been used to classify plants for some given conditions and they have applied them to farm the fields with those plants to get better results.

B. Disease detection : This technique involves the identification of disease that affected the crop by seeing an image of the plant or their leaves. However it mainly consists of CNN and deep learning architectures to classify the diseased images. It give the type of disease that occurred among the available classes of diseases.

C. Yield estimation : To know the estimated production rate of crop that is being farmed this regression technique will helps to predict the approximate value by using machine learning and deep learning technique of regression.

D. Pesticides recommendation : Pesticides help to eliminate the pest that damages the crops in agriculture. We have to know the appropriate pesticide for the pest that observed in the crop. Recommendation of the pesticides will help the farmers to make decision on usage of pesticides.

E. Weed detection : Weeds compete with crops for sunlight, water, nutrients, and space. In addition, they harbor insects and pathogens, which attack crop plants. We need to detect and identify these weeds to use suitable solution to prevent weed growth in the fields. Weeds can be detected by their images using deep learning techniques.

DEEP LEARNING :

Artificial intelligence is evolving and expanding it's art of learning to all branches of the current technical world. The latest developed computational resources are helping to achieve more efficient results in this AI Technology. Machine learning is a sub-branch of AI, it uses self-learning approach to derive meaningful insights from presented data without manual rules. Deep learning is a type of machine learning that uses neural networks to build more complex models. At the earlier stages of AI they have been limited in terms of computational resources. But with latest advancements we can build more complex and large computational models by using deep learning to process large data effectively. As the name suggests AI Neural networks imitates the human brain nerve mechanism to learn from presented data. Deep learning has many variations based on the given input data such as images, text, numerical etc. Convolutional Neural Networks are used for processing image data and their usage has been applied to solve many computer vision problems. CNN process the input data by applying many convolution functions and filters to extract features from the given input images.

Data Acquisition **:** As the machine learning or deep learning models require a lot of data to extract information and learn from them to solve problems we have to collect the proper data from different sources.

Data Pre-Processing **:** This step is very important in the process of model building to solve a problem. The acquired raw data may consists of noise, missing values, outliers or any other irrelevant data. We need to process this raw data in such a way that the model can learn effectively. This pre-processing step involves several techniques:
For a textual or numerical data :

- We need to replace the missing values with proper corresponding measures of central tendency or other ways of imputations.
- The outliers which will results in wrong predictions needs to be handled.
- Scaling of data needs to be done as the continuous values maybe measured at different scales.
- Encoding of categorical values or string type variables.

And there can be several other pre-processing steps such as data deduplication, data distribution transformations etc. needs to be done as per the observed data.
For an image data :

- ***Data Augmentation :*** The data augmentation helps in visual transformations. The transformation that is mainly focused on image classification are flipping, color modifications, cropping, rotation, geometric transformation, padding, re-scaling, zooming, gray scaling, darkening and brightening, random erasing etc. When we don't have a large image dataset, it's a good practice to artificially introduce sample diversity by applying random, yet realistic, transformations to the training images, such as rotation and horizontal flipping. This helps expose the model to different aspects of the training data and reduce overfitting.
- ***Image Resizing and Rescaling :*** It is better to resize all the training images to the same size as the model learns in more efficient way. Rescaling makes all the numerical values in a standard scale of measure.
- ***Image Segmentation :*** it is a process of partitioning the image into multiple segments knowns as regions (Collection of pixels) to simplify the representation of an image and extract information easily. It extracts the boundaries, edges, regions, contours and such type of information from the image. It will group the pixels such that the same group pixels has certain common characteristics.

Feature Extraction : Feature extraction is a dimensionality reduction technique by which a raw data is reduced to some groups known as features for processing. Large datasets need more computational power to process them and very difficult to extract accurate information from them. Feature extractions is a collection of methods those tries to reduce the amount of data without loosing much information from the raw data. It has many benefits like removal of redundant data, reduction computational resources and it facilitates the speed of training, generalization. Principal Component Analysis and Linear discriminant analysis are linear dimensionality reduction techniques frequently used in many machine learning procedures. Fig1 explains the general workflow of Machine Learning models development.

