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Intercropping Using NRC Algorithm

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Abstract:

Current To predict the crop rotation for varied sorts of soil and might be done through soil fertility, water level, chemical level, climatic condition and etc. Here, mistreatment totally different data processing techniques over agriculture land soil testing is that the methodology is mistreatment wide wherever that crop is often farmed when that crop. As an example, rice is going to be cultivated at intervals seven months to eight months. The remaining time the farm won't be left empty. Another crop could cultivate for the opposite four months.

The main aim is to reduce unnecessary fertilizer usage during the cultivation of lands and to increase soil vitality. With this approach, we can improve crop productivity as well as the nation economy. And a collection of soil testing reports are pre-processed to generate training data sets are available. The training data sets are subjected to data mining techniques like Grouping and clustering methods. Finally, decisions tracked based on group characterization rules implemented. The training data samples Mineral ratios, crop cultivation used to generate various interesting measures for decision support on cultivation.

Keywords: Data Mining Methods, NRC Algorithm, Random Forest Algorithm, NPK Calculation.

1. Introduction

1.1 Crop Rotation

1.1.1 What Is Crop Rotation?

Crop rotation is that the systematic planting of various crops during a particular order over several years in the same growing space. This process helps maintain nutrients in the soil, reduce soil erosion, and prevents plant diseases and pests. The length of rotation time between different plants also will vary counting on the requirements of the gardener.

1.1.2 Need for Crop Rotation

In the previous few years, crop rotation has gained attention wrt its economic, environmental and social importance which explains why it may be highly beneficial for farmers. This paper presents a mathematical model for the Crop Rotation Problem (CRP) that was adapted from literature for this highly complex combinatorial problem. The CRP is devised to seek out vegetable planting program that takes under consideration green fertilization restrictions, the set-aside period, planting restrictions for neighbouring lots and for crop sequencing, demand constraints, while, at the same time, maximizing the profitability of the planted area.

This study is to develop a genetic algorithm and test it in a practical context. The genetic algorithm involves a constructive heuristic to build the initial population and therefore operators of crossover, mutation, migration and elitism. The computational experiment was performed for a medium dimension real planting area with some slots, considering 29 crops of 10 different botanical families and a twoyear planting rotation. Results showed that the algorithm determined feasible solutions in a reasonable computational time, thus proving its efficacy for dealing with this practical application.

1.1.3 Determining optimal Crop rotation with algorithm

Research and knowledge have proven that a wellplanned crop rotation provides more consistent yields, increases profit potential, helps in pest control and maintains or improves soil structure and organic matter levels. Recent literature reports plan to model rotations and a growing interest to use computational tools to supply optimal crop rotations considering one optimization objective. The existence of contradictory objectives, as risky cultivation options with optimal returns, means the necessity to research trade-offs solutions. it's exacerbated when the analysis includes other economic and environmental issues. Considering a farm with many cultivation parcels the matter may become huge. In fact, for one season having k sorts of crops and m parcels the entire number of possible combinations is km.

Multi-objective Evolutionary Algorithms (MOEAs) have shown to be useful to explore large search spaces.

This work proposes the utilization of MOEAs to work out crop rotations considering various cultivation parcels and a number of other optimization objectives simultaneously. This work tries to supply trade-off solutions for a crop rotation problem considering various cultivation parcels and crop alternatives with the subsequent objectives: to attenuate the entire investment cost, to maximise the build-up of nutrients in soils, to maximise economic return, to attenuate economic risk and to market diversification of crops in subsequent seasons and adjacent parcels within the same season. This section briefly describes these objectives. the entire investment cost is that the sum of fixed and variable costs of rotations. Fixed costs are those not influenced by chemical characteristics of soils, thus, it's the sum of fixed costs for crops in sequence. Variable cost depends on crop needs and soil characteristics. Soil test results are wont to determine the variable cost at the start, estimations of soil conditions are utilized in subsequent periods. to get these costs the subsequent data is needed: fixed costs and nutritional demands of crops; soil treatment costs for crops consistent with soil characteristics per hectare; soil test results, size, and site of parcels and knowledge about nutrients absorbed and extracted by crops (to estimate soil conditions after a season). the entire investment cost is an objective to maximise.

