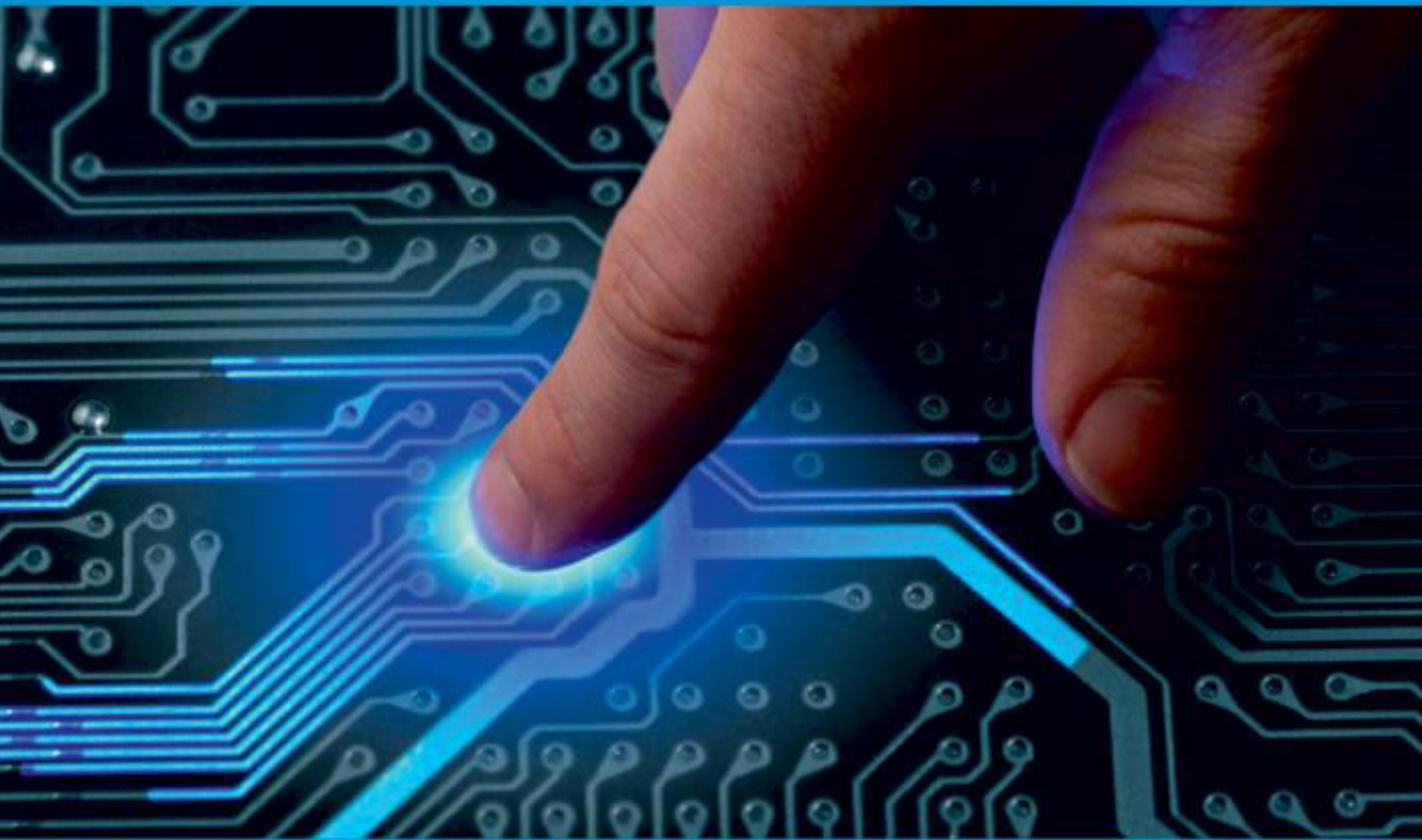
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 6, June 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.165

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006125 |

Krushi Mitra-Crop Selection Using Machine Learning

Prof.Preethi B[1], Meghamala C[2], Sujan G[3],Sriraksha N S[4], Rohit K S[5]