Model Evaluation **:** Models should be evaluated in such a way that the they learned more generalized and give test results also accurate. Accuracy score is the ratio of total no. of correct predictions to total no. of samples.

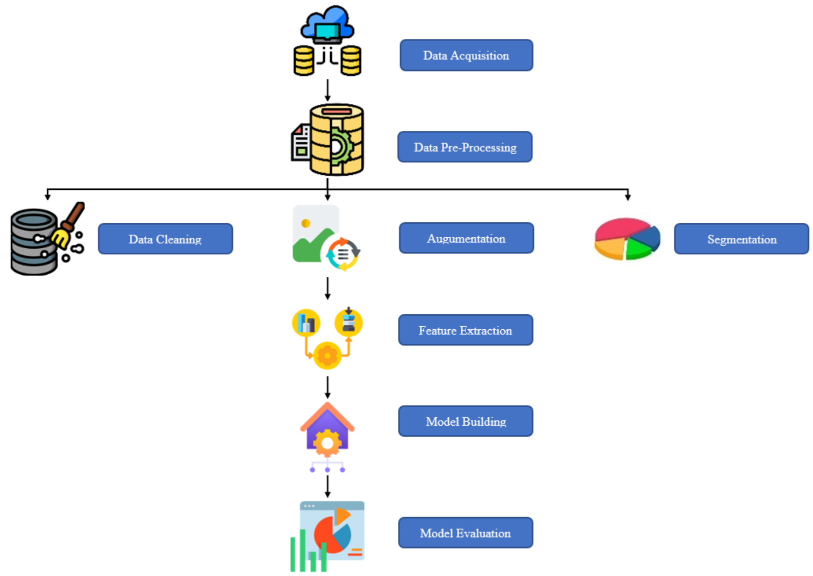

Fig1 : Regular workflow of ML Modelling

Table 1 : Comparison of different Techniques used in Smart farming

Ref Author's Name and Year	Dataset Used	Crops	Model / Techniques Used	Estimated Variables / Research Approaches	Advantages
[1] Moises Alencastre-Miranda, Richard M Johnson and Hermano Igo Krebs (2020)	USDA Sugarcane Dataset	Sugarcane with varieties HoCP 09-804, HoCP 96-540, L 01-299	Transfer Learning Process CNN Architecture model	Healthy Sugarcane billets Classification	Valid to any Sugarcane variety and enables farmers to plant quality billets
[2] W. Li, T. Zhu, X. Li, J. Dong and J. Liu (2022)	Baidu AI, IP 102 Datasets		Faster RCNN, Mask RCNN, YOLO v5	Pests Identification	Yolov5 can more accurately identify insect pests in images with a simple background
[3] Dhivya Elavarasan and P.M. Durairaj Vincent (2020)	Custom dataset is used	Paddy	DRQN Model	Using climatic, land, hydrological, and agricultural characteristics to predict agricultural yield	When predicting agricultural productivity, the use of DRQN-based procedures eliminates the requirement for prior information and expert dependence.
[4] K.S Neethu and P. Vijay Ganesh (2017)	Custom dataset is used	Lemon, Mango	K means clustering algorithm	Disease detection	Based on the disease detected, fertilizer also recommended.
[5] T. Daniya and Dr.S. Vigneshwari (2021)	Rice Grain disease Dataset	Rice	RideSpider Water Wave Based Deep Recurrent Neural Network	Disease detection	The model was able to achieve its highest levels of precision, sensitivities, and selectivity.