1.2 NPK Calculation

The letters N-P-K are short for the scientific names of nutrients in fertilizers:

- N stands for nitrogen
- P stands for phosphor
- K stands for potash (or potassium)

Nitrogen, phosphor and potash are the main nutrients for plants. Nitrogen is necessary for its growth and phosphor for the development of roots, buds and flowers. Potash is vital for sturdiness, flowering and fruiting, and a better resistance (as in protection from mould and diseases).

1.2.1 How are they calculated?

The figures following the letters show the nutrients' proportions in that particular fertilizer. For instance, a fertilizer with the code N-P-K 12-10-18 contains 12 percent nitrogen, 10 percent phosphor and 18 percent potash.

For example if you have a liquid concentrated fertilizer that has a composition of N = 12000 ppm, K = 20000 ppm and P = 4000 ppm which was prepared with 200g of added salts. The NPK ratio of this solution would be :

Total Solution Weight = 1000g (1L of water) + 200g (added salts)

N = 12000 ppm = 12000 mg/L = 12g/L

K = 20000 ppm = 20000 mg/L = 20 g/L

P = 4000 ppm = 4000 mg/L = 4 g/L

Percentage of Nitrogen = (12g/1200g)*100 = 1%

Percentage of K as K2O5 = (20g/1200g)*1.2046 (K to K2O conversion factor)*100 = 2%

Percentage of P as P2O5 = (4g/1200g)*2.2914 (P to P2O5 conversion factor)*100 = 0.76%

The final NPK ratio is therefore 1 - 0.76 - 2.

1.3 NRC Algorithm

NRC stands for Nominal Ratio Classification

Classification is a data mining task that aims to get a simple schematic representation of complex data. There are different types of Data and Measurement Scales are Nominal, Ordinal, Interval and Ratio. These are simply ways to sub-categorize different types of data. Here in this paper we use nominal and ratio type for data classification.

1.3.1 Nominal

Nominal scales are used for labelling variables, without any quantitative value. Nominal scales could simply be called labels. Notice that all the examples of these scales are mutually exclusive (no overlap) and none of them have any numerical significance. A good way to remember all of this is that 'nominal' sounds a lot like 'name' and nominal scales are kind of like names or labels.

Examples of Nominal Scales

Note: a sub-type of nominal scale with only two categories (e.g. male/female) is called dichotomous. If you are a student, you can use that to impress your teacher.

Bonus Note #2: Other sub-types of nominal data are 'nominal with order' (like cold, warm, hot, very hot) and nominal without order (like male/female).

1.3.2 Ratio

Ratio scales are the ultimate nirvana when it comes to data measurement scales because they tell us about the order, they tell us the exact value between units, and they also have an absolute zero which allows for a wide range of both descriptive and inferential statistics to be applied. At the risk of repeating myself, everything above about interval data applies to ratio scales, plus ratio scales have a clear definition of zero. Good examples of ratio variables include height, weight, and duration.

Ratio scales provide a wealth of possibilities when it comes to statistical analysis. These variables can be meaningfully added, subtracted, multiplied, divided (ratios). Central tendency can be measured by mode, median, or mean; measures of dispersion, such as standard deviation and coefficient of variation can also be calculated from ratio scales.

This Device Provides Two Examples of Ratio Scales (height and weight)

1.4 Random Forest Algorithm

Random forest may be a supervised learning algorithm that's used for both classifications still as regression. But however, it's mainly used for classification problems. As we all know that a forest is created from trees and more trees mean more robust forests. Similarly, the random forest algorithm creates decision trees on data samples then gets the prediction from each of them and at last selects the simplest solution by means of voting. it's an ensemble method that's better than one decision tree because it reduces the over-fitting by averaging the result.

