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▶ To cite this version:

Vaishnavi Jayaraman, Saravanan Parthasarathy, Arun Raj Lakshminarayanan, S. Sridevi. Crop Recommendation by Analysing the Soil Nutrients Using Machine Learning Techniques: A Study. 4th International Conference on Computational Intelligence in Data Science (ICCIDS), Mar 2021, Chennai, India. pp.15-26, 10.1007/978-3-030-92600-7_2 . hal-03772947

HAL Id: hal-03772947
https://inria.hal.science/hal-03772947

Submitted on 8 Sep 2022

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Crop Recommendation by Analysing the Soil Nutrients using Machine Learning Techniques: A Study

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Abstract. According to India Brand Equity Foundation (IBEF), 32% of the global food market is dependent on Indian agricultural sector. Due to urbanisation, the fertile land have been utilised for non-agricultural purposes. The loss of agricultural lands impacts the productivity and results with diminishing yield. Soil is the most important factor for the thriving agriculture, since it contains the essential nutrients. The food production could be improved through the viable usage of soil nutrients. To identify the soil nutrients, the physical, chemical and biological parameters were examined using many machine learning algorithms. However, the environmental factors such as sunlight, temperature, humidity, and rainfall plays a major role in improving the soil nutrients since it is responsible for the process of photosynthesis, germination, and saturation. The objective is to determine the soil nutrient level by accessing the associative properties including the environmental variables. The proposed system termed as Agrarian application which recommends crops for the particular land using classification algorithms and predicts the yield rate by employing regression techniques. The application will help the farmers in selecting the crops based on the soil nutrient content, environmental factors and predicts the yield rate for the same.

Keywords: Soil nutrients, environmental factors, machine learning, prediction, crop recommendation system, yield rate.

1 Introduction

Fertile soil deposited by the rivers is a plinth of ancient civilizations. In the initial years, the availability of nutrient soil and abundant water in delta regions motivate humans to perform agricultural practices. The nutrient enriched alluvial soil boosted the plant growth and increased the yield.

Since humans are connected to the land through agriculture, the soil nutrients played a key role in anthropological evolution which leads to cultural progress. In India, about 52% of the people rely on agricultural industry and it contributes around 18% of GDP. According to 'The Energy and Resource Institute' (TERI) [1], about 2.5% of Indian economic system relies on soil quality. The physical, chemical, and biological properties of soil determine the agricultural outcome. The soil textures, porosity, capacity of holding water, pH, Electrical Conductivity (EC), Organic Carbon (OC) are some of the physical and chemical properties of the soil. Since most of the nutrients are soluble in acidic soil, the pH value is an important attribute in nutrient management [2]. EC is used to calibrate the soil salinity which integrated the macro and micronutrients. In general, 2-10% of the total dry weight of the soil is covered by OC. The decayed animals, plants, and microorganisms exhibit OC, which is ingested by the crops. The mineral and non-mineral nutrients were determined by the biological properties [3]. The mineral nutrients can be classified into macronutrients, secondary nutrients, and micronutrients.

Table 1: List of Mineral Nutrients

Nutrient type	**Nutrients**	**Symbol**
Macronutrients	Nitrogen Phosphorous Potassium	N P K
Secondary nutrients	Calcium Magnesium Sulphur	Ca Mg S
Micronutrients	Iron Manganese Zinc Copper Boron Molybdenum Chlorine Nickel	Fe Mn Zn Cu B Mo Cl Ni

Nitrogen (N) is the most widely exploited elementary unit which holds all the proteins and the component of chlorophyll. The saplings acquired the Nitrogen either in the form of ammonium or nitrate. Phosphorus (P) is the least utilized supplement that is enriched with the nucleic acid. It strengthens the root, which is absorbed as orthophosphate ions. The soil pH and the ratio of orthophosphate are inversely proportional. Potassium (K) is essential for activating the enzymes and regulating osmosis. The secondary nutrients are required in a smaller quantity when compared to the macronutrients. Calcium (Ca), Magnesium (Mg), and