Assistant Professor, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[1]

B.E Student, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[2]

B.E Student, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[3]

B.E Student, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[4]

B.E Student, Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere, Karnataka, India[5]

ABSTRACT: Agriculture seems to be a key part of both a country's food security and its economic growth. Choosing which crops to grow is one of the most important parts of planning agriculture. The suggested system helps farmers choose crops that will do well in their area. For agriculture to grow, it's important to be able to make accurate predictions about which crops to grow. We've given you a machine-learning method called "Random Forests" that can predict how crop choices will change based on the current climate and biophysical changes. We have gathered a lot of information about crop selection from many different places. These numbers are used both to train and test the model. From different results, it's clear that RF is a good machine-learning algorithm for predicting crops in their current state and has a very high level of accuracy when analysing data. RF algorithm also helps to find the right fertiliser by taking into account NPK values, soil moisture, and the name of the crop. Since a long time ago, plant leaf disease has been one of the biggest threats to food security because it lowers crop yield and lowers the quality of the crop. Accurately diagnosing diseases has been a big problem, but recent advances in computer vision made possible by deep learning have made it possible to use a camera to help diagnose diseases in plat leaf. It talks about the new way to find diseases and use deep learning and convolutional neural networks. neutral networks (CNNs) has done a great job of putting plant leaf diseases into groups. Using an image dataset of plant diseases that was available to the public, a CNN was used to apply and train a number of neuron-wise and layer-wise visualisation methods. So, it was found that neutral networks can pick up on the colours and textures of lesions that are unique to each disease. This can be compared to how humans make decisions.

KEYWORDS: RF and CNN Algorithm.

I. INTRODUCTION

Predicting what crops will grow well is an important part of farming, and machine learning algorithms have become very important in this area in recent years. In this age of technology and data science, agriculture stands to gain a lot from techniques that are used well. Feature selection and classification are two very important aspects of machine learning. The goal of feature selection is to pick out the most important parts of a dataset. It involves choosing a subset of appropriate attributes from a larger set of original attributes based on a predefined benchmark, such as classification performance or class separability, which plays a big role in machine learning applications. Attributes are chosen using three different ways: the filter, the wrapper, and the embedded. Filter methods can be run quickly, but wrapper methods are more likely to be recognised. In this work, wrapper feature selection techniques are used to choose the best attributes from the dataset, and classification is used to predict the best crop for a certain piece of land based on the selected attributes. There are three common ways for machines to learn: supervised learning, unsupervised learning,

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006125 |

and learning by doing. Predictions are made in this work by using supervised learning classification techniques. The main contribution of this work is to find the best combination of a feature selection technique and a classification method to predict the best crop to grow based on soil and environment.

Agriculture is very important to the economic growth of a country like India because it gives people in the countryside a way to make a living and find work, and it is also a major source of food. As time goes on, the need for crop production also grows. In India, it makes up about 20% of the country's GDP. Today, farmers grow crops based on the knowledge they've gained from the past. Because they still use old methods, farmers don't know how much interest there is in the horticultural economy right now. The farmers will suffer because of this. The choice of crop is one of the most important parts of planning for agriculture. Losses are kept to a minimum when farmers know exactly what crops will do best in their fields during each season. There are many things that affect how fast a crop grows:

1. Things like the weather (rainfall, temperature, humidity, etc.), the soil (such as soil moisture), and the geography of a place (e.g., slope). Different sets of data about these attributes are gathered and then looked at. When making a prediction model, getting the data from the right source is important because it affects how accurate the model is. The process of analysing data by using different kinds of logic and analysis to judge each part of the data is very important. When doing a research analysis, one of the many steps that must be taken is to look at things in this way. array is one way to look at and process data.
2. There are already several models for predicting crops, but farmers don't know about them. This could be because they are too complicated or don't save enough money. So, a model needs to be made that is easy to use, cheap, and accurate.
3. All of the current methods are only based on location, but in our algorithm, location is also based on the season. This makes the prediction more accurate. Here, crop selection forecast models are made based on crop weather studies so that yields can be estimated long before the crops are actually picked.