Working of Random Forest Algorithm

We can understand the working of Random Forest algorithm with the help of following steps –

- Step 1 First, start with the selection of random samples from a given dataset.
- Step 2 Next, this algorithm will construct a decision tree for every sample. Then it will get the prediction result from every decision tree.
- Step 3 In this step, voting will be performed for every predicted result.
- Step 4 At last, select the most voted prediction result as the final prediction result.

The following diagram will illustrate its working -

1.5 Data Mining Methods

Coming to Data Mining Methods, here we use Grouping and Classification techniques.

1.5.1 Grouping

It is a method of partitioning a collection of knowledge into clusters or groups of objects. The clustering is finished using algorithms. it's a kind of unsupervised learning because the label information isn't known. Clustering methods identify data that are similar or different from one another, and analysis of characteristics is finished. Cluster analysis is often used as a pre-step for applying various other algorithms like characterization, attribute subset selection, etc. Cluster Analysis can even be used for Outlier detection like high purchases in MasterCard transactions

1.5.2 Classification

Classification helps in building models of important data classes. A model or a classifier is built to predict the category labels. Labels are the defined classes with discrete values like 'yes' or 'no', 'safe' or 'risky'. it's a sort of supervised learning because the label class is already known.

Data Classification is a two-step process:

1. Learning step: The model is constructed here. A pre-defined algorithm is applied to the data to analyze with a class label provided and the classification rules are constructed.

2. Classification Step: The model is used to predict class labels for given data. The accuracy

of the classification rules is estimated by the test data which if found accurate is used for classification of new data tuples.

The items in the itemset will be assigned to the target categories to predict functions at the class label level.

2. Literature Survey

Clark, P. and Niblett, T., [1] the use of instance selection algorithms for scaling down the data sets before the subgroup discovery task. The results show that CN2-SD can be executed on large data set sizes pre-processed, maintaining and improving the quality of the subgroups discovered.

R. Agrawal, T. Imielinski, and A. Swami. [2] a step towards enhancing databases with functionalities to process queries such as (we have omitted the confidence factor specification): Find all rules that have \Diet Coke" as consequent. These rules may help plan what the store should do to boost the sale of Diet Coke. Find all rules that have \bagels" in the antecedent. These rules may help determine what products may be impacted if the store discontinues selling bagels. Find all rules that have \sausage" in the antecedent and \mustard" in the consequent. This query can be phrased alternatively as a request for the additional items that have to be sold together with sausage in order to make it highly likely that mustard will also be sold. Find all the rules relating items located on shelves A and B in the store. These rules may help shelf planning by determining if the sale of items on shelf A is related to the sale of items on shelf B.

Cesar Ferri-Ram' Irez, Peter A. Flach, and Jose Hernandez-Orallo. [3] proposed how a single decision tree can represent a set of classifiers by choosing different labelling of its leaves, or equivalently, an ordering on the leaves. In this setting, rather than estimating the accuracy of a single tree, it makes more sense to use the area under the ROC curve (AUC) as a quality metric. And also proposed a novel splitting criterion which chooses the split with the highest local AUC.

M. Banek, Z. Skocir, and B. Vrdoljak. [4]. developed a methodology for data warehouse design from the source XML Schemas and conforming XML documents. As XML data is semi-structured, data warehouse design from XML brings many particular challenges. In this paper the final steps of deriving a conceptual multidimensional scheme are described, followed by the logical design, where a set of tables is created according to the derived conceptual scheme. A prototype tool has been developed to test and verify the proposed methodology.

M. Body, M. Miquel, Y. B'edard, and A. Tchounikine [5] This paper addresses the problem of how to specify changes in multidimensional databases. These changes may be motivated by evolutions of user requirements as well as changes of operational sources. The multi version-based multidimensional model we provide supports both data and structure changes. The approach consists in storing star versions according to relevant structure changes whereas data changes are recorded through dimension instances and fact instances in a star version. The model is able to integrate mapping functions to populate multi version-based multidimensional databases.