Sulphur (S) is responsible for fortifying the cell wall, maintaining the electrical balance and enriching the amino acids respectively. Even though the requirements of micronutrients are less than 1%, they make a significant impact on plant growth and agricultural turnout. The micronutrients such as Zn, Mg, Cu, and Fe induce the activation of enzymes, whereas the Fe, Zn, and Mg are also allied to chlorophyll. The non-mineral elements such as Carbon (C), Oxygen (O), and Hydrogen (H) are obtained through the air (CO_2) and water (H_2O). Though the utilization level of nutrition varies, every nutrient plays an imperative part in keeping soil fertility. The factors including erosion, leaching, and continuous farming affect the soil nutrients and result in a reduction of productivity. Organic and inorganic fertilizers are used to tackle this situation. On the contrary, the excessive use of fertilizers leads to the loss of natural replenishment of soil. The traditional laboratory-based soil analysis required plenty of time and resources. Instead, the Machine Learning Techniques are competent to accost these issues with minimal time and cost. The applicability and advancements of Machine Learning Techniques were discussed in this study.

2 Literature Survey

Suchitra et.al, predicts the soil fertility index and soil pH [4] using Extreme Learning Machine Algorithm (ELM). The fertility index defines the quality of soil to ensure plant growth and the pH is to measure the acidity or alkalinity of the same. The data were collected from various farming lands in the state of Kerala. The physical and chemical parameters of the samples were examined in the soil laboratory. The Extreme Learning Machine Algorithm was implemented with various activation functions such as tri-angular basis, sine-squared, hard limit, Gaussian Radial Basis (GRB), and hyperbolic tangent. ELM-GRB performs best with accuracy of 80%, in calibrating the soil fertility index by considering both the accuracy and kappa. ELM-hyperbolic achieves accuracy of 75%, for predicting the soil pH. Zonlehoua Coulibali et.al proposed an approach that predicts the optimal macronutrient (NPK) requirements [5]. They were usually determined by the soil type, weather, and many other variables. The dataset for the crop potato was collected from Quebec, Canada. The key features were extracted by using the Extra Tree Regressor function. An optimum model was developed and correlated from KNN, Gaussian model, Random Forest, Mitscherlich model, and Neural Network. Since its R^2 value is between 0.60 and 0.69, the Gaussian model predicted the macronutrient level in a better way than the other models.

The better nutrient management would result in the production of first grade Peach fruit. D. Betemps et.al. suggests that the above-mentioned outcome could be achieved through Humboldtian Diagnosis [6] and Machine Learning Techniques such as Random Forest, Neural Networks, Support Vector Machine, and Stochastic Gradient Descent. In this study, Random Forest predicts the soil nutrients effectively with 80% of accuracy. H. Mollenhorst et.al. employed a couple of Machine Learning algorithms to predict the soil phosphorus with the application of dairy farm manure [7]. A historic dataset for the past 24 years was collected from the farm DeMark, Netherlands. Gradient Boosting Machine (GBM) and Decision Tree were engaged for predicting the phosphorus content before the application of the first manure. The GBM model outperforms the other one, with an RMSE value between 7.33 and 8.22.

A Decision Support System (DSS) for the proper usage of macronutrient fertilizer was developed by R. Meza-Palacios et.al, to enhance sustainability [8]. The physical and chemical properties of the soil were analysed in the laboratory. The key variables chosen were Electrical Conductivity, soil organic matter, and soil texture. The DSS consists of two fuzzy models; the Edaphic condition model (EDC) and the NPK fertilization model. The physical and chemical index of the soil was controlled by the EDC model. The outcome of EDC, available macronutrients, and yield rate was controlled by the NPK model. The R^2 rates of macronutrients (NPK) shown in DSS were 0.981, 0.9702, and 0.9691. Thus, the DSS model suggests NPK accurately.

Chunyan Wu et.al, recommended the required soil quality and nutrient contents of Dacrydium pectinatum [9] in China. In this study, six Support Vector Machine (SVM) models, and four Neural Networks (NN) models were utilised. The soil was collected from the four corners and center part of the field. The sample had been examined in a laboratory using the Kjeldahl method. The macronutrients and organic matter present in the soil were considered in the analysis. The adapted SVM models were Local Mixture-based Support Vector Machine (LMSVM), Fast local kernel Support Vector Machine (FSVM), Proximal Support Vector Machine (PSVM), Localized Support Vector Machine (LSVM), KNN and SVM integrated algorithms (SVM-KNN and KNN-SVM). The NN models, applied were Back-Propagation Neural Network (BPNN), Field Probing Neural Network (FPNN), MultiLayer-Propagation feed-forward Neural Network (MLPNN), Generalized Regression Neural Network (GRNN). From all these 10 models GRNN model with the least RMSE value performs best in the NN model and KNN-SVM (partial SVM) out-performs all the other SVM models with accuracy of 95%.

