



## **Machine learning-based Prediction of Cotton farming using ARIMA Model**

Saima Malik<sup>1</sup>, Naveed Umar<sup>2</sup>

<sup>1</sup> MPhil Scholar, Department of Computer Science and Technology, The Islamia University of Bahawalpur, Pakistan.  
Email: Samimalik1616@gmail.com

<sup>2</sup> MPhil Scholar, Department of Computer Science and Technology, The Islamia University of Bahawalpur, Pakistan.  
Email: naveedumarbwp@gmail.com

### **ARTICLE INFO**

#### **Article History:**

Received: August 05, 2021

Revised: October 25, 2021

Accepted: December 29, 2021

Available Online: December 31, 2021

#### **Keywords:**

Cotton crop

ARIMA model

Agriculture industry

Prediction

Machine learning.

### **ABSTRACT**

Disease detection in agriculture is critical in severe weather conditions. Keeping an eye on many cotton fields is challenging for farmers. Deep learning and image processing identify agricultural ailments before they spread and further damage. Cotton crop with the most important correlation quantities among pest disease existence are inspected by predictors. In this study, transfer learning methods for analysis are checked. The machine learning approach developed accurately distinguishes healthy and unhealthy plants. As a result, the proposed model may be used to monitor a wide range of areas for more rapid analysis and action, leading to increased productivity. It is possible to anticipate a timeline using ARIMA. A long-term study reveals that the value swipes widely during short and long periods due to random influences. It is also inspected how the recommended approach is affected by using several cotton crop characteristics. In addition to separating green crops from other crops in the field, this procedure can also separate harvests such as Cotton from other crops.



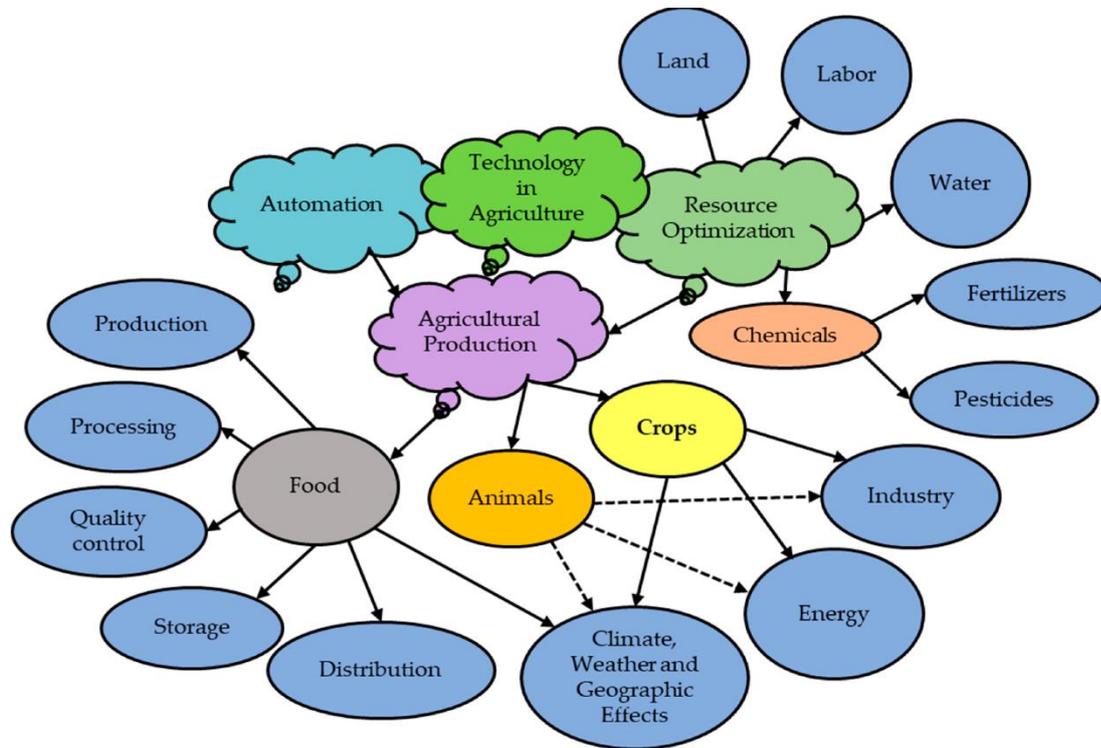
© 2021 The Authors, Published by iRASD. This is an Open Access article under the Creative Common Attribution Non-Commercial 4.0

Corresponding Author's Email: [Samimalik1616@gmail.com](mailto:Samimalik1616@gmail.com)

## **1. Introduction**

The weather has a much more significant impact on agriculture. Crop pest and disease populations are frequently linked to meteorological conditions. This association can only be discovered by watching for pests and diseases. It is possible to anticipate the appearance of pests and diseases based on this correlation (Durgabai, Bhargavi, & Jyothi, 2019; Jamuna et al., 2010). The problems and conditions that can harm cotton crops are being studied as part of this research. The cotton industry employs 42 million people, mostly small-scale farmers pests and diseases in cotton cause massive losses, exacerbated by poor soil and weather. Pests and diseases are currently causing cotton yields to drop from 5% to 15%. Losses of up to 50% may result from a lack of safety and control procedures (Ramesh & Vydeki, 2018; Virnodkar, Pachghare, Patil, & Jha, 2020).

Getting rid of pests before they get a foothold in the crop field is one way to prevent outbreaks. Recently integrated pest control studies have found that meteorological conditions significantly affect pest and disease infestations. Integrated pest control in Cotton necessitates an effective pest and disease surveillance system (IPM). Plant protection measures can be implemented only when necessary to save money and clean the environment (Rehman, Akhtar, & Alhazmi, 2021). Pests and diseases can be predicted using machine learning techniques. Employed an extensive residual network to classify problems that significantly impact cotton productivity. Figure 1 showed the Attribute of agriculture production



**Figure 1 Attribute of Agriculture Production**

Pest and disease management rely heavily on forecasting models. It is crucial to consider its life cycle. An agriculture framework was created to explain how pests and illnesses are related to weather, IoT devices, and drones. A comprehensive examination of the literature on pest and disease forewarning revealed the following research needs (Mishra, Mishra, & Santra, 2016).

When it comes to agricultural automation, even using a single method to locate specific crops, it's tough to separate photographs acquired in the field into different crops. Cotton, one of the country's four major cash crops, is critical to its expansion by (Y. Li, Cao, Xiao, Lu, & Zhu, 2015). The crop classifier is set up in this paper's RGB vector colour space using a new technique. Deep learning is used to implement this strategy. Many wild cotton fields have had crops observed with digital cameras, although this method of segmenting crops is still understudied. This study illustrates how cotton plants and raw Cotton grow in a cotton field to show how the proposed method works. According to tests (natural Cotton), our solution outperforms existing algorithms for segmentation cotton plants tests (raw Cotton).

## 2. Literature Review

In precision farming, IFC segmentation is an intricate problem that has not been adequately addressed. Deep Cotton, a coarse-to-fine cotton segmentation technique, is recommended by Cao *et al.* 2017 (Y. Li, Cao, Xiao, & Cremers, 2017). The FCN stream and the interference region reduction stream are two separate streams. As a first step, an end-to-end prediction is made using FCN. The FCN's ability to perform regression analysis and the convolutional networks that make up the FCN allow it to segment objects accurately. "UP" is an approach that uses unary brightness transformation and pairwise region comparison to produce an interference map that can be used to enhance the coarse map. Our technique outperforms previous methods that have been tested on the IFC dataset. Whether it's a single or numerous plants, this holds. With the "UP" algorithm, coarse results are much improved.

Khobragade and Raghuwanshi (2015) represented that the Prediction of many crops and acres of land in the state relies heavily on agricultural forecasts. Commodity markets estimate crop production based on how many crops are available for sale and field forecasts from organizations like Crop Advisory Board. Crop acres can be obtained as usual, but it is

time-consuming, pricey, and impossible for an entire county. Agricultural acreage data becomes more critical in a natural disaster for making informed decisions, such as compensating farmers for their losses. Because of the lack of reliable and thorough projections, agrarian commodity prices need to be established according to a consistent strategy. Finally, the application of machine learning algorithms to analyze remote sensing photos has shown to be a superior technique to track crops than complex classification methods. Machine learning algorithms that can be utilized to analyze satellite data were discussed in this research.