P. Burte, B. Aleman-meza, D. B. Weatherly, R. Wu, S. Professor, and J. A. Miller [6]. we examine the details of thread concurrency and resource locking protocols, our deadlock prevention scheme, and the Java-based implementation of these design decisions. We show the effectiveness of our design with performance tests that simulate typical transactions on a highly concurrent database system.

W. Chung and H. Chen. [7]. we propose the development of a new class of BI systems based on rough set theory, inductive rule learning, and information retrieval methods. We developed a new framework for designing BI systems that extract the relationship between the customer ratings and their reviews.

Josh C.Bongard, Paul D. H. Hines, Dylan Conger, Peter Hurd, and Zhenyu Lu. [8]. This paper describes a new approach to machine science which demonstrates for the first time that non-domain experts can collectively formulate features, and provide values for those features such that they are predictive of some behavioural outcome of interest. This was accomplished by building a web platform in which human groups interact to both respond to questions likely to help predict a behavioural outcome and pose new questions to their peers. This results in a dynamically-growing online survey, but the result of this cooperative behaviour also leads to models that can predict user's outcomes based on their responses to the user-generated survey questions.

Kashif Javed, Haroon A. Babri, and Mehreen Saeed. [9]. we propose a new FR algorithm, termed as class-dependent density-based feature elimination (CDFE), for binary data sets. Our theoretical analysis shows that CDFE computes the weights, used for feature ranking, more efficiently as compared to the mutual information measure.

Li Zeng, Lida Xu, Zhongzhi Shi, Maoguang Wang, and Wenjuan Wu. [10]. This article reviews the concept of Business Intelligence and provides a survey, from a comprehensive point of view, on the BI technical framework, process, and enterprise solutions. In addition, the conclusions point out the possible reasons for the difficulties of broad deployment of enterprise BI, and the proposals of constructing a better BI system. As businesses continue to use computer systems for a growing number of functions in today's competitive, fastevolving world, most companies face the challenges of processing and analyzing huge amounts of data and turning it into profits. They have large volumes of detailed operational data, but key business analysts and decision makers still cannot get the answers they need to react quickly enough to changing conditions because the data are spread across many departments in the organization or are locked in a sluggish technology environment. In these cases, Business Intelligence (BI) is presented, which are sets of tools, technologies and solutions designed for end users to efficiently extract useful business information from oceans of data.

Cao, L.J., Tay [11]. This paper deals with the application of SVM in financial time series forecasting. The feasibility of applying SVM in financial forecasting is first examined by comparing it with the multilayer back-propagation (BP) neural network and the regularized radial basis function (RBF) neural network. The variability in performance of SVM with respect to the free parameters is investigated experimentally.

Rashina Hoda, James Noble [12]. Self-organizing teams have been recognized and studied in various forms—as autonomous groups in socio-technical systems, enablers of organizational theories, agents

of knowledge management, and as examples of complex-adaptive systems.

3. Motivation

Our approach towards Crop Rotation Using NRC Algorithm is quite different as our aim is to create a platform where one can get suggestion tables of different crop rotations suitable as according to the requirements. Random Forest Algorithm is used to compare the efficiency and performance of NRC Algorithm and Random Forest Algorithm. Previously existing system has decision analysis, a decision tree can be used to visually and explicitly represent decisions and decision making. In data mining, a decision tree describes data but not decisions; rather the resulting classification tree can be an input for decision making. That deals with decision trees in data mining. The goal is to create a model that predicts the value of a target variable based on several input variables. Each interior node corresponds to one of the input variables, there are edges to children for each of the possible values of that input variable. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf.

But the problem there exist is in learning an optimal decision tree is known to be NP-complete under several aspects of optimality and even for simple concepts. Consequently, practical decision-tree learning algorithms are based on heuristics such as the greedy algorithm where locally optimal decisions are made at each node. Such algorithms cannot guarantee to return the globally optimal decision tree. Decision-tree learners can create over-complex trees that do not generalise well from the training data. (This is known as over fitting) Mechanisms such as pruning are necessary to avoid this problem. There are concepts that are hard to learn because decision trees do not express them easily, such as XOR, parity or multiplexer problems. In such cases, the decision tree becomes prohibitively large. Approaches to solve the problem involve either changing the representation of the problem domain or using learning algorithms based on more expressive representations (such as statistical relational learning or inductive logic programming). For data including categorical variables with different numbers of levels, information gain in decision trees is biased in favour of those attributes with more levels. So, to overcome this problem, decision tree classification method using modified NRC algorithm is used.