The Walkley-Back method [10] of soil examination was done by K. John et.al, to estimate the soil organic compound in alluvial soil with specific parameters. The predictors considered were clay index, base saturation, Normalized Difference Moisture Index (NDMI), Land Surface Temperature (LST), Normalized Difference Built-Up Index (NDBI), Soil Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI), and Ratio Vegetation Index (RVI). The digital mapping of soil with the environmental variables was also implemented with the Cubist Regression, ANN, Multi-Linear Regression (MLR), Random Forest, and SVM. The Random Forest performed better than other algorithms with the R^2 value of 0.68.

Chunyan Wu et.al, identified the features of topsoil nutrients and biomass in the dark brown soil of Northeast forest in China. To predict the above-ground biomass [11], Chunyan Wu utilized various ML models, out of which GRNN brought a higher accuracy, with a gradient of 0.937. The adapted NN algorithms were the Group Method Of Data Handling (GMDH), Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Generalized Regression Neural Network (GRNN), and Support Vector Machine (SVM). The result shows that if the depth of the soil increases, soil nutrients decrease. M. Shahhosseini et. al, aimed to predict the nitrate loss using Agriculture Production Systems SiMulator Cropping System (APSIM) model [12] with historical data from US Midwest. To assist the subsequent progress of the decision support tool the four ML algorithms such as Extreme Gradient Boosting, LASSO Regression, Random Forest, Ridge Regression and their ensembles were executed as metamodels for APSIM. Random Forest predicts the nitrate loss more precisely, with an RRMSE of 54%.

C. Ransom et. al, proposed an approach to optimize the economically optimal N rates (EONR) using eight statistical and ML approaches [13]. The statistical and ML approaches applied were Stepwise Regression, Ridge Regression, Least Absolute Shrinkage, And Selection Operator (LASSO), Elastic Net Regression, Principal Component Regression (PCR), Partial Least Squares Regression (PLSR), Decision Tree and Random Forest have been implemented to design an Nitrogen recommendation tool. The ML model that balanced the Nitrogen recommendation tool was Random Forest with an inclined R^2 value between 0.72 and 0.84. The RMSE value lied between 41 and 94 kgNha−1. However, the Decision Tree dealt with a minimal quantity of parameters, and results with an inclined R^2 value between 0.15 and 0.51. The RMSE value of this model lied between 16 and 66 kgNha−1.

J. Massah et.al, used the cone penetrometer [14] to examine the sample soil which contains rotten matter, decayed leaves, and water, to estimate the modification in soil penetration resistance (SPR). The SPR was analysed using the following algorithms KNN, SVM, ANN, Random Forest, Levenberg-Marquardt backpropagation ANN, Naïve Bayes, and Decision Tree. SVM- Gaussian kernel achieves higher accuracy in forecasting the modifications in SPR, with the R^2 value of 0.982 and the mean square error (MSE) value between 0.02 and 0.09. Soft sensors based on DBN-ELM (Data Belief Network-Extreme Learning Machine) measuring the nutrients in the water content of soil-free cultivation [15]. The parameters considered were EC, pH, Circulation speed, and temperature. RMSE values of Least Square LS, ELM, and DBN-ELM are 2.3877, 1.7838, and

1.2414 respectively. From the derived RMSE value, the integrated ML model DBN-ELM performed better than the others.

M.S. Sirsat proposes et.al, a village-wise prediction of soil fertility index for micronutrients [16]. The soil samples of ten villages were collected from the state of Maharashtra. The Neural networks, Extreme Randomised Regression, Profound Learning, LASSO, Ridge Regression (RR), Bayesian model, Support Vector Regression, and Random Forest were the models used in this examination. Extreme Randomised Regression Trees out-performed the others through their fastness, with the accuracy rate of 97.5%. Yuefen Li et.al, proposed a machine learning approach to identify the other nutrients mandatory for plant growth other than Carbon, Phosphorus, and Potassium [17]. The proposed approach also aimed to predict the nutrients present in the soil. A couple of algorithms such as Radial Basis Function Neural Network (RBFNN) and SVM, were used to predict the nutrient content. The overall performance of both SVM and RBFNN models predicts the soil nutrients in an efficient manner with a prediction accuracy of 99.85% and 98.45% respectively.