II. LITERATUE SURVEY

A farmer, without a doubt, is the ideal person to make decisions on what crops to grow. Cultivar prediction is currently done by hand in labs, and farmers must rely on the advice of specialists in order to identify which crops are most suited to a given plot of land. In order to provide recommendations on the best crops to grow, the specialists gather soil samples from a certain area and evaluate them in the lab. Predictions take time to develop, and deciding which crops to plant is a difficult process in the agricultural industry. Climate change and other environmental variables that impact agricultural production have rendered manual forecast essentially ineffective. An increase in output may be achieved by accurately predicting which crops are most suited for cultivation. Several elements, including genotype and climate interactions, are used to construct crop prediction features. Understanding the functional link between cultivation and interdependent elements like genotype and environment is essential for accurate crop prediction. Furthermore, it is necessary to have access to extensive datasets and efficient algorithms in order to investigate these links. It's clear that machine learning methods are necessary in this research since they allow us to accurately anticipate the best crop for a particular plot of land based on variables like soil and environmental conditions. This review looks at a variety of similar research.

1) Boosting was used to construct a novel hybrid approach to feature selection that took into account both the advantages and disadvantages of the filter and wrapper approaches. Real-world datasets from the UCI repository were used to conduct the experiments in this study. Using the suggested technique, the findings showed that it was much quicker than the wrapper method.
2) Huan Liu and Lei Yu investigated how classification and clustering algorithms currently pick features. After that, they offered an intermediate step on a unifying platform.
3) For the reverse complement properties of the gapped k-mer composition, Al Maruf et al. showed that it outperformed all other compositions. The Radial Basis Function (RBF) kernel of the Support Vector Machine (SVM) was employed as a classification technique. It has a correlation coefficient and sensitivity of 69.41% and 84.57% and an accuracy rate of 84.58% when compared to the Matthews method. iRSpot-SF performs much better than the Matthews method.
4) There is no search strategy in the feature selection approach suggested by Jana Novovicova and her colleagues, and it is best suited for multimodal datasets.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |
|| Volume 10, Issue 6, June 2022 ||
| DOI: 10.15680/IJIRCCE.2022.1006125 |

5) In their work, Jia-You Hsieh et al. addressed Rice Blast Disease (RBD). With the help of Auto-recursive Sklearn's feature elimination approach, we identified essential RBD characteristics.
6) It was their goal to create a model that may serve as a warning system for RBD.
7) Isabelle Guyon et al. used a Support Vector Machine (SVM) approach based on the RFE for gene selection.
8) The RFE is a newly-developed approach for selecting features for small sample classification problems, among the several ways used to do so.MarcSebban and Richard Nock used information gain and a statistical test to analyse the filter model. It was decided to replace the minimal spanning tree with the closest neighbour as a means of implementing a hybrid model.
9) The quick correlation-based filter was suggested by Lei Yu and Huan Liu as a correlation filter approach. Real-world data was used to test their method, with and without feature selection, using two alternative techniques.
10) Somol and his colleagues created a flexible hybrid floating-search algorithm that combines the advantages of the filter and wrapper techniques. There was a benefit to the suggested technique in that it allowed the wrapper-based feature selection strategy to cope with issues of larger dimensions while maintaining flexibility in terms of tradeoffs between quality and computing time. The WAVEFORM dataset from the UCI repository and the SPEECH dataset from British Telecom were used in the experiments.
11) Classification techniques were used to evaluate the performance and efficiency of a variety of feature selection algorithms. They used 15 datasets from the UCI library for their experiments. Most Feature Selection Algorithms (FSA) considerably decreases data dimensionality without harming model performance, according to these findings.
12) To find the most important features, Kursa et al. used the all-relevant feature selection approach known as Boruta. Traditional feature selection techniques, on the other hand, focus on a limited group of features that provide the lowest possible error on a given classifier. This is the minimum optimum approach.
13) Marcano Cedeno et al. suggested a feature selection approach based on sequential forward selection and the feedforward neural network to discover the prediction error as a criteria for selection.
14) Zahra Karimi et al. created a feature ranking technique for intrusion detection in a typical dataset using a hybrid filter feature selection methodology. According to the experiments, our approach is more accurate than other ways.
15) Using Particle Swarm Optimization and Support Vector Machine (PSO-SVM), Surabhi Chouhan et al. suggested a hybrid technique for selecting features from a dataset. This method was tested on a variety of benchmark datasets.
16) Using natural variation in photosynthesizing capacity to boost yields via a functional phylogenetic analysis for large-scale genetic screening is a time-consuming process, according to David Heckman et al. Brassica oleracea and Zea mays, C3 and C4 seeds, were examined to determine whether leaf reflectance spectroscopy could be used to estimate photosynthetic efficiency parameters; the results demonstrate that phenotyping leaf reflectance is an efficient way for improving crops' photosynthetic capacity.
17) A random forest (RF) model using the RFE was created by Aileen Bahl et al. to increase prediction accuracy.
18) For the purpose of predicting crop selection, Maya Gopal and Bhargavi examined the performance of ML systems using a range of feature selection strategies. Compared to other ML algorithms, the random forest produced better outcomes.
19) Bhargavi and Maya Gopal came up with the idea of sequential forward selection, which is a unique way of selecting consecutive features. To discover the "best" feature subset, this approach repeatedly selects features based on the classification performance of the classifiers iteratively.

