

ANALYZING THE CROP CULTIVATION BASED ON THE SEASONAL DISASTERS

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ABSTRACT:

India's backbone is agriculture, and the economy predominantly depends on agriculture's yield, growth, and Argo industry products. Data analysis is an emerging research field in crop yield analysis. Yield prediction is a very important issue in agriculture. Natural disasters in India as per India's National Policy on Disaster Management, the natural disasters that India is prone to are earthquakes, floods, droughts, cyclones, tsunamis, landslides, and avalanches. The disasters are classified based on seasonal disasters. Seasonal disasters like weather and climatic changes like rainfall cause regular issues for farmers across India. Using the dataset and with the suitable attributes for creating a suitable model using a machine learning algorithm. Key word: Agriculture, Seasonal Disaster, Natural disaster.

I. INTRODUCTION:

Agriculture plays a very important role in India and also contributes to a major part of the Indian economy. Today, the climatic conditions in India are changing day by day, which is too unpredictable, and it also affects agriculture. Data analysis is also an emerging technology which is being used here for seasonal disasters like weather and climatic changes like rainfall, which cause regular issues for farmers across India. A decision-tree machine learning algorithm is used here for the prediction of crop cultivation based on the seasonal disaster across India.

II. OBJECTIVE:

India is known for its agricultural products and productivity. Nowadays, agriculture productivity is lower in India because of global warming, pollution, a lower amount of rainfall, etc. In order to increase the productivity in agriculture, the past data on crop cultivation based on the seasonal disasters across India is being analysed here with a decision tree machine learning algorithm.

III. RELATED WORK:

Mr. M. V. K. Sivakumar has done research on climate change prediction and agriculture: current status and future challenges that the farmer's has to face, World Meteorological

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The authors: U.S.De, R.K.Dube¹ and G.S.Prakasa Rao² made a analysis on Extreme Weather Events over India in the last 100 years, Visiting faculty Department of Environmental Science/University of Pune, India and Former Additional Director General of Meteorology (Research), Pune 1 Retd. ADGM, Flat No.69, Mausam Apartments, Delhi 110 034 2 India Meteorological Department, National Data Centre, Pune 411 005. [5]

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ElizabethBrainerd and NidhiyaMenon¹ has made a research on Seasonal effects of water quality that has a major role on The hidden costs of the Green Revolution to infant and child health in India, Journal of Development Economics Volume 107, March 2014, Pages 49-64.[6]

The Climate change and water availability in Indian agriculture: Impacts and adaptation gives the future researcher a clear idea which is was given by the authors: H PATHAK¹, P PRAMANIK², M KHANNA³ and A KUMAR⁴; Indian Agricultural Research Institute, New Delhi 110 012. Indian Journal of Agricultural Sciences 84 (6): 00–00, June 2014. [9]

IV. METHODOLOGY:

A. DECISION TREE CLASSIFIER:

Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset. there are two nodes, which are the Decision Node and Leaf Node. Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches. This algorithm is used in this case to forecast a seasonal disaster in India with the appropriate attributes. The Decision Tree doesn't accept the string values, so the string values will be converted to numeric values for fitting the values in decision tree classifier function and then get the features for the decision tree and finally plot and show the output of decision tree. Using d-tree viz library, the decision tree will graphically be visualized for the easy understandability of the tree

B. GINI METHOD IN DECISION TREE:

The Gini Index or Gini Impurity is one of the attribute measures in the decision tree. It helps the larger partitions and very easy to implement. In simple terms, it calculates the probability of a particular randomly selected feature that was classified incorrectly. It varies between 0 and 1, where 0 represents the purity of the classification and 1 denotes random distribution of elements among various classes. A Gini Index of 0.5 shows that there's equal distribution of elements across some classes. The Gini method uses this formula: $Gini = 1 - \left(\frac{x}{n}\right)^2 - \left(\frac{y}{n}\right)^2$ Where x is the number of positive answers, n is the number of samples, and y is the number of negative answers, which gives us this calculation.