Agricultural workers worldwide are dealing with a great deal of difficulty because of rice blast illness. Farmer losses will be minimal if this illness is spotted early. Plant diseases can be detected using a machine learning system. For the new method being established, photographs of vigorous and blight-infected leaves are taken recommended by (Ramesh & Vydeki, 2018). The characteristics of the rice leaf's healthy and sick portions are considered. All the photos in the data set are divided into training and testing sets of 300 images. There are two distinct representations of a leaf in these photographs.

Rani, Jakka, and Kanuru (2022) demonstrated that farming contributes significantly to economic growth. To meet the ever-increasing demand for food, farmers play an essential role in ensuring that adequate high-quality food supplies are produced. Various factors, including plant disease, can harm crop yields. Early detection of plant diseases could have a significant impact on the success of farmers. They may be able to reduce their risk and generate more money. Plant disease detection must be automated to prevent its spread and minimize its impact on the environment. An image processing and ensemble machine learning system that may be used to identify and analyze plant diseases is the focus of this study.

The number of cotton plants in a given area is critical to replanting in regions with low plant density, reducing yields. It takes a long time and can be imprecise to count plants in the field recommended by (Oh et al., 2020). This study uses photos from unmanned aircraft systems to calculate plants uniquely (UAS; DJI Mavic 2 Pro, Shenzhen, China). Plant canopy feature geometry and statistical properties were too complex for previous image-based algorithms to be applied effectively in a wide range of field situations. A deep learning-based plant counting technique was presented to reduce the number of variables and eliminate the necessity for geometric or statistical information. The suggested approach was tested on four different UAS datasets.

Plant size, overall light, and background brightness varied widely among these datasets. As a result of the object detection algorithm's training on various plant sizes, ground wetness, and lighting circumstances, the system had an error rate than it would have been if it hadn't been trained on Cotton. Cotton seedlings are typically easy to distinguish from one another at this stage. New plant counting algorithms functioned well when 0–14 plants per linear meter of row. This research aims to figure out how to use UAS data to determine how quickly plants develop in the field.

Abdazimov, Radjabov, and Omonov (2019) presented that Cotton harvesting machine reviewers claim that they can only tell how well the machines perform by looking at digital photos of cotton rows before and after harvesting. There are algorithms and software that can be used to figure out how well a cotton harvester is working and how well the field's agricultural background is represented in photographs taken from various perspectives. Using the proposed method, testing machines may be done in a segment of the time and cost, and their performance can be quickly assessed while the tests are still in progress. Automated testing can take advantage of the software and hardware already in existence. Agricultural machinery, particularly cotton harvesting machines, can also be monitored and controlled using this technology.

Bodhe, Taiwade, Yadav, and Aote (2018) displayed that detecting and diagnosing disease patterns are critical in a research project. Cotton plant diseases are typically observed on the plant's leaves, blooms, or fruits. Cotton leaf diseases will be the subject of study and investigation. Prototypes for Android mobile apps can be made by combining templates. New technology has been developed to detect the early stages of disease patterns.

The cotton crop can be effectively combated with the fungicide elutriator, widely available at agricultural supply stores by (Yang et al., 2015). It is necessary to identify where it is present in fields so that site-specific technology may be utilized to apply fungicide solely to the afflicted areas. There were six supervised classification techniques, including NDVI, minimum distance, Mahalanobis distance, maximum likelihood, spectral angle mapper (SAM), neural net, and support vector machine (SVM), that could be used to map cotton root rot from airborne multispectral imagery, and it was essential to see how well they worked. Root rot has affected two cotton fields in Texas the USA; therefore, they were chosen for this investigation (Kantale & Thakare, 2020; Ramesh & Vydeki, 2018; Virnodkar et al., 2020). Before harvesting in 2011, the disease had spread to all lots; hence the photographs were captured in various colours. Four-band pictures were separated into infected and uninfected areas by eight changed methods. Indexes ranging from 0.90 to 1.00 indicate high levels of categorization agreement between the eight various methods used in both sectors. Root rot-infected sites could be accurately identified using eight tested methods. Cotton root rot can be found using any of these eight approaches, and they all seem to be equally effective in pinpointing the exact location of the illness. The NDVI-based categorization and the NDVI-based minimum distance and SAM can be easily implemented without complicated image processing. Cotton farmers and crop advisors can use these techniques to create maps that are both successful and inexpensive for controlling root rot in Cotton

### 3. Background Studies

Precision farming relies heavily on identifying cotton fields from photographs captured by remote sensing systems suggested by H. Li et al. (2021). This study aims to locate cotton fields in China's Wei-Ku region using high-resolution (16 m) photos from the Gaofen1 satellite (GF-1). The compactly connected neural network (Dense Net) was improved by using an rationalized model. Convolutional neural networks ResNet, VGG SegNet, and DeepLab v3+ are well-known classics (CNNs). To ensure the accuracy of the results, they also employed them. DenseNet's training convergence results suggest quickly identifying cotton crop characteristics. Since the introduction of the DenseNet Model, it has made significant progress over the other key models. When it came to accuracy got an F1 score of 0.948, an MIou of 0.911, and retrieval precision got an F1. As long as mountains or buildings in its path don't cast any clouds or shadows, it is far more effective than other techniques at determining the delicate structures of cotton fields.

Prashar, Talwar, and Kant (2019) showed that Pest infections and bacterial or viral contagions cost the cotton farming business money. An estimated 10% to 20% of Indian farmers' profit is lost each year. According to one theory, the visual traits of cotton leaf diseases can determine which ones are harmful. This research demonstrates the use of an expert system to detect crop diseases in a collection of photographs. An MLP system employing flexible stacking has been developed to categorize the leaves to distinguish between diseased and healthy plant leaves. This has been accomplished using overlapping pooling. To locate corresponding portions in a database, the graph-based MLP network model has been utilized to modify the orientation of features. KNN and SVM are employed for the overlap layer of Classification to reduce the risk of incorrect double-layered modelling. This Model can identify the sick area with greater than 96% accuracy using morphological segmentation, pattern matching, and colour matching.

There has been a long history of research on satellite-based remote sensing (RS). Sugarcane crops' chlorophyll meditation has been restrained using RS techniques to preserve tabs on them by Narmilan et al. (2022). Unscrewed aerial vehicles (UAVs) and spectral vegetation indices processed with multiple machine learning algorithms provide a new method for determining how much chlorophyll sugarcane plants have at the canopy level in this study. The Sugarcane Research Institute in Uda Walawe, Sri Lanka, conducted research from 2020 to 2021 on various fertilizer applications in a sugarcane field. The aerial photos used to create the vegetation indices were obtained using an unmanned aerial vehicle (UAV) equipped with a multispectral camera. To determine how much fertilizer was in the sugarcane field, leaf chlorophyll was measured on the ground. It was possible to anticipate the amount of sugarcane chlorophyll in the area next Year. Before feature

selection (BFS) and after feature selection (AFS) were two methods of using machine learning algorithms (AFS). All twenty-four vegetation indices with five spectral bands were used to train the algorithms before feature selection, and only fifteen vegetation indices were used to prepare the algorithms after feature selection was performed. Algorithms that employed both BFS and AFS approaches were compared using R2 and root mean square error (RMSE). Researchers discovered that using spectral indices like RVI and DVI to determine the amount of chlorophyll in sugarcane fields was the most accurate method yet.