Literature Summary

Research shows that feature selection and categorization are critical to machine learning approaches based on the literature review. There are a few ways that may be used to determine which crops are best suited to the soil and the current environmental conditions. Feature selection approaches may be used to identify the most important qualities in a dataset for crop prediction. Improves prediction accuracy by reducing the amount of characteristics without losing critical information and by eliminating unnecessary data. The RFE, Boruta, and Sequential Forward Feature Selection (SFFS) are only a few of the feature selection approaches explored in this research. In order for the SFFS to work properly, it must choose just one feature and then repeat the procedure for each characteristic that is to be selected. This may take a long time. Even though there is no ranking system in Boruta, feature selection and rejection are carried out concurrently, using minimal time. The RFE uses a ranking approach to identify the most correct qualities, allowing for higher prediction accuracy. Additionally, crop forecasting relies heavily on classification, which helps determine the best crop to grow on a given piece of land.Each record in a dataset is assigned a classification using classification. k-Nearest Neighbor (KNN) [28], Naive Bayes (NB) [21], Decision Tree (DT) [28], SVM [29], Random Forest (RF) [26], and Bagging (30) are some of the supervised learning methods used in this work for prediction. Although data scaling is

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006125 |

required, the KNN makes no assumptions about the data. If the training data isn't representative of the population, then the NB isn't scalable. The DT can handle both numerical and categorical data, but it requires a lot of work to learn how to do so. Processing time for huge datasets necessitates use of a well-known classifier known as the SVM. The RF can process enormous amounts of data with high-dimensional features, but only if the qualities are predictive. Over fitting in the model may be mitigated by the use of bagging. High variation is reduced with the use of n learners with the same size and the same learning procedure. However, under fitting of the data is not helped by this method. The prediction mechanism is unique to each algorithm. The optimal feature selection strategy for crop prediction using a classifier is thus required. There are a variety of methods for determining which attributes are most essential, and these methods may also be used to make predictions. Research on the performance of the RFE, Borate, and SFFS feature selection algorithms for crop prediction has not been done to our knowledge, as far as we know. Accordingly, the research is aimed at discovering an appropriate feature selection method and classifier to forecast the best crop/s for a given field. This means that a classifier that can be used with the crop dataset must be used to choose features. To do this, a comparison of several approaches is carried out and the results are reviewed. Farmers may determine the best crop for their area using these methods.
A solicitation must be sent to the registered mobile phone number, and the area will be sent as an SMS after the number has been validated. Then GSM is turned off and GPS is reactivated. The scope and longitude values of the gadget are included in the SMS. Using the Android app, this value can be seen and the resulting direction may be plotted accordingly. Associating the cell receiving wire with the GPRS module is part of the area transmitting system. Using the GPS module, the location is then sent to the data storage servers. A vehicle's location is shown on this website when data from data set servers is obtained. The GSM and GPS units have been put through their paces. Obviously, it offers us with the finer points of the framework's hardware and software components. The portable unit and the central station make up the set-equipment.. up's Information on how GPS, mobile, and GSM work together as well as the various situations they can withstand may be found in the product setup. The difference between using a standard GPS and a differential GPS.