[6] R. Salini, A. Farzana and B. Yamini (2021)	Dataset that contain classes of leaf smut, bacterial leaf blight and brown spot		SVM Classifier, custom colour-based segmentation model	Disease detection & Fertilizer recommendation	
[7] Syeda I Hassan, Muhammad M Alam, Usman Illah, Mohammed A Al Ghamdi, Sulthan H Almotri and Mazliham M Suud (2021)			Approaches utilizing the Internet of Things, spatial information, NIR, RGB, multispectral and ML	crop illnesses, weed control, pesticides management, drainage management	Give a succinct overview of the advances in smarter agricultural on the efforts of many researchers.
[8] T. Daniya and Dr.S. Vigneshwari (2022)	Rice Plant Dataset, Rice Plant Disease Dataset	Rice	ExpRHGSO-based Hybrid Deep Learning	Disease identification	In terms of precision sensitivities, and selectivity, great results were achieved.
[9] Farhana T Pinki, Nipa Khatun and S.M. Mohidul Islam (2017)	Paddy Leaf Disease Dataset	Paddy	K-means clustering, SVM Classifier	Disease Detection & Fertilizer Recommendation	Achieved overall accuracy about 92%
[10] J. Chen, D. Zhang, Y.A. Nanehkaran and D. Li (2020)	Custom Dataset prepared based on Rice Plant Diseases	Rice	DENS-INCEP network model	Disease Detection	With usage of Image acquisition technique model achieved average accuracy of 98.63%
[11] S.K.S Durai and M.D Shamili (2022)	Crop recommender, soil, scientific_names datasets from Kaggle	Different Corps	XGBoost regressor, Random forest classifier, Randomized CV, and RESNET152V2 pre-trained algorithm are used to optimise the Random forest classifier.	Weed detection, pesticide prescription, agricultural cost planning, and crop suggestions	Not just predicting weeds and pests, but also recommending the pesticides and herbicides
[12] Rayner Alfred, Joe H Obit, Christie P Chin, Haviluddin and Yuto Lim (2021)	Datasets from Lens website	Different Corps	Linear Regression Model, Decision-tree, KNN, NN and SVM	Crop Recommendation, Weed Identification, Pests Identification	With the usage of Hyperparameter tuning model received accuracy of 95.45%
[13] S. Mishra, D. Mishra and G.H. Santra (2016)		Soya bean, Rice, Sugarcane	Decision-tree, Markov-Chain Model, k-means clustering, KNN and SVM etc.	Crop Yield Prediction based on Climate forecasting	
[14] T. Daniya and Dr.S. Vigneshwari (2019)	Custom Dataset prepared based on Rice Plant Diseases	Rice	ML, image processing & segmentation techniques	Disease recognition	Provides a comparison of the many techniques used to identify rice diseases

[15] H. James Deva Koresh (2021)		Maize, Chickpea	Soil Evaluation and testing techniques like Machine driven analysis, Mineralogical testing, Agrochemical analysis etc.	Soil Quality, Soil Helath Metrics, pH values of Soil	Water and climate variables were quickly discussed, and their relationships with soil quality are correctly plotted. These factors all affect how productive a crop is.
[16] J. Sustain, DR. D. Sivaganesan (2021)			Wireless blockchain based network	OCT, PSR, TSR and TRS	With more relay nodes, OCT and TRS work better, and numerical simulations are used to confirm the theoretical concept's accuracy.

IV. COMPARATIVE STUDY

In order to identify pests, recommend crops based on soil and climate conditions, and recommend fertilizers and herbicides based on disease and weed, the table above i.e Table 1 provides a brief comparison of the various Deep Learning and machine learning approaches utilized in the agriculture area. This is a summary analysis that was created from research published in a variety of periodicals, focusing on the different problems solved in agricultural farming activities by using machine learning and deep learning .

V. CONCLUSION AND FUTURE SCOPE

Agriculture field always need to be developed according to the new technologies in the era. By integrating these technologies into this farming field will be highly beneficial to farmers. However more research need to be done in this sector to build more feasible solutions to the problems faced by many farmers. Solving the real time problems frequently encountered by farmers need to be solved by using the advanced techniques, will be the future scope of this paper. This paper

makes two significant contributions. The first step is to provide a thorough study of research publications that make use of the Deep Learning technique. Each paper's originality, models, and experiments are elaborated. The second step is to know what are the general machine learning procedures to build efficient systems for smart farming. The most common smart farming techniques used are plants classification, yield estimation, disease detection and many other. Deep learning helped to build more efficient systems for such class of problems. These DL Techniques were used in almost all relevant problems and gave better results in real time.