R2 was 0.94 and 0.93, respectively, for them. The XGB model, which has a high R2 and a low RMSE, is used by both BFS and AFS. However, the KNN and SVR algorithms have the worst accuracy when testing. ACCORDING TO THESE FOUR EXPERIMENTS, the AFS validation score is higher than the BFS score in MLR, XGB, and KNN. Regardless of how low the ANN model's AFS validation score may be, it is still valid. Over a vast sugarcane field, a multispectral UAV can be utilized to determine chlorophyll content and assess crop health. The old-fashioned method of measuring sugarcane chlorophyll concentration will be eliminated, making it simpler to regulate sugarcane plant nutrition in real-time

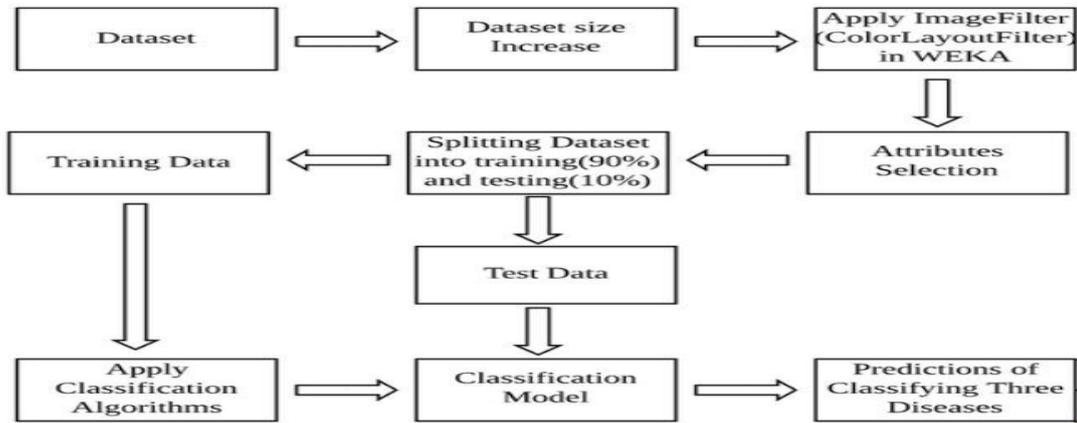
#### 4. Methodology

The training step is completed to ensure that the Model is precise and stable. Eight datasets (DS1-DS8) were used to test the proposed system's ability to forecast when pests would appear. Table 1.1 displays the pertinent information.

**Table 1**  
**Average growths and ripening of the cotton plant**

STAGE	PERIOD	PLANT AGE
Planting to emergence	4 to 10 days	4-10 days
Emergence to first true leaf	8 days	12-18 days
Emergence to second true leaf	9 days	21-27 days
Second true leaf to pinhead square (seventh node)	18 to 21 days	39-48 days
Pinhead square to matchhead square	9 to 10 days	48-58 days
Matchhead square to first one-third grown square	3 to 6 days	51-64 days
First one-third grown square to first white bloom	12 to 16 days	63-80 days
First white bloom to first open bolls	40 to 60 days	103-140 days
Harvest bolls set on first four weeks of blooming	96%	91-128 days

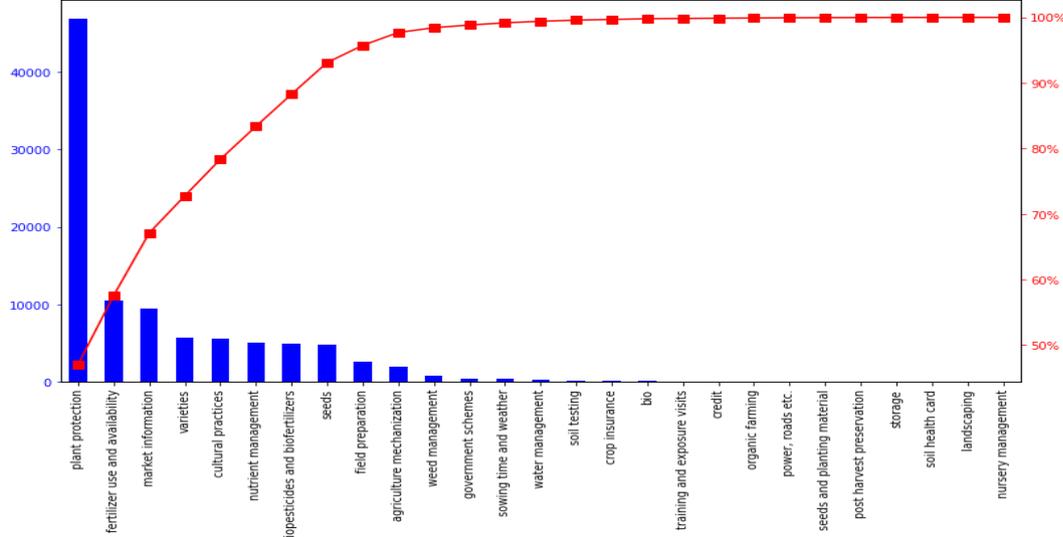
It's a part of the feature industrial: Time Series Mechanisms are used by those employed on this issue. For the problem, the graphs above are visible. Might argue that the type of question, or Target, is seasonal and shifts depending on the time of the Year (Kumar, Ratan, & Desai, 2022; Rajak et al., 2017). Figure demonstrated 2 Block diagram cotton crop using a machine learning approach Target has a distinct style (Not the same thing all the time). To keep track of the seasonality of the weather, I'm going to use some essential characteristics.



**Figure 2. Block Diagram Cotton Crop sing a Machine Learning Approach**

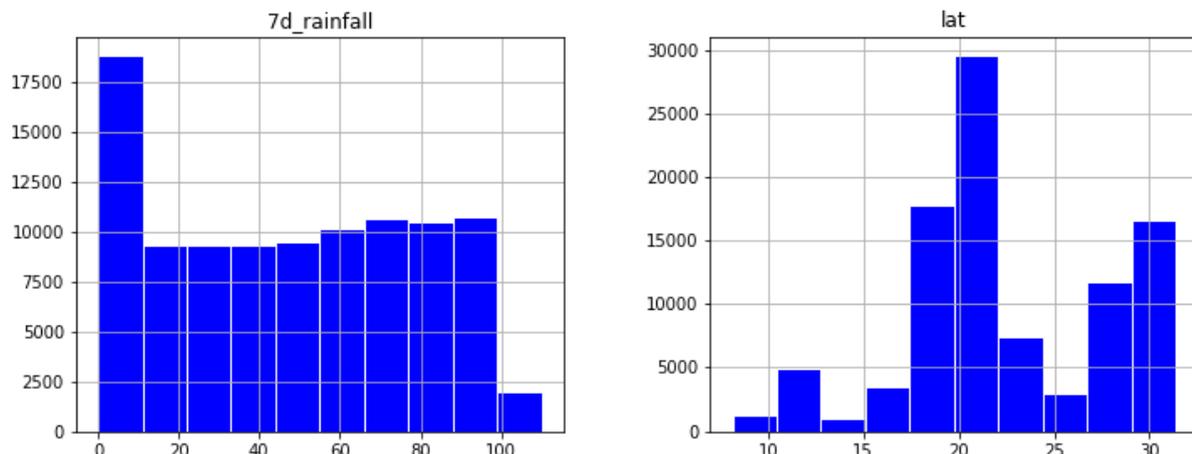
**4.1 Dataset**

These data (Mat, MinT, MRH, ARH, ERH, WD, and RF) were collected over two years using sensor networks. Weather conditions were resolute by analyzing chronological data from the India Meteorological Department's 2012–2018. Figure 3 represents the classification values of crop plant varieties. Scales are available in increments as large as 1164. Large datasets were utilized to accomplish what has been outlined above (Akhtar et al., 2019).