4. Problem Statement

The implementation is about K-Mine and various mining techniques. In data mining, association rule learning is a popular and well researched method for discovering interesting relations between variables in large databases. Piatetsky-Shapiro describes analysing and presenting strong rules discovered in databases using different measures of interestingness. Based on the concept of strong rules, Agrawal introduced association rules for discovering regularities between products in large scale transaction data recorded by point-of-sale (POS) systems in supermarkets. For example, the rule {onion, potatoes} = {burger} found in the sales data of a supermarket would indicate that if a customer buys onions and potatoes together, he or she is likely to also buy burger. Such information can be used as the basis for decisions about marketing activities such as, e.g., promotional pricing or product placements. In addition to the above example from market basket analysis association rules are employed today in many application areas including Web usage mining, intrusion detection and bioinformatics. In computer science and data mining, K - Mine is a classic algorithm for learning association rules. K - Mine is designed to operate on databases containing transactions (for example, collections of items bought by customers, or details of a website frequentation). Other algorithms are designed for finding association rules in data having no transactions

General Process Association rule generation is usually split up into two separate steps: 1. First, minimum support is applied to find all frequent item sets in a database. 2. Second, these frequent item sets and the minimum confidence constraint are used to form rules. While the second step is straight forward, the first step needs more attention. Finding all frequent item sets in a database is difficult since it involves searching all possible item sets (item combinations). The set of possible item sets is the power set over I and has size 2n - 1 (excluding the empty set which is not a valid itemset). Although the size of the powerset grows exponentially in the number of items n in I, efficient search is possible using the downward-closure property of support (also called anti-monotonicity) which guarantees that for a frequent itemset, all its subsets are also frequent and thus for an infrequent itemset, all its supersets must also be infrequent. Exploiting this property, efficient algorithms (e.g., K - Mine and Eclat) can find all frequent item sets.

5. Problem Methodology & Solution

Our approach towards Crop Rotation Using NRC Algorithm is quite different as our aim is to create a platform where one can get suggestion tables of different crop rotations suitable as according to the requirements. Random Forest Algorithm is used to compare the efficiency and performance of NRC Algorithm and Random Forest Algorithm.

As an alternative for Decision Analysis which had its drawback, we developed this with decision tree classification method using modified NRC algorithm. The algorithm we selected for this purpose is NRC Algorithm as it was the most efficient algorithm and was proved by comparing with Random Forest Algorithm.

The traditional approach for Crop Rotation is by using optimal decision tree, is known to be NPcomplete under several aspects of optimality and even for simple concepts. Consequently, practical decision-tree learning algorithms are based on heuristics such as the greedy algorithm where locally optimal decisions are made at each node. Such algorithms cannot guarantee to return the globally optimal decision tree. Decision-tree learners can create over-complex trees that do not generalise well from the training data. Mechanisms such as pruning are necessary to avoid this problem.

In this new approach, Decision tree learning algorithm has been successfully used in expert systems in capturing knowledge. The main task performed in these systems is using inductive methods to the given values of attributes of an unknown object to determine appropriate classification according to decision tree rules. We examine the decision tree learning algorithm ID3 algorithm implement this using C# and programming. We first implement basic ID3 in which we dealt with the target function that has discrete output values. We also extend the domain of ID3 to real valued output, such as numeric data and discrete outcome rather than simply Boolean value. The Java applet provided at last section offers a simulation of decision-tree learning algorithm in various situations.

By using this new approach even large amounts of data can be analysed using standard computing resources in reasonable time. And people are able to understand decision tree models after a brief explanation. Also performs well even if its assumptions are somewhat violated by the true model from which the data were generated.