III. COMPONENTS USED

PROCESSOR: Computers are powered by processors, which are integrated electronic circuits. Instructions transmitted from an operating system are executed by the CPU, including arithmetic, logic, input/output (I/O), and other fundamental functions (OS). A processor's actions are required for the majority of other processes. We suggest using a CPU with at least 1 GHz of processing power, however we would like S2GHz or more. The arithmetical logic and control unit (CU) of a processor provides the following measurements of its capability.

- Ability to process instructions at a given time
- Maximum number of bits/instruction
- Relative clockspeed

Figure 3.1: Processor

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006125 |

ETHERNETCONNECTION (LAN)OR

A WIRELESSADAPTER (Wi-Fi)

In wireless local area networking (WLAN), Wi-Fi refers to a group of radio technologies based on the IEEE 802.11 family of standards. Wi-Fi technology may be used by a wide variety of devices, including computers, laptops, smartphones, tablets, printers, digital music players, and digital cameras, as well as automobiles and drones.

Connected Wi-Fi devices and Ethernet-enabled devices may communicate with one other and access the Internet through a wireless access point. A hotspot (or access point) with a range of roughly 20 metres (66 feet) inside and a wider range outside may be found. Multiple access points may be used to extend hotspot coverage across huge distances, from a few square metres to hundreds of square miles.

Figure 3.2: Ethernet

HARD DRIVE

Hard drives are electro-mechanical data storage devices that employ magnetic storage to store and retrieve digital information using one or more rigid quickly spinning discs, known as platters, covered with magnetic material. Data is written to and read from the platters by magnetic heads that are attached to moving actuator arms. In a random-access system, data may be accessed in any sequence, rather than being accessible in sequential order. Because HDDs are non-volatile storage devices, they maintain data even if the computer is turned off. The suggested system should have at least 32 GB of RAM. System.

Figure 3.3: Hard Drive

MEMORY(RAM): Currently utilised data and machine code are stored in RAM, a kind of computer data storage. Data may be read or written from or to a random-access memory device in about the same amount of time regardless of where it is physically located inside the memory. Integrated chips are the current type of random-access memory (RAM). Non-volatile RAM has also been created, however RAM is often associated with volatile memory (such as DRAM modules), which loses data when the power is turned off. It is suggested that the proposed system have at least 2 GB of RAM.