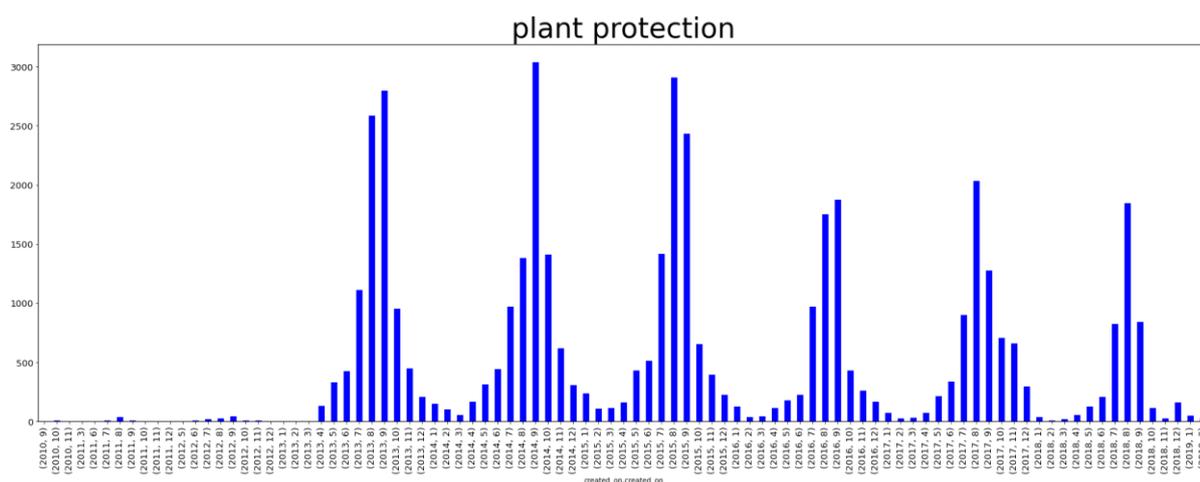
**Figure 3. Classification Values of Crop Plant Varieties**

Week of the Year, a fortnight of the Year, or a month are all acceptable options. Climate changes use the Year as a placeholder for a new feature because it will be more dynamic and less seasonal as time (Pagariya & Bartere, 2014). Figure 4 demonstrated Rainfall comparison early week or delay. However, to investigate the possibility of adding the Year to the Classification.

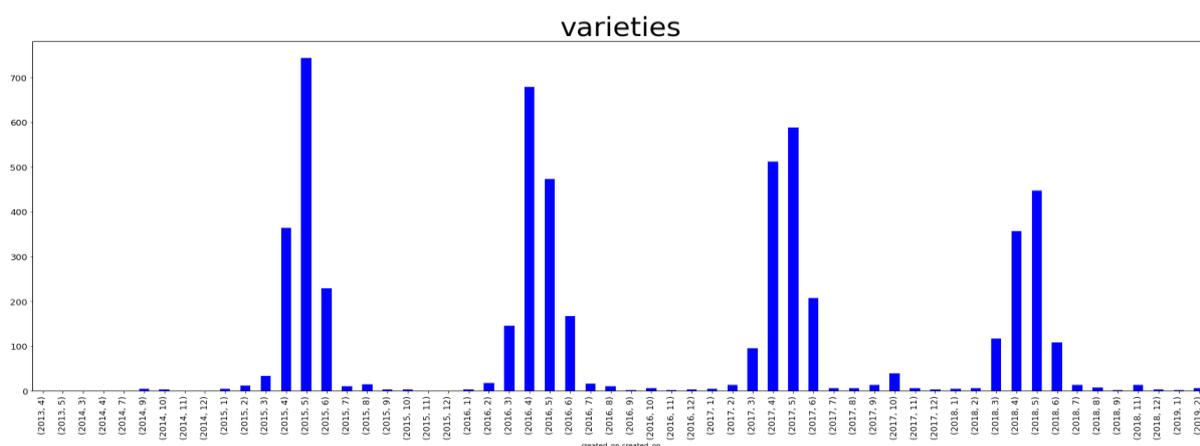


**Figure 4. Rainfall Comparison Early Week or Delay**

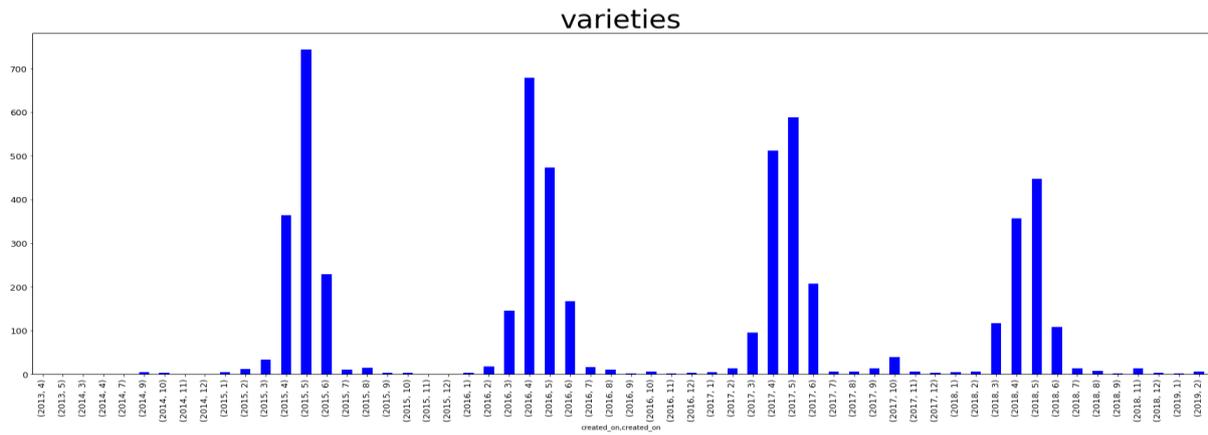
According to this hypothesis, it doesn't matter when it was made or how long it took to obtain it. The Inverse of Term Frequency will be used to find things in the raw text (query text essential). The Sklearn API can be used to extract features(Nandy & Singh, 2020). TF-IDF isn't awful because the text is all on one line. TF-IDF might not have worked as effectively as it should have if there were long phrases and Saccasam in the raw text body. To find out the relationship depicted in the diagram below. 5, 6 and 7 represent the categories of plant protection, varieties, and seeds.



**Figure 5. Crop Plant Protection Varieties**

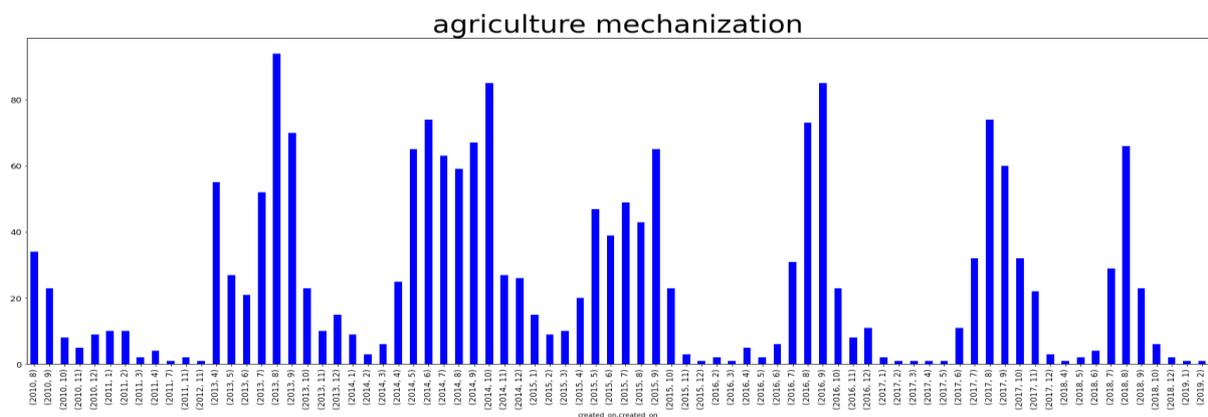


**Figure 6. Crop Plant Varieties Fertilizers**



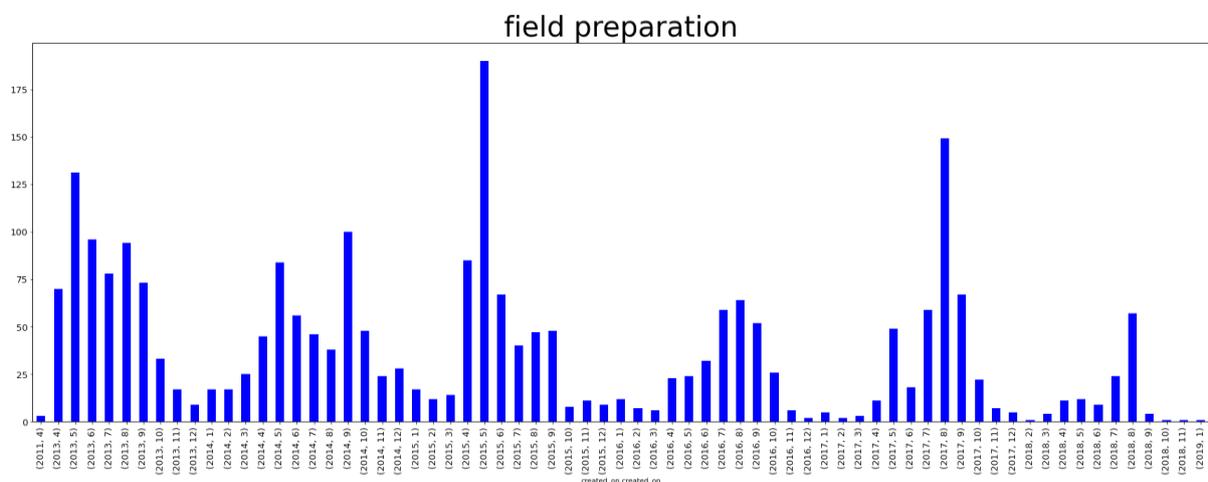
**Figure 7. Crop Plant Varieties Seeds**