VI REFERENCES

[1] M. Alencastre-Miranda, R. M. Johnson and H. I. Krebs, "Convolutional Neural Networks and Transfer Learning for Quality Inspection of Different Sugarcane Varieties", in IEEE Transactions on Industrial Informatics, Volume 17, Issue 2, pp. 787–794, February 2021.

[2] Wei Li, Tengfei Zhu, Xiaoyu Li, Jianzhang Dong and Jun Liu, " Recommending Advanced Deep Learning Models for Efficient Insect Pest Detection", in MDPI on Application of Machine Learning in Agriculture , Volume 12, Issue 7, 1065, pp. 1–17, June 2022.

[3] D. Elavarasan and P.M.D. Vincent, "Crop Yield Prediction Using Deep Reinforcement Learning Model for Sustainable Agrarian Applications", in *IEEE Access*, Volume 8, pp. 86886–86901, April 2020.

[4] K.S Neethu and P. Vijay Ganesh, "Leaf Disease Detection and Selection of Fertilizers using Artificial Neural Network", in IRJET on Computer Science Journal, Volume 4, Issue 6, pp. 1852–1858, June 2017.

[5] T. Daniya and Dr.S. Vigneshwari, "Deep Neural Network for Disease Detection in Rice Plant Using the Texture and Deep Features", The Computer Journal, Volume 65, Issue 7, pp. 1812–1825, July 2022.

[6] R. Salini, A. Farzana and B. Yamini, "Pesticide Suggestion and Crop Disease Classification using Machine Learning", in IRJET on Computer Science Journal, Volume 11, Issue 4, pp. 27997–27999, April 2021.

[7] S.I. Hassan, M.M. Alam, U. Illahi, M.A. Al Ghamdi, S.H. Almotiri and M.M. Su'ud, "A Systematic Review on Monitoring and Advanced Control Strategies in Smart Agriculture", in *IEEE Access*, Volume 9, pp. 32517–32548, January 2021.

[8] T. Daniya and Dr.S. Vigneshwari, "Exponential Rider-Henry Gas Solubility optimization-based deep learning for rice plant disease detection", in Springer, International Journal Of Information Technology, pp. 1–11, July 2022.

[9] F.T. Pinki, N. Khatun and S.M.M. Islam, "Content based paddy leaf disease recognition and remedy prediction using support vector machine," 20th International Conference of Computer and Information Technology (ICCIT), pp. 1–5, December 2017.

[10] Junde Chen, Defu Zhang, Yarser A Nanehkaran and Dele Li, "Detection of rice plant diseases based on deep transfer learning", Journal of the Science of Food and Agriculture, Volume 100, Issue 7, pp. 3246–3256,

March 2020.

[11] Senthil Kumar Swami Durai and Mary Divya Shamili, "Smart farming using Machine Learning and Deep Learning techniques", Decision Analytics Journal, Volume 3, 100041, ISSN 2772–6622, pp. 1–30, March 2022.

[12] R. Alfred, J.H. Obit, C.P.Y. Chin, H. Haviluddin and Y. Lim, "Towards Paddy Rice Smart Farming: A Review on Big Data, Machine Learning, and Rice Production Tasks", in *IEEE Access*, Volume 9, pp. 50358–50380, March 2021.

[13] S. Mishra, D. Mishra and G.H. Santra, "Applications of Machine Learning Techniques in Agricultural Crop Production: A Review Paper", Indian Journal of Science and Technology, Volume 9, Issue 38, pp. 1–14, October 2016.

[14] T. Daniya and Dr.S. Vigneshwari, "A Review on Machine Learning Techniques for Rice Plant Disease Detection in Agricultural Research", International Journal of Advanced Science and Technology, Volume 28, Issue 13, pp. 49–62, October 2019.

[15] H. James Deva Koresh, "Analysis of Soil Nutrients based on Potential Productivity Tests with Balanced Minerals for Maize-Chickpea Crop", Journal of Electronics and Informatics, Volume 3, ISSN 2582–3825, Issue 01, pp. 23–35, March 2021.

[16] J. Sustain, DR. D. Sivaganesan, "Performance Estimation of Sustainable Smart Farming with Blockchain Technology", Wireless Systems, Volume 03, ISSN 2582–3167, Issue 02, pp. 97–106, June 2021.