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006125 |

Figure 3.4: RAM

IV. SYSTEM ARCHITECTURE

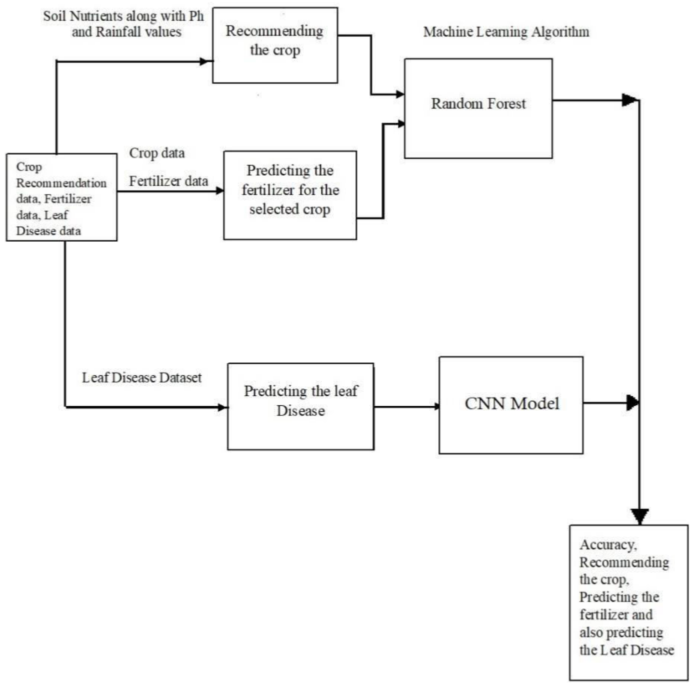


Figure4.1:System architecture of proposed system

Users may make informed decisions about which crops to grow and which fertiliser they should use for the crops they are considering by comparing soil nutrient levels and crop yields, as shown in the image. We combined multiple datasets for leaf disease prediction to produce a dataset for crop recommendation and fertiliser advice. With the use of this data, the Random Forest algorithm can accurately estimate the growth and use of a certain crop and fertiliser. This technique is also capable of accurately forecasting leaf disease with the use of CNN.

Leaf disease prediction uses a dataset that includes all of the numerous plant leaf diseases that we have taken into consideration. To achieve the highest level of accuracy, the module is repeatedly trained. An picture that hasn't been seen before may be compared to other images that have been seen before. It then returns the correct result.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006125 |

IV. METHODOLOGY PRESENTED

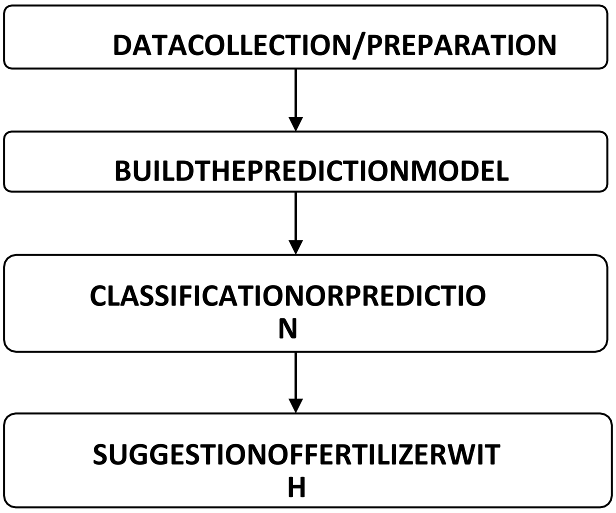


Figure 5.1.1: Methodology diagram of Crop

Recommendation

Shows how this project came to be. Pre-processing of the input data begins with a search for the missing values, elimination of duplicated data, standardisation of dataset, and conversion of goal qualities into factors. Wrapper feature selection approaches are used to extract the most important qualities from the pre-processed data. To begin with, the dataset is divided into training and testing stages, with classification algorithms used to the optimal characteristics. It is used to train the algorithm to identify the optimum crop to cultivate on a given amount of land using the training dataset. With the help of the classifier, the training dataset is utilised to make predictions about the crop that will be grown in the field. By employing many performance criteria, we are able to produce a satisfactory harvest. An acceptable classification approach and the most effective feature selection strategy are uncovered by the investigation.

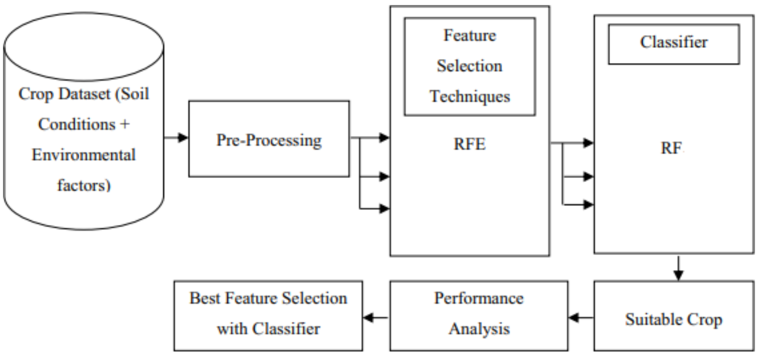


Figure 5.1.2: Flowchart of Fertilizer Prediction

To begin, data on fertilisers such as potassium, nitrogen, and phosphorus must be gathered, followed by the development of a prediction model, and finally, the expected crop must be taken into account in relation to this fertiliser for the desired crop.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006125 |