The types of queries are seasonal features, query text raw, state name, district name, and 7-day rainfall in lat and longitude. TF-IDF features are also included. Feature and encoding modifications B: There are many people at most features. Groups of components can be found here. Because there are so many things to do, it's not a good idea. Figure 8 shows crop plant agriculture mechanization varieties.



**Figure 8. Crop Plant Agriculture Mechanization Varieties**

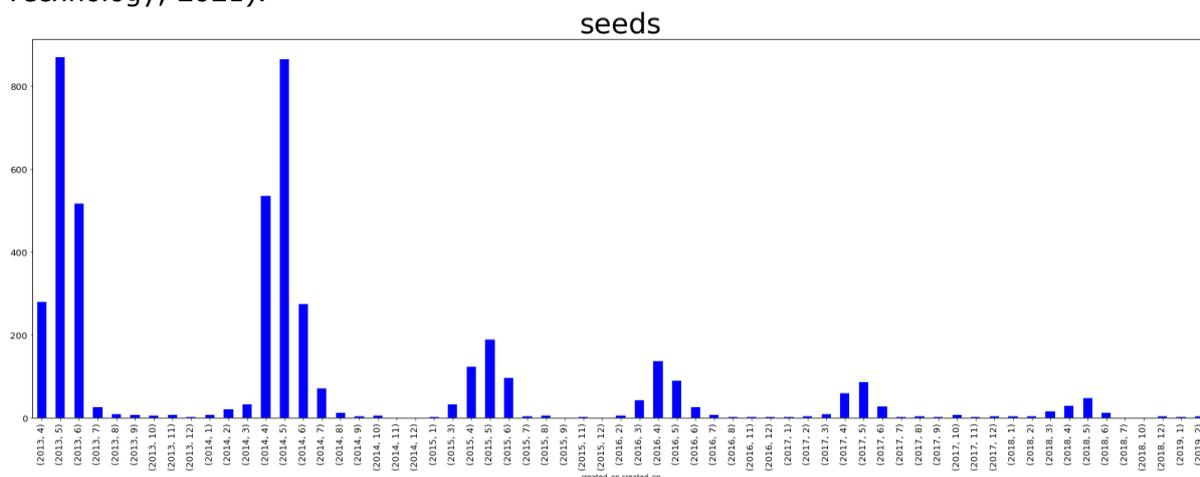
Model selection in step C. There are a number of them. However, Logistic Regression is what I'd like to begin with. It's a simpler model that indicates how well the model will perform in practice. Figure 9 presents crop plant field preparation A Linear Model is the best option if the data are linked linearly. When it comes to creating stuff, it's a godsend. Logistic Regression can't do all of these things.



**Figure 9. Crop Plant Field Preparations**

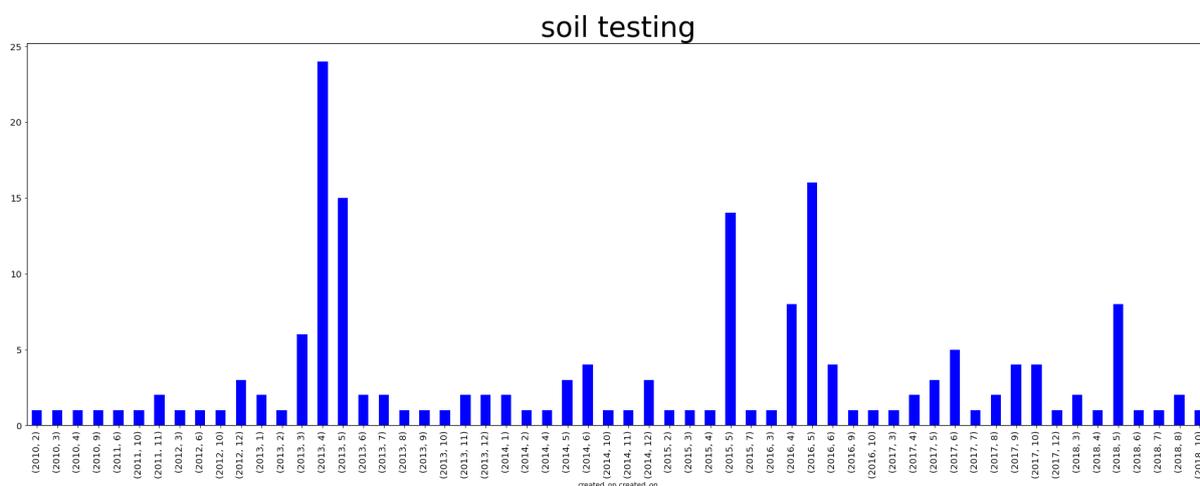
XOR relationships like this one don't work well for it: Problem: Let's imagine that have  $x_1 = 1, 0, 0, 1$ ; and  $x_2 = 1, 0, 1$ . Then get the value of  $y = 0$ .  $P(y=1|x_1=1)$  and

$P(y=1|x_2=1)$  are both 0 in this situation. It follows then that  $y = 1$  and  $x_2 > 1$  are both equal to 0. Because Sklearn does not have a Logistic Regression API that encodes the target, which can handle massive category features. Figure 10 showed that crop plant seeds varieties Boost CatBoost does a great job because the data is nonlinear(Qadri & Technology, 2021).



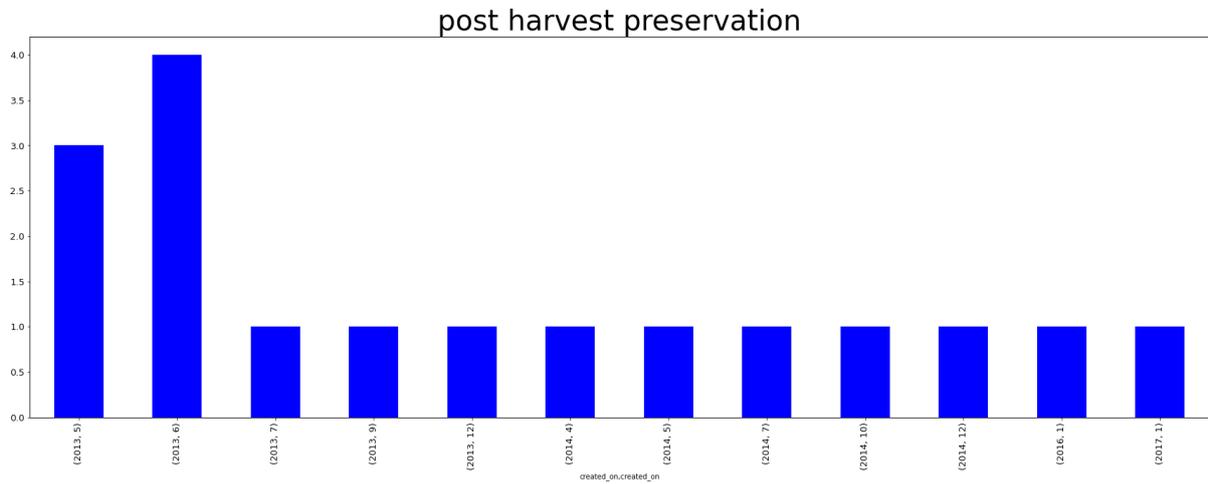
**Figure 10. Crop Plant Seeds Varieties**