Multiple statistical techniques were employed by M. Hosseini et.al, to predict the soil Phosphorus (P) using the ML models. The employed statistical techniques were fuzzy inference system, Adaptive neuro-fuzzy inference system, Regressions, ANN, Partial Least Square Regression (PLSR), and Genetic Algorithms (GA) [18]. ANN forecasts the soil Phosphorus level better than other algorithms with the R^2 rate of 0.912 and RMSE rate of 4.019, by considering the soil organic matter and pH. To predict the soil phosphorus, a couple of models GA and PLS came up with statistical formulas to find the best fit. A comprehensive model based on SVM was designed to classify the soil quality [19]. The soil samples were collected from Taiyuan city, the heavy metals such as Cadmium, lead, chromium, and Nickel were chemically determined, to find the combination of contaminated soil and quality soil. Using this correlated dataset, the designed SVM model predicts the soil quality with accuracy of 98.33%.

A decision model based on a fuzzy Bayesian approach was devised to predict the soil fertility level, which would help in selecting the paddy variety [20]. The sample soil was collected from various farming lands in Vellore and was tested in the district soil test laboratory. The attributes considered were EC, pH, N, P, K, Zn, Fe, Cu, and Mn. The study identified the soil quality and suggested the paddy type. The fuzzy Bayesian approach achieved the accuracy of 90.2%. Hao Li et. al, evaluated the nutrient content of the soil and using a pair of ML models. GRNN, SVM, and MLR [21] were used. The prediction accuracy of SVM and MLR was 77.87% and 83.00% respectively, whereas the accuracy achieved by GRNN was 92.86%. Hence, GRNN predicts the soil nutrients in a better way a minimal error rate (MSE =0.27).

Table 2 : Key findings and Interpretations

S. No	**Author(s)**	**Methodology Used**	**Outcome**	**Advantage**	**Disadvantage**
1	Suchithra, M. S., & Pai, M. L. (2020) [4]	ELM with various activation functions: tri- angular basis, sine-squared, hard limit, Gaussian radial basis, and hyperbolic tangent	Soil fertility index- ELM-GRB - accuracy 80% Soil pH - ELM-hyperbolic - accuracy 75%	Very fast, efficient and saves time in analysing the soil	The other soil nutrients such as N_2O, P_2O_5, and K_2O were not considered
2	Coulibali, Z., Cambouris, A. N., & Parent, S. É. (2020) [5]	KNN, Gaussian model, Random Forest, Mitscherlich model, and NN	Macronutrient level - Gaussian model with R^2 value between 0.60 and 0.69	Effective performance	The size of dataset is minuscule
3	Betemps, D. L., De Paula, B. V., Parent, S. É., Galarça, S. P., Mayer, N. A., Marodin, G. A. B., Rozane, D. E., Natale, W., Melo, G. W. B., Parent, L. E., & Brunetto, G. (2020) [6]	Random Forest, Neural Networks, SVM, and Stochastic Gradient Descent	Soil nutrient level - Random Forest predicts effectively with 80% of accuracy	Good performance with a minimal number of errors	The assessment was against minimal data points
4	Mollenhorst, H., de Haan, M. H. A., Oenema, J., & Kamphuis, C. (2020) [7]	Gradient Boosting Machine and Decision Tree	Soil Phosphorus content - GBM model outperforms with an RMSE value between 7.33 and 8.22	A closer coherence between the application of P and yield will lead to a great profit	This method is applicable only for sandy soil and almost impossible to scale up