C. WORK FLOW

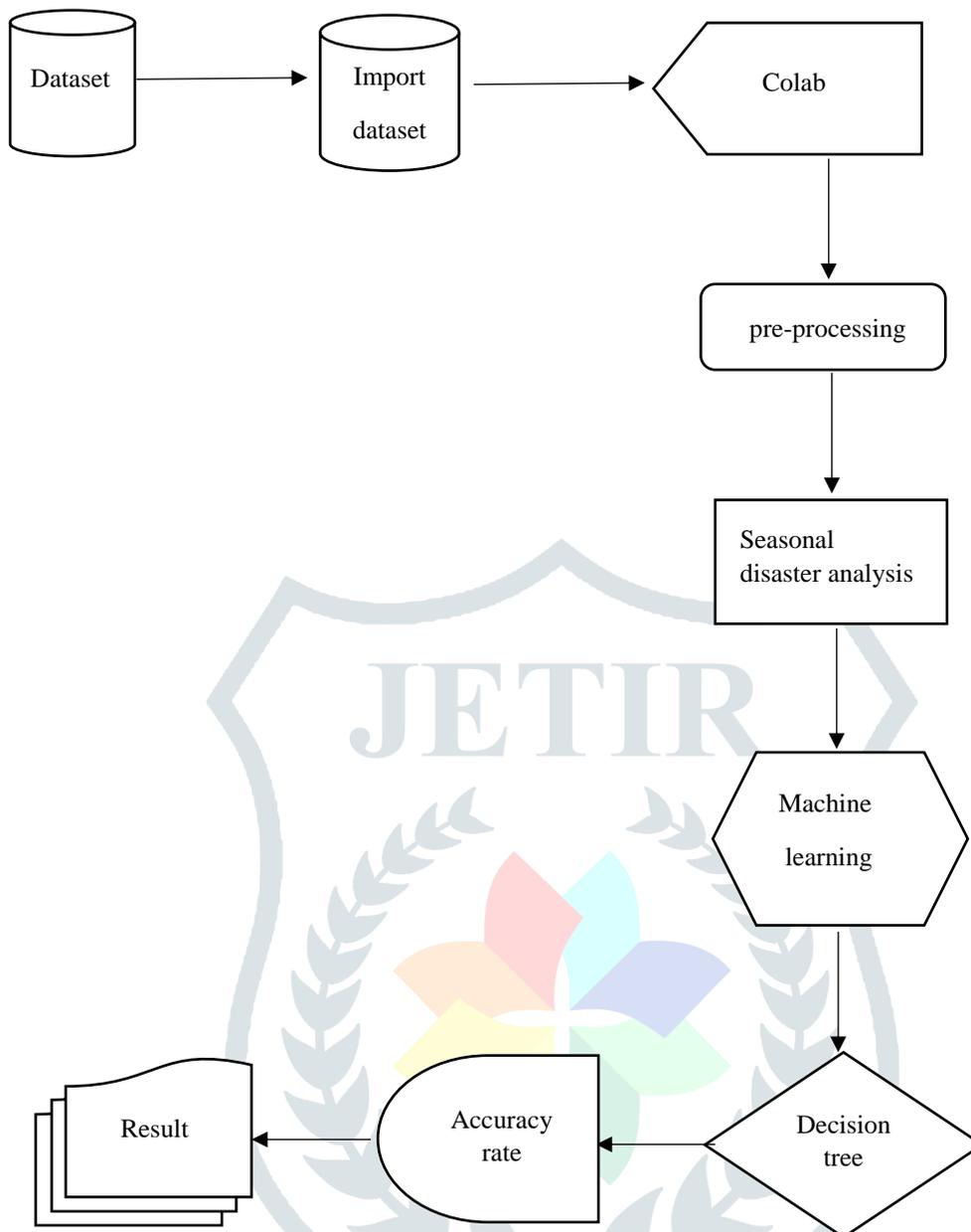


Fig.4.1

The fig.4.1 explains how the workflow is implemented.

IMPLEMENTATION:

Once, the dataset is taken from Kaggle and is imported into the colab. The pre-processing is done in order to eliminate the null data set for the implementation. The coding is being implemented and visualized. The decision tree machine learning algorithm is used here to find out the accuracy, and the decision tree is displayed with the respective attributes and the result is displayed below.