Especially when there are many data, it works well. It's capable of handling a wide range of functions. The API does not need to be encoded before using internal implementation—figure 11 displayed crop plant-soil testing. Gradient Boosting is limited in the following ways. Because GBM is composed of trees, monotonic numerical characteristics don't perform well. "7-day Rainfall Feature" could be a better name for our situation. An illustration can help clarify



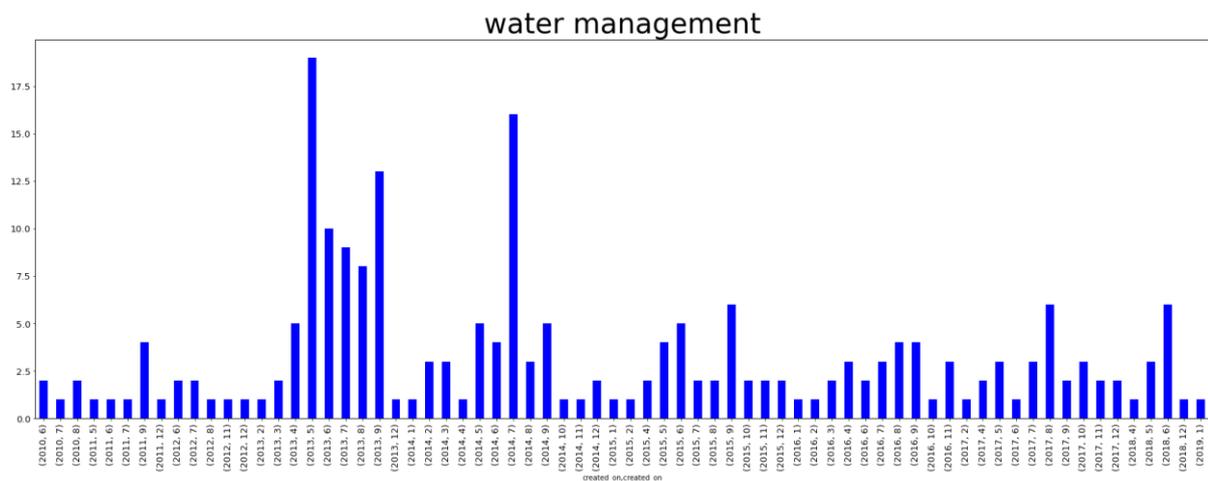
**Figure 11. Crop Plant-soil testing**

Let's travel back in time for a moment. How it works:  $x=1,2,3,4$ ;  $y=1,4,6,8$ ;  $x=1$  With the data I've provided, I'm able to build a GBM model. The model will then yield an average of  $x = 5$ , i.e.  $x = 1, 2, 3, 4$ , and  $5 \times 5 = 5$ . Instead, it's close to ten. Even while a linear model can demonstrate this, it does not. D: The Cross-Validation Approach. Figure 12 demonstrated crop plant post-harvest preservation.



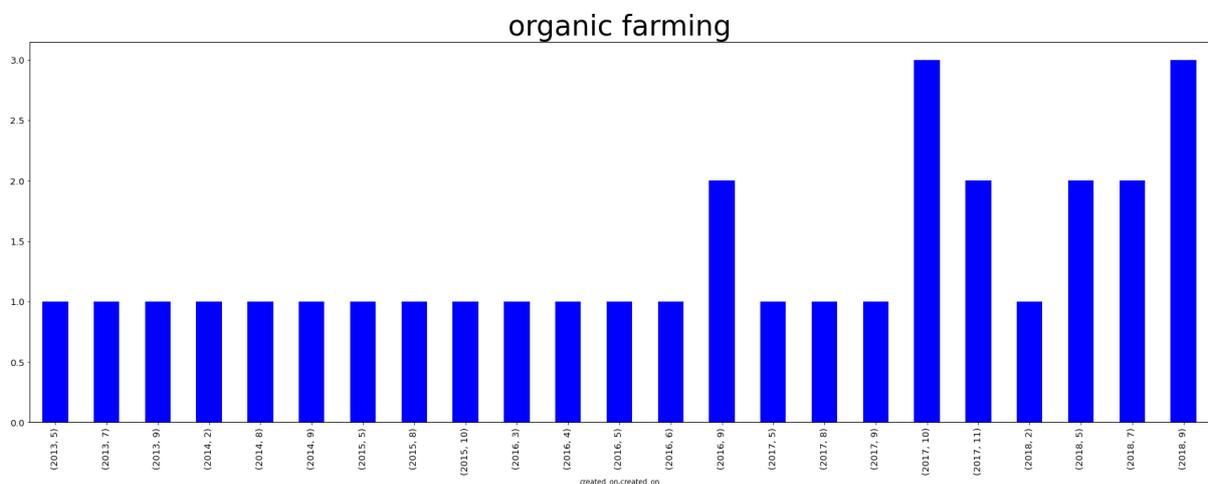
**Figure 12. Crop Plant Post-harvest Preservation**

Model Evaluation in E: Choosing the Loss Function and Metric a lot about this is complex. Seeing things from a variety of perspectives is possible. Here are a few of the metrics that should utilize for multiclass categorization. Figure 13 represents the crop plant water management.



**Figure 13. Crop Plant Water Management**

Picking a Feature Making a model more accurate can be accomplished in various ways. The model could be made more accurate by using this method to remove noise (Balducci, Impedovo, & Pirlo, 2018; Nesarani, Ramar, Pandian, & Innovation, 2020). Figure 14 displays the crop plant organic farming.



**Figure 14. Crop Plant Organic Farming**

Two approaches were utilized to classify information: decision-tree classification and case-based classification. Clusters of data were discovered using a variety of techniques. Predicting when pests and diseases might appear was more accessible with the weka tool. Used microclimate data from previous years to begin creating time-series data. Figure 15 displays correlation analysis-based Prediction.

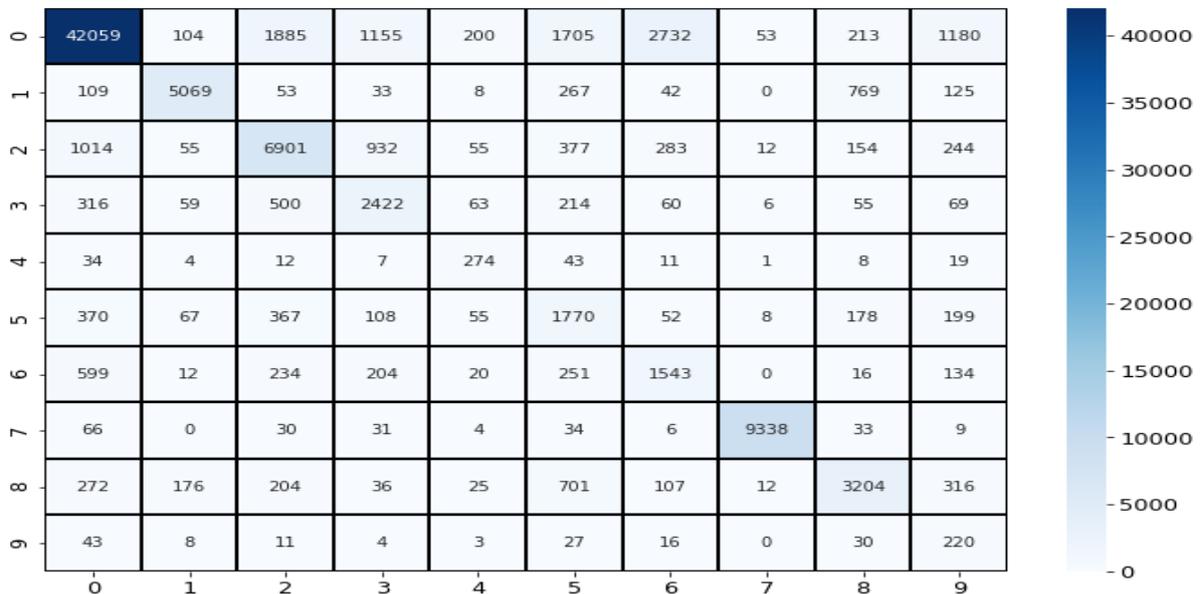


Figure 15. Correlation Analysis based Prediction

Additional characteristics were also based on seasonality (day of the week), trend (weekday or weekend), and time (time zone). The data was plotted as a line chart to visualize the climate. In the microclimate data, there is a distinct trend. The significance of three p values was found (0.01, 0.05, and 0.1). Figure 16 showed Catboost feature prediction. Many people devised a method for determining the current level of pest and disease activity and the degree of seasonal variation experienced over the previous one or two weeks.