6. Design & Technical Description

Up to now we have only discussed about what are we doing and why are we doing?

As we exactly know the methods or modules to implement, let us now discuss about the

design and implementation of these modules. Also there are two interfaces, one for admin and one for user/farmer, our main part here is to get the suggestion tables of different crops using some inputs like NPK ratios, and Soil types, land types and soil textures. And then we start calculating. It calculates and displays some result tables with months and different crops suitable for that months. From that we can search for suggestion tables and finally we would observe some output which is accurate.

And coming to admin side we come to see there are different interfaces like calculating NPK values, calculating NRC, Random Forest Calculation and different data mining techniques like grouping and classification. We came to know about how NPK is calculated. And now we will see how NRC is calculated?

Algorithm for NRC Calculation

Declaration

Soil Type: ST, Land Type: LT HU, Soil Text : STX, N: Nitrogen, P:Phosphorus, K:Potassium

Consider: Month, Crop

Algorithm

Start

set crop1 to Empty, set crop2 to Empty, set crop3 to Empty

Provide input for calculation : ST,LT,STX,N,P,K

Get Cropname for ja[i],fe[i],ma[i],ap[i],my[i],ju[i],jl[i],au[i],se[i],oc[i], no[i],de[i],cr[i] to add j[]

Set : ST,LT,STX

Calculate Range: N,P,K

Calculate: ST :N, ST: P, ST:K

LT :N, LT:P, LT:K

STX :N, STX:P, STX:K

Finalize (ST:N,P,K : LT:N,P,K : STX:N,P,K)

Create Suggestion : j[] count = 1 then Update : crop

Update crop1 repeat process

if

ja[i],fe[i],ma[i],ap[i],my[i],ju[i],jl[i],au[i],se[i],oc[i], no[i],de[i] [] count = 2 then

update crop1, crop2 repeat process

ja[i],fe[i],ma[i],ap[i],my[i],ju[i],jl[i],au[i],se[i],oc[i], no[i],de[i] [] count = 3 then

Update crop1, crop2, crop3

Repeat for other values

Stop Process

Based on these output accuracies we compute the overall performance and efficiency of both the techniques NRC Algorithm and Random Forest Algorithm.

7. Results & Analysis

7.1 Independent Images:

These are the output resultant images that are processed through our network. As there are two interfaces, one is for admin and another for farmer/user, Fig. 7.1.1, Fig. 7.1.2, Fig 7.1.3, Fig. 7.1.4, Fig. 7.1.5, Fig. 7.1.6 are from admin side. And Fig. 7.1.7, Fig. 7.1.8, Fig 7.1.9, Fig. 7.1.10 belongs to farmer side.



Fig 7.1.1: Login page



Fig 7.1.2: Home Page

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Fig 7.1.3: Nominal Ratio Classification

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Fig 7.1.4: Random Forest Algorithm

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Pre process	soilid	fertiliid	locid	timeid	cropid	pattid	fertitype	stypeid	villid	villname	distcode	block	calyear	soiltype	soiltextu	landclass	j
Classification & Grouping	3426	91126	126	9876	91126	7126	urea, super phosphate	8126	226476	Kongupatti	DGL	ODC	2005	Black	SCL	garden_lands	; 3
NPK Calculation	3452	91152	152	9902	91152	7152	ammonium nitrate or urea,superphosphate	8152	226502	Kongupatti	DGL	ODC	2006	Black	SCL	garden_lands	; 11
NRC Calculation	3478	91178	178	9928	91178	7178	ammonium nitrate or urea,superphosphate	8178	226528	Kongupatti	DGL	ODC	2007	Black	SCL	dry_lands	T
Random Forest	3504	91204	204	9954	91204	7204	urea, super phosphate	8204	226554	Kongupatti	DGL	odc	2008	Black	SCL	garden_lands	;)
Performance	3530	91230	230	300080	13404	1104	urea, super phosphate	8230	226579	Kongupatti	DGL	ODC	2009	Black	SCL	wet_lands	3
llear db	3556	91256	256	400056	13430	3110	urea, super phosphate	8256	226605	Kongupatti	DGL	ODC	2010	Black	SCL	dry_lands	r
ogout	9911	200482	319	500069	13493	13103	ammonium nitrate or urea,superphosphate	7163	1163	Pethanayakanpatty	DGL	Palani	2006	Red sandy	SCL	garden_lands	- 1
	9880	200449	286	400086	13460	6110	urea, super phosphate	7130	1130	Velusamudram	DGL	Palani	2005	Black	SCL	dry_lands	1
	9886	200455	292	400092	13466	8106	urea, super phosphate	7136	1136	Vadipatti south	DGL	Palani	2005	Red sandy	L	wet_lands	