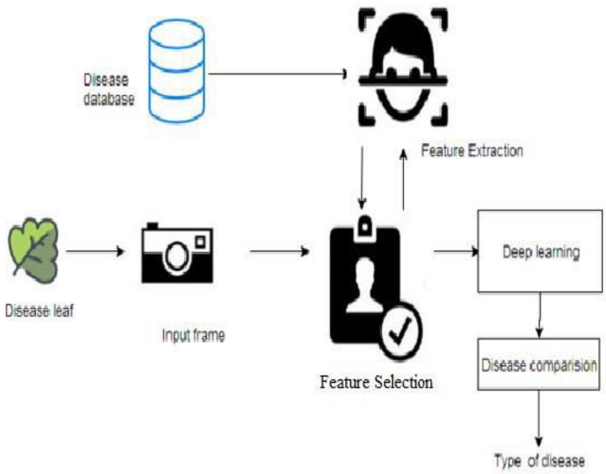


Figure 5.1.3: Working Scenario of CNN Algorithm

The database shown in the graphic above includes all of the distinct plant leaf diseases that we've taken into consideration. To achieve the highest level of accuracy, the module is repeatedly trained. New images are compared to the database's learned features when a new picture is presented to the module. Finally, this results in a suitable outcome.

V. CONCLUSION

The goal of this project is to gather information on the crop in order to conduct a harvest that is both efficient and fruitful. The current system, on the other hand, is a little sluggish in its ability to foresee. The predicted outcome was not as exact as the original. We've come up with a solution to this problem using a random forest method. Its operations are quick, and its predictions are very accurate. A CNN model may be used to predict the presence of leaf diseases based on images from a training dataset. This sheds light on how to anticipate plant leaf disease. There is a chance that farmers will learn about plant leaves that have never been grown before thanks to this system since it lists all conceivable plant leaves. This helps farmers make better decisions about which crops to grow. Help the farmer get a better idea of what plants are in demand and how much they cost.

FUTURE SCOPE

Farmers are increasingly taking their own lives, and this technique may assist anticipate crop sequences and maximise production rates and monetary rewards. Further breakthroughs in agriculture may be made if machine learning is effectively integrated with agriculture in the fields of crop disease prediction and crop simulation, which can lead to increased yield and more efficient use of resources.

REFERENCES

[1]S. Das. Filters, wrappers and a boosting-based hybrid for feature selection. In International conference on machine learning 1 (2001), pp. 74–81.

[2] H. Liu and Y. Lei, toward integrating feature selection algorithms for classification and clustering, IEEE Trans. Knowl. Data Eng. 17 (2005), pp. 491–502. doi:10.1109/ TKDE.2005.66.

[3] A. Maruf, M. Abdullah, and S. Shatabda, iRSpot-SF: Prediction of recombination hotspots by incorporating sequence-based features into Chou's Pseudo components, Genomics 111 (2019), pp. 966–972. doi: 10.1016/j.ygeno.2018.06.003

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 6, June 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1006125 |

[4] I. Kononenko, Estimating attributes: Analysis and extensions of RELIEF. European conference on machine learning 784 (1994), pp. 171–182.

[5] J. Pavel Pudil, N.N. Choakjarernwanit, and J. Kittler, Feature selection based on the approximation of class densities by finite mixtures of special type, Pattern Recognit 28 (1995), pp. 1389–1398. doi:10.1016/0031-3203(94)00009-B.

[6] J. Novovicová, P. Pudil, and J. Kittler, Divergence based feature selection for multimodal class densities, IEEE Trans. Pattern Anal. Mach. Intell. 18 (1996), pp. 218–223. doi:10.1109/ 34.481557.

[7] H. Liu and H. Motoda, Feature Selection for Knowledge Discovery and Data Mining, 1st ed., Springer, US, 1998.

[8] M. Dash, K. Choi, P. Scheuermann, and H. Liu. Feature selection for clustering-a filter solution. IEEE International Conference on Data Mining, 2002, Proceedings., Maebashi City, Japan, pp. 115–122.