5	Meza-Palacios, R., Aguilar-Lasserre, A. A., Morales-Mendoza, L. F., Rico-Contreras, J. O., Sánchez-Medel, L. H., & Fernández-Lambert, G. (2020) [8]	DSS and a pair of fuzzy models; Edaphic condition model (EDC) and NPK fertilization model	NPK level - DSS model suggests NPK with R^2 value 0.981, 0.9702, and 0.9691	The designed tool will perform better for the following crops maize, avocado, grasses, sorghum	The efficiency of the system relied on the diversification of data. The unavailability led to inefficiency.
6	Wu, C., Chen, Y., Hong, X., Liu, Z., & Peng, C. (2020) [9]	LMSVM, FSVM, PSVM, LSVM, SVM-KNN, KNN-SVM, BPNN, FPNN, MLPNN, and GRNN.	Soil quality - GRNN and KNN-SVM outperforms the other algorithms	Higher prediction accuracy and convergence rate	Uncertainty in generating new models and data acquisitions
7	John, K., Isong, I. A., Kebonye, N. M., Ayito, E. O., Agyeman, P. C., & Afu, S. M. (2020) [10]	Cubist regression, ANN, MLR, Random Forest, and SVM	Organic Compound - Random Forest performed better with the R^2 value of 0.68.	Better nutrient management	The other physical parameters had not been considered along with the soil types
8	Wu, C., Chen, Y., Hong, X., Liu, Z., & Peng, C. (2020) [11]	GMDH, ANN, ANFIS, GRNN, and SVM	Soil Nutrients - GRNN brought a higher accuracy, with a gradient of 0.937	The relatively best model with higher efficiency	Lack of effective driving attributes
9	Shahhosseini, M., Martinez-Feria, R. A., Hu, G., & Archontoulis, S. V. (2019) [12]	Extreme Gradient Boosting, LASSO Regression, Random Forest, RR and their ensembles	Nitrate loss - Random Forest predicts more precisely, with an RRMSE of 54%.	An impressive result was obtained using a small dataset.	The greater exception will lead to a high chance of errors

10	Ransom, C. J., Kitchen, N. R., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernández, F. G., Franzen, D. W. Laboski, C. A. M., (2019) [13]	Stepwise regression, ridge regression, LASSO, elastic net regression, PCR, PLSR, Decision Tree, and Random Forest	Nitrogen recommendation - Random Forest and Decision Tree with an inclined R^2 value	Achieved greater accuracy with a minimum number of variables	Auxiliary parameters such as soil pattern, weather, and plant genetics had not been taken into account
11	Massah, J., Asefpour Vakilian, K., & Torktaz, S. (2019) [14]	KNN,SVM, ANN, Random Forest, Levenberg-Marquardt back propagation ANN, Naïve Bayes and Decision Tree	SPR – SVM Gaussian kernel achieves higher accuracy with the R^2 value of 0.982 and MSE value between 0.02 and 0.09	SPR prediction using ML models acts as an alternative to instruments like cone penetrometer	The model only dealt with the data collected from one particular region
12	Wang, X., Hu, W., Li, K., Song, L., & Song, L. (2019) [15]	LS, ELM and DBN-ELM	Water Content - DBN-ELM performed better with an RMSE value of 2.3877, 1.7838, and 1.2414	Excellent feature extraction and higher accuracy	Deliberate performance
13	Sirsat, M. S., Cernadas, E., Fernández-Delgado, M., & Barro, S. (2018) [16]	NN, Extreme randomised regression, Deep Learning, LASSO, Ridge Regression, Bayesian model, Support Vector Regression, and Random Forest.	Soil fertlity index - Extreme Randomised Regression Trees out-performed with the accuracy rate of 97.5%.	Relatively fast and high performance	Macronutrients and secondary nutrients were not contemplated
14	Li, Y., Liang, S., Zhao, Y., Li, W., & Wang, Y. (2017) [17]	RBFNN and SVM	Soil Nutrients - SVM and RBFNN produced the accuracy as 99.85% and 98.45%	Fast performance, higher credibility, and precision	Particular type of soil and plant alone was considered

			respectively		
15	Hosseini, M., Rajabi Agereh, S., Khaledian, Y., Jafarzadeh Zoghalchali, H., Brevik, E. C., & Movahedi Naeini, S. A. R. (2017) [18]	Fuzzy inference system, Adaptive neuro-fuzzy inference system, Regressions, ANN, PLSR and GA	Soil Phosphorus - ANN forecasts better with the R^2 rate of 0.912 and RMSE rate of 4.019	Simple, fast, and effective performance	The possibility of Empirical error occurrence is high.
16	Liu, Y., Wang, H., Zhang, H., & Liber, K. (2016) [19]	SVM based soil quality model	Soil quality level- the designed SVM model achieved accuracy of 98.33%.	A feasible and reliable model	Sensitive to outliers and overfits
17	Lavanya, K., Saleem Durai, M. A., & Iyengar, N. C. S. N. (2015) [20]	Fuzzy Bayesian, Naïve Bayesian, and Neural networks	Soil fertility level - fuzzy Bayesian approach achieved the accuracy of 90.2%.	Suitable for both rich and poor datasets	The environmental variables and secondary nutrients were not included
18	Li, H., Leng, W., Zhou, Y., Chen, F., Xiu, Z., & Yang, D. (2014) [21]	GRNN, SVM, and MLR	Soil nutrients - GRNN achieved accuracy of 92.86% with a MSE of 0.27	Effective and fast performance	Fluctuation is relatively lower and pattern recognition had not been considered