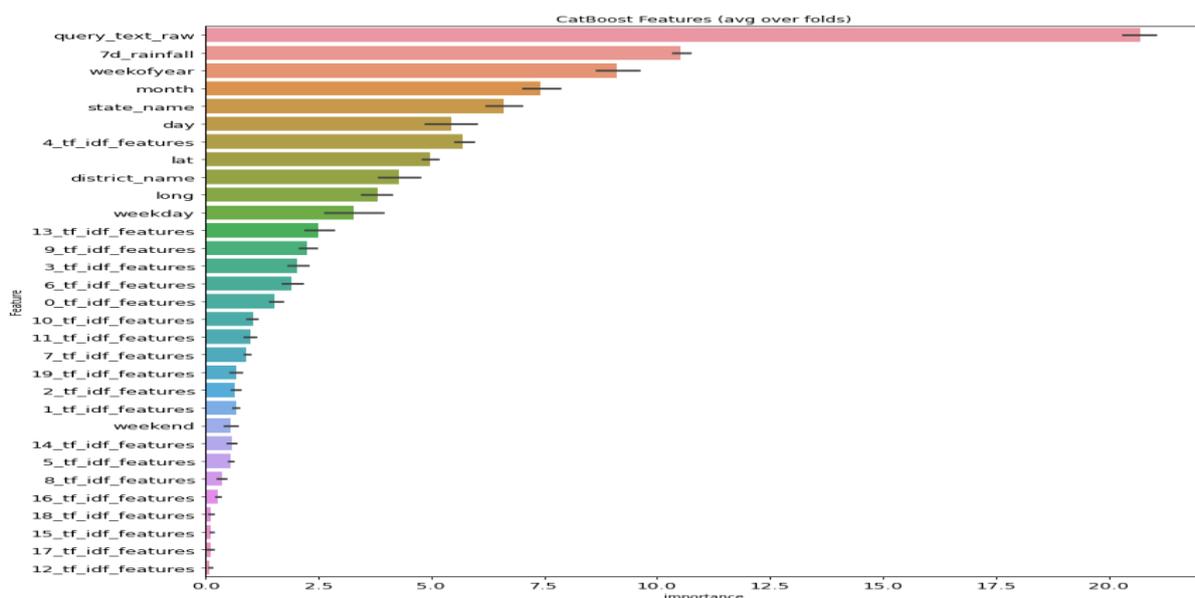
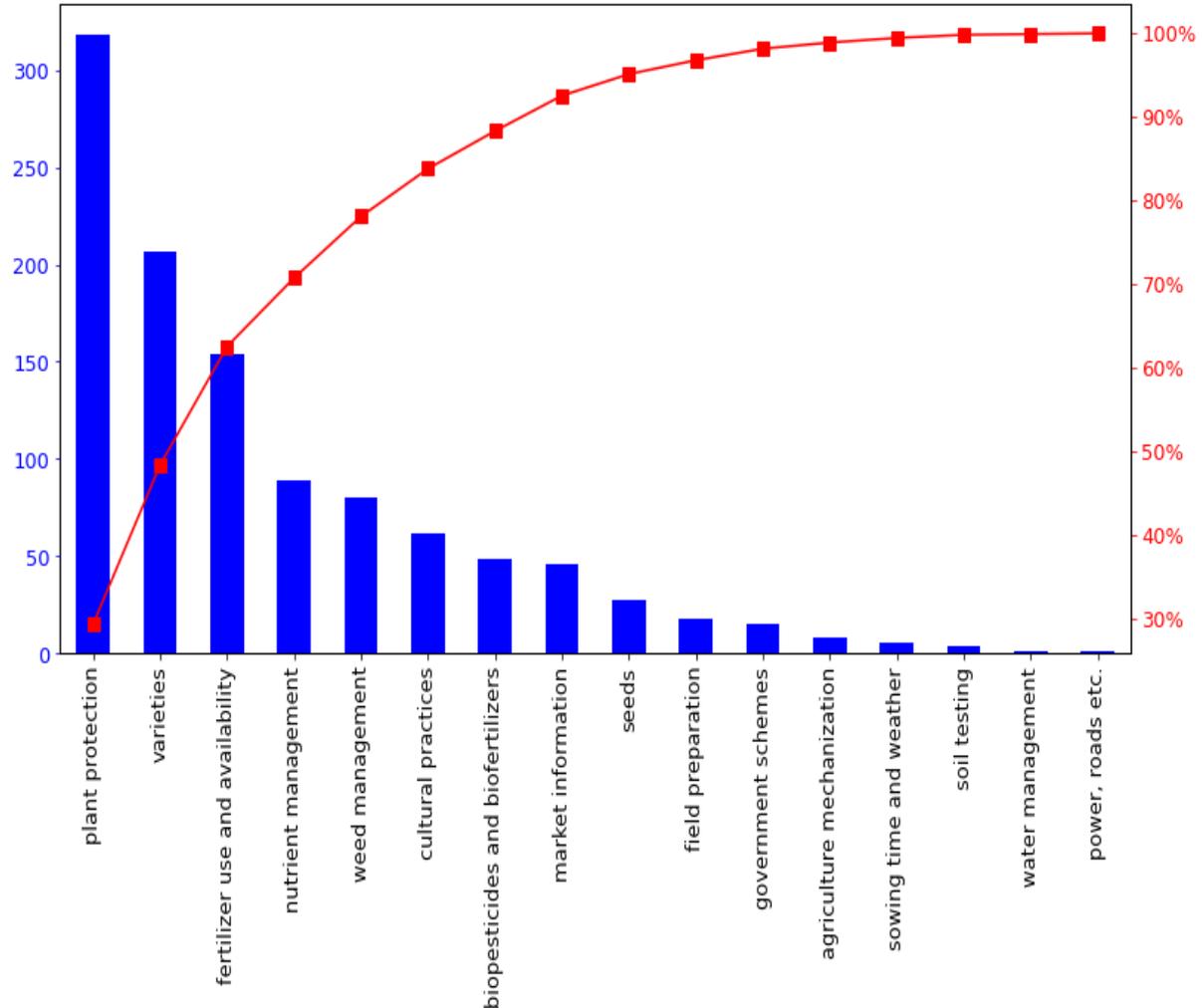


Figure 16. Catboost Feature Prediction

For pests and diseases in cotton crops once a week, the autoregressive integrated Model (ARIMA) was applied. Climate with the most important correlation coefficients among pest disease occurrence and pest disease incidence in the preceding week were scrutinized by predictors. It is possible to anticipate a timeline using ARIMA. A long-term analysis reveals that the value swings widely during short and long periods due to random

influences. It is called autoregressive if the initial values of the variable impact the current values of the series (Balducci et al., 2018; Nesarani et al., 2020).

It is necessary to make use of several linear regression models. In this experiment, we're looking for the correlation between the dependent variable and the other factors. Figure 17 represents the Attributes vales comparison for crop plants. There were three parameters to examine in the ARIMA model ( $p$ ,  $d$ , and  $q$ ).  $P$ , the first parameter, is the autoregressive parameter that quantifies how the values interact over time.



**Figure 17. Attributes Vales Association for Crop Plant**

Respectively value in the series is affected by the early value in the sequence in a first-order auto regression. It's  $D$ , the second one. Climate variations want to know how often a time series changes (Papageorgiou, Aggelopoulou, Gemtos, Nanos, & agriculture, 2013) how many non-seasonal variations among a set of values and its predecessors. The third parameter,  $q$ , represents the number of past forecast errors.