Fig 7.1.5: Classification

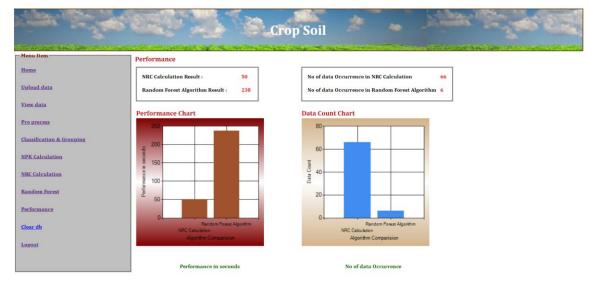


Fig 7.1.6: Performance Chart



Home

Logout



Fig 7.1.7: Farmer Home Page

	and the	Crop So		
Menu Item	Soil Type	Black T	Crop Rotate 1 Crop Rotate 2	
Home	Land Type	wet_lands ▼		
	Soil Text	SCL V		
Calculation	N(Nitrogen)	From 0 To 70		
Change Password	P(Phosphorus)	From 0.0 To 400		
	K(Potassium)	From 0 To 500		
Logout		Calculate		
	Result 1		Search Result 2 Search	
	jan feb mar apr		jan feb mar apr may jun jul aug sep oct nov dec cropname	
		no no no no no no no no paddy no no no no yes yes no no mango	yes no paddy no no no no no yes yes no no no no mango	
		no no no no no yes yes yes paddy	no no no no no yes yes no no no no no mango no no yes yes yes no no no no no no groundnut	
		no yes yes yes yes yes no sunflower	no no no no no no no no yes yes no no mango	
	yes no no no	no no no no no no yes banana	yes no no no no no no no no yes guava	
	yes no no no	no no no no no no yes banana	no no no no no no yes yes yes yes onion	
	no no no no	no no yes yes yes no no no bajra	no no no no yes yes no no no bajra	
	no no yes yes	yes no no no no no no bajra	yes yes no no no no no no yes yes ginegelly	
	no no yes yes	yes no no no no no no tomato	yes yes no no no no no no yes yes paddy	
	yes no no no	no no no no no no yes cotton	no no no no yes yes yes yes yes no sunflower	
	no yes yes no	no no no no no no no bajra	yes no no no no no no no no yes banana	
		yes yes yes no no no no grapes	yes no no no no no no no no no yes banana	
		yes no no no no no no ragi	no no no no no yes yes no no no bajra	
		no no no no no no no paddy	no no yes yes yes no no no no no no bajra	
	, ,	no no no no no no no no red_gram no yes yes no no no no no sugarcane	no no yes yes yes no no no no no no tomato ves no no no no no no no no no ves cotton	
	no no no no	no yes yes no no no no sugarcane	no ves ves no no no no no no no no no bajra	
			yes yes yes yes yes yes no no no no no grapes	
			no no yes yes no no no no no no ragi	
			no yes yes no no no no no no no no paddy	
			no yes yes no no no no no no no no red_gram	
			no no no no yes yes no no no no sugarcane	
			no no no no no no no yes yes no no blackgram	