3 Research gap

Fertile soil is not only the combination of essential nutrients alone, the other environmental factors such as sunlight, temperature, humidity, and rainfall, should also be considered. However, the majority of research works concentrated on predicting the level of nutrients to optimize the production. The physical, chemical and biological properties would differ to a great extent with respect to the environmental factors [22]. Soil nutrient management could be achieved through the sustainable agricultural practices. The main objective of the proposed system is to identify the soil nutrient level and assess the same with environmental factors. The consolidated dataset will contain physical, chemical, biological, and environmental factors, whereas the existing system, examines any one of the above factors for predicting the crop yield. The proposed Agrarian application equipped with the state-of-art classification and regression algorithms. The system would also employ the correlation techniques to find the relationship between the crop growth and the other factors. It would help in suggesting the crop for a particular farm and predict the yield rate.

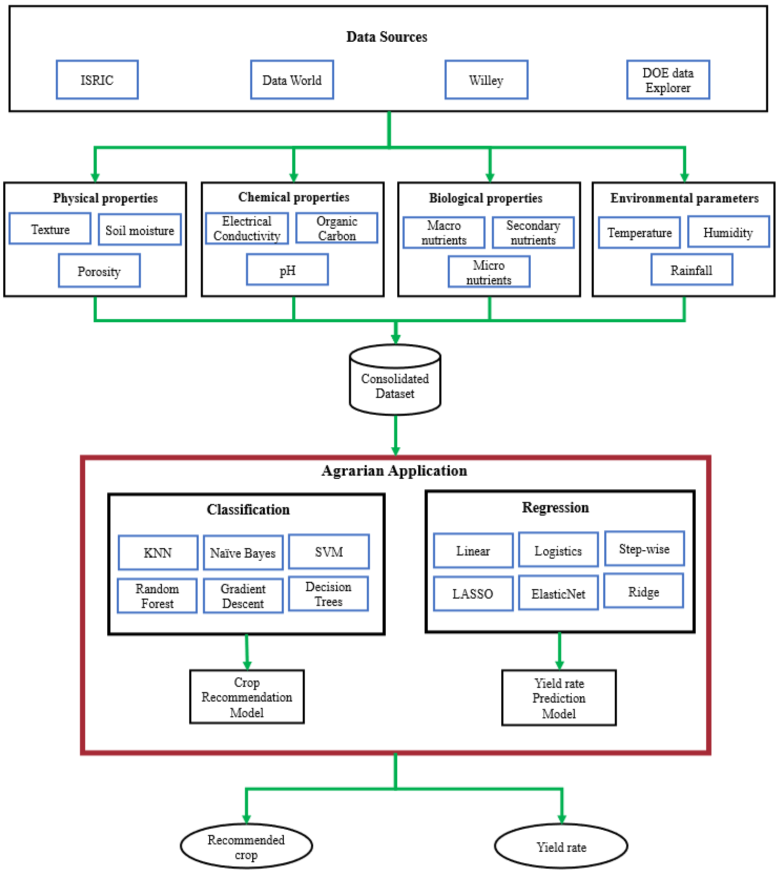

Figure 1: The Proposed Agrarian application workflow

4 Conclusion and future work

The nutrient content of the soil is a key factor for the agricultural outcome. The presence of sixteen essential nutrients is necessary for the optimal outcome along with the environmental parameters. Most of the research studies concentrates on evaluating the total amount of nutrients, physical and biological characteristics of soil to optimize the crop yield rate. However, the environmental factors have a higher influence on the level of soil nutrients. The sustainability of the soil could only be ensured by maintaining the proper environmental conditions. The objective of this study is to design a model that suggests the suitable crop for the particular farm using the state-of-art classification algorithms and predicts the yield rate of the recommended crop by employing regression techniques. The proposed Agrarian model would help the farmers in selecting the crops which is expected to give optimum yield, without taking soil tests in laboratories. This work could be further extended by implementing ANN, into the system. Since the ANN is embodied with actvation functions, it is capable of learning any dynamic input-output interaction. Hence, ANN would be employed to improve the soil fertility prediction and recommend the fertilizers based on the variation in environmental factors.

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