[9] I. Guyon, S. Gunn, M. Nikravesh, and L.A. Zadeh (eds.), Feature Extraction: Foundations and Applications, 1st ed., Springer-Verlag, Berlin Heidelberg, 2008.

[10] I. Guyon and A. Elisseeff, An introduction to variable and feature selection, J. Mach. Learn. Res. 3 (2003), pp. 1157–1182.

[11] W. Paja, K. Pancerz, and P. Grochowalski, Generational feature elimination and some other ranking feature selection methods, in Advances in Feature Selection for Data and Pattern Recognition, International Publishing, Springer, Charm, Vol. 138, 2018, pp. 97–112.

[12] J.-Y. Hsieh, W. Huang, H.-T. Yang, C.-C. Lin, Y.-C. Fan, and H. Chen. Building the rice blast disease prediction model based on machine learning and neural networks., Easy chair the world of scientists (2019), pp. 1–8.

[13] R. Kohavi and G.H. John, Wrappers for feature subset selection, Artif. Intell. 97 (1997), pp. 273–324. doi:10.1016/S0004-3702(97)00043-X.

[14] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik, Gene selection for cancer classification using support vector machines, Mach Learn 46 (2002), pp. 389–422. doi:10.1023/ A:1012487302797.

[15] M. Sebban and R. Nock, A hybrid filter/wrapper approach of feature selection using information theory, Pattern Recognit 35 (2002), pp. 835–846. doi:10.1016/S0031- 3203(01)00084-X.

[16] Y. Lei and H. Liu. Feature selection for high-dimensional data: A fast correlation-based filter solution. In Proceedings of the 20th International Conference on Machine Learning, Washington, DC, USA, 2003.

[17] P. Somol, J. Novovičová, and P. Pudil, Flexible-hybrid sequential floating search in statistical feature selection, in Joint IAPR International Workshops on Statistical Techniques in Pattern Recognition (SPR) and Structural and Syntactic Pattern Recognition (SSPR), Dy. Yeung, J. T. Kwok, A. Fred, F. Roli, D. de Ridder eds., Vol. 4109, Springer, Berlin, Heidelberg, 2006, pp. 632–639.

[18] A. Salappa, M. Doumpos, and C. Zopounidis, Feature selection algorithms in classification problems: An experimental evaluation, Optimisation Methods and Software 22 (2007), pp. 199–212. doi:10.1080/10556780600881910.

[19] M.B. Kursa, A. Jankowski, and W.R. Rudnicki, Boruta–a system for feature selection, FundamentaInformaticae 101 (2010), pp. 271–285. doi:10.3233/FI-2010-288.

[20] A. Marcano-Cedeno, J. Quintanilla-Domínguez, M.G. Cortina-Januchs, and D. Andina. Feature selection using sequential forward selection and classification applying artificial metaplasticity neural network. In Industrial electronic conference, 36th annual conference on IEEE industrial electronics society, Glendale-USA, 2010.

[21] Z. Karimi, M.M.R. Kashani, and A. Harounabadi, Feature ranking in intrusion detection dataset using combination of filtering methods, International Journal of Computer Applications 78 (2013), pp. 21–27. doi:10.5120/13478-1164.

[22] S. Chouhan, D. Singh, and A. Singh, An improved feature selection and classification using decision tree for crop datasets, International Journal of Computer Applications 142 (2016), pp. 5–8. doi:10.5120/ijca2016909966.

[23] D. Heckmann, U. Schlüter, and A.P.M. Weber, Machine learning techniques for predicting crop photosynthetic capacity from leaf reflectance spectra, Mol Plant 10 (2017), pp. 878–890. doi: 10.1016/j.molp.2017.04.009.

[24] P.S. Maya Gopal and R. Bhargavi., Feature selection for yield prediction in Boruta algorithm, International Journal of Pure and Applied Mathematics (2018), 139–144.

INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 8.165

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर
NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462   6381 907 438   ijircce@gmail.com

Scan to save the contact details