Fig 7.1.8: Wet lands result

	Crop Sc	oil	*		-				
Menu Item		Crop R	otate 1		all 2 Mills	Crop	Rotate 2	No. (NY)	Southers.
Soil Type	Black	-	crop1	crop2	crop3	month		crop2 crop	3
Home	wet had -	jan	paddy	paddy	banana	jan	paddy	guava ginege	ly
Home Land Type	wet_lands v	feb	paddy	bajra	grapes	feb	ginegelly	paddy bajra	
Soil Text	SCL V	mar	bajra	tomato	bajra	mar	groundnut	bajra tomato	
Calculation		apr	bajra	tomato	grapes	apr	groundnut	bajra tomato	
N(Nitrogen)	From 0 To 70	may	bajra	tomato	grapes	may	groundnut	bajra tomato	
		jun	sunflower	grapes	sugarcane	jun	mango	bajra sunflo	wer
Change Password P(Phosphorus)	From 0.0 To 400		sunflower		grapes	jul			
			sunflower			aug	onion	bajra sunflo	
K(Potassium)	From 0 To 500		mango	sunflower		sep	mango	onion sunflo	
Logout			mango	paddy	sunflower	oct	mango	onion ginege	Iy
	Calculate		paddy paddy	sunflower banana	banana	nov	onion	ginegelly paddy onion ginege	1
Described.					Danana	dec	guava	onion ginege	-
Result 1	or may jun jul aug sep oct nov dec cropname	Search			mar inn it	al and	sen oct no	dec cropname	Search
yes no no n			yes no					no paddy	
no no no n			no no					no mango	
yes yes no			no no					no groundnut	
no no no n			no no					no mango	
yes no no n			yes no					yes guava	
yes no no n			no no					yes onion	
no no no n	o no no yes yes yes no no no bajra		no no	no no			no no no		
no no yes y	s yes no no no no no no bajra		yes yes	no no	no no no			yes ginegelly	
	s yes no no no no no no tomato		yes yes		no no no			yes paddy	
yes no no n	o no no no no no no yes cotton		no no	no no	no yes ye	es yes	yes yes yes	no sunflower	
no yes yes n	o no no no no no no no bajra		yes no	no no	no no no	o no	no no no	yes banana	
yes yes yes	es yes yes yes no no no no grapes		yes no	no no	no no no	o no	no no no	yes banana	
no no yes y	es yes no no no no no no ragi		no no	no no	no no ye	es yes	yes no no	no bajra	
no yes yes i	o no no no no no no no paddy		no no	yes yes	yes no no	o no	no no no	no bajra	
no yes yes n	o no no no no no no no red_gram		no no	yes yes	yes no no	o no	no no no	no tomato	
no no no n	o no yes yes no no no no sugarcane		yes no	no no	no no no	o no	no no no	yes cotton	
			no yes	yes no	no no no	o no	no no no	no bajra	
			yes yes	yes yes	yes yes ye	es no	no no no	no grapes	
			no no	yes yes	yes no no	o no	no no no	no ragi	
			no yes	yes no	no no no	o no	no no no	no paddy	
			no yes	yes no	no no no	o no	no no no	no red_gram	
			no no	no no			no no no	no sugarcane	
			no no	no no	no no no	o no	yes yes no	no blackgram	

Fig 7.1.9 Wet lands Crop rotation result



Fig 7.1.10: Dry lands crop rotation result

8. Conclusion & Future work

The results shown are useful in various holdings which require the rotation of cultures. This current work based on the present one would be finding other methods which would bring improvements to the actual method. The development can be made as well as for the choice of the algorithm. This study can be made for improved algorithms or on the effects of using crop rotation in agriculture and what improvements can be brought to crop rotation from the agriculture. Another direction of developing this subject is to find other methods used in agriculture for improving productions with as low as possible costs and avoiding damage over the environment. All the result has been verified and output has been generated as per commitment.

And coming to the future work, this technique can be implemented by using seasonal reports and Indian weather reports so that it become easy to get the suggestions of different types of crop rotations suitable for the fields based on soil texture, soil type and land type and also we can include other crisis that we want to.

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