## 5. Conclusion

To help farmers get the answers they need quickly, an app and an interactive voice response system were created. The proposed method provides the best detection rate and the fewest false alarms according to the testing results. Other methods, such as the ANN and SVM, were tested against the suggested approach to see how well it performed. It was found that the proposed model was more accurate, had a lower average root-mean-square error, and had a lower average percentage error compared to other work. Aside from the obvious financial benefits of using less pesticide and producing more Cotton, lands also considered the environmental benefits of switching to the new system. Since pesticides were used correctly and properly, the service cost was reduced, with no pesticide residues. As a result, an autocorrelation plot (ACP) created the ARIMA model using stationary time-

series data. Data from the farm field and model predictions were used to test the ARIMA model. Forecasting pest and ailment incidences using microclimate data is complete more manageable by ARIMA. Preventing pests and diseases from spreading is one of the many benefits e-agriculture products can provide farmers with Prevention and control measures. Many web and mobile technologies are available to assist farmers in receiving critical alert information.

## References

- Abdazimov, A., Radjabov, S., & Omonov, N. (2019). *Automation of agrotechnical assessment of cotton harvesting machines*. Paper presented at the Journal of physics: Conference series.
- Akhtar, N., Rehman, A., Hussnain, M., Rohail, S., Missen, M. S., Nasir, M., . . . Pasha, M. J. I. A. (2019). Hierarchical coloured petri-net based multi-agent system for flood monitoring, prediction, and rescue (fmpr). 7, 180544-180557. doi:10.1109/ACCESS.2019.2958258
- Balducci, F., Impedovo, D., & Pirlo, G. J. M. (2018). Machine learning applications on agricultural datasets for smart farm enhancement. 6(3), 38. doi:10.3390/machines6030038
- Bodhe, K. D., Taiwade, H. V., Yadav, V. P., & Aote, N. V. (2018). *Implementation of Prototype for Detection & Diagnosis of Cotton Leaf Diseases using Rule Based System for Farmers*. Paper presented at the 2018 3rd International Conference on Communication and Electronics Systems (ICCES).
- Durgabai, R., Bhargavi, P., & Jyothi, S. (2019). *Classification of Cotton Crop Pests Using Big Data Analytics*. Paper presented at the International Conference On Computational And Bio Engineering.
- Jamuna, K., Karpagavalli, S., Vijaya, M., Revathi, P., Gokilavani, S., & Madhiya, E. (2010). *Classification of seed cotton yield based on the growth stages of cotton crop using machine learning techniques*. Paper presented at the 2010 International Conference on Advances in Computer Engineering.
- Kantale, P., & Thakare, S. (2020). *A review on pomegranate disease classification using machine learning and image segmentation techniques*. Paper presented at the 2020 4th International conference on intelligent computing and control systems (ICICCS).
- Khobragade, A. N., & Raghuwanshi, M. M. (2015). Contextual soft classification approaches for crops identification using multi-sensory remote sensing data: machine learning perspective for satellite images. In *Artificial Intelligence Perspectives and Applications* (pp. 333-346): Springer.
- Kumar, S., Ratan, R., & Desai, J. (2022). A Study of iOS Machine Learning and Artificial Intelligence Frameworks and Libraries for Cotton Plant Disease Detection. In *Machine Learning, Advances in Computing, Renewable Energy and Communication* (pp. 259-270): Springer.
- Li, H., Wang, G., Dong, Z., Wei, X., Wu, M., Song, H., & Amankwah, S. O. Y. J. A. (2021). Identifying cotton fields from remote sensing images using multiple deep learning networks. 11(1), 174. doi:10.3390/agronomy11010174
- Li, Y., Cao, Z., Xiao, Y., & Cremers, A. B. J. J. o. E. I. (2017). DeepCotton: in-field cotton segmentation using deep fully convolutional network. 26(5), 053028. doi:10.1117/1.JEI.26.5.053028
- Li, Y., Cao, Z., Xiao, Y., Lu, H., & Zhu, Y. (2015). *A novel denoising autoencoder assisted segmentation algorithm for cotton field*. Paper presented at the 2015 Chinese Automation Congress (CAC).
- Mishra, S., Mishra, D., & Santra, G. H. J. I. J. S. T. (2016). Applications of machine learning techniques in agricultural crop production: a review paper. 9(38), 1-14. doi:10.17485/ijst/2016/v9i38/95032
- Nandy, A., & Singh, P. K. J. B. A. I. J. (2020). Application of fuzzy DEA and machine learning algorithms in efficiency estimation of paddy producers of rural eastern India. doi:10.1108/BIJ-01-2020-0012
- Narmilan, A., Gonzalez, F., Salgadoe, A. S. A., Kumarasiri, U. W. L. M., Weerasinghe, H. A. S., & Kulasekara, B. R. J. R. S. (2022). Predicting canopy chlorophyll content in sugarcane crops using machine learning algorithms and spectral vegetation indices derived from UAV multispectral imagery. 14(5), 1140. doi:10.3390/rs14051140

- Nesarani, A., Ramar, R., Pandian, S. J. E. T., & Innovation. (2020). An efficient approach for rice prediction from authenticated Block chain node using machine learning technique. *20*, 101064. doi:10.1016/j.eti.2020.101064
- Oh, S., Chang, A., Ashapure, A., Jung, J., Dube, N., Maeda, M., . . . Landivar, J. J. R. S. (2020). Plant counting of cotton from UAS imagery using deep learning-based object detection framework. *12*(18), 2981. doi:10.3390/rs12182981
- Pagariya, R., & Bartere, M. J. I. J. o. A. R. i. C. S. (2014). Identification of Cotton Crop Diseases and Provide their Remedies using Kmeans Clustering. *5*(8).
- Papageorgiou, E., Aggelopoulou, K., Gemtos, T., Nanos, G. J. C., & agriculture, e. i. (2013). Yield prediction in apples using Fuzzy Cognitive Map learning approach. *91*, 19-29. doi:10.1016/j.compag.2012.11.008
- Prashar, K., Talwar, R., & Kant, C. (2019). *CNN based on overlapping pooling method and multi-layered learning with SVM & KNN for American cotton leaf disease recognition*. Paper presented at the 2019 International Conference on Automation, Computational and Technology Management (ICACTM).
- Qadri, S. J. L. G. U. R. J. o. C. S., & Technology, I. (2021). A Spatial Model of K-Nearest Neighbors for Classification of Cotton (*Gossypium*) Varieties based on Image Segmentation. *5*(1), 25-40. doi:10.54692/Igurjcsit.2021.0501173
- Rajak, R. K., Pawar, A., Pendke, M., Shinde, P., Rathod, S., Devare, A. J. I. R. J. o. E., & Technology. (2017). Crop recommendation system to maximize crop yield using machine learning technique. *4*(12), 950-953. doi:10.1177/1550147719879379
- Ramesh, S., & Vydeki, D. (2018). *Rice blast disease detection and classification using machine learning algorithm*. Paper presented at the 2018 2nd International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE).
- Rani, J. V., Jakka, A., & Kanuru, H. (2022). Disease Detection in Crop Management Using Ensemble Machine Learning. In *Sentimental Analysis and Deep Learning* (pp. 907-916): Springer.
- Rehman, A., Akhtar, N., & Alhazmi, O. H. J. S. P. (2021). Formal Modeling, Proving, and Model Checking of a Flood Warning, Monitoring, and Rescue System-of-Systems. *2021*. doi:10.1155/2021/6685978
- Virnodkar, S. S., Pachghare, V. K., Patil, V., & Jha, S. K. J. P. A. (2020). Remote sensing and machine learning for crop water stress determination in various crops: a critical review. *21*(5), 1121-1155. doi:10.1155/2017/6961387.
- Yang, C., Odvody, G. N., Fernandez, C. J., Landivar, J. A., Minzenmayer, R. R., & Nichols, R. L. J. P. A. (2015). Evaluating unsupervised and supervised image classification methods for mapping cotton root rot. *16*(2), 201-215. doi:10.1007/s11119-014-9370-9