V. RESULT:

TOTAL NO OF DIAASTERS OCCASIONAL/SEASONAL:

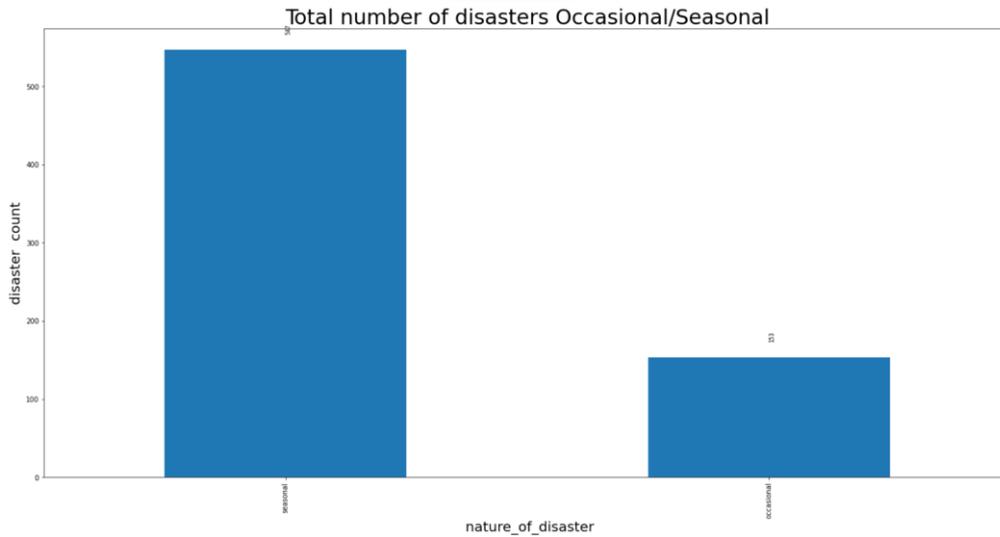


Fig.5.1

The Fig.5.1 shows the total number of disaster occurred seasonally and occasionally and also the count of disaster occurred in each season.

SEASONAL DISASTER IN WINTER:

	year	season	crops_affected	nature_of_disaster	state_name
223	2003	winter	moong	seasonal	Tamil Nadu
402	2009	winter	cardamon	seasonal	Tamil Nadu
428	2011	winter	chillies	seasonal	Tamil Nadu
481	2013	winter	moong	seasonal	Tamil Nadu
496	2013	winter	moong	seasonal	Tamil Nadu
536	2015	winter	milletts (small)	seasonal	Tamil Nadu
570	2017	winter	tea	seasonal	Tamil Nadu
589	2017	winter	tea	seasonal	Tamil Nadu
640	2018	winter	cardamon	seasonal	Tamil Nadu

Fig.5.2

The Fig.5.2 shows the seasonal disaster that occurred in Tamil Nadu in winter season with the year and also with the affected crop.

SEASONAL DISASTER IN SUMMER:

	year	season	crops_affected	nature_of_disaster	state_name
129	1999	summer	onion	seasonal	Tamil Nadu
146	2000	summer	gram	seasonal	Tamil Nadu
147	2000	summer	jute	seasonal	Tamil Nadu
252	2004	summer	coffee	seasonal	Tamil Nadu
253	2004	summer	gram	seasonal	Tamil Nadu
259	2004	summer	coffee	seasonal	Tamil Nadu
280	2005	summer	banana	seasonal	Tamil Nadu
306	2006	summer	millets (small)	seasonal	Tamil Nadu
353	2008	summer	gram	seasonal	Tamil Nadu
371	2008	summer	coffee	seasonal	Tamil Nadu
415	2010	summer	millets	seasonal	Tamil Nadu
417	2010	summer	moong	seasonal	Tamil Nadu
458	2012	summer	chillies	seasonal	Tamil Nadu
512	2014	summer	coffee	seasonal	Tamil Nadu
513	2014	summer	gram	seasonal	Tamil Nadu
533	2015	summer	other oilseeds	seasonal	Tamil Nadu
541	2015	summer	banana	seasonal	Tamil Nadu
545	2015	summer	millets (small)	seasonal	Tamil Nadu
611	2018	summer	banana	seasonal	Tamil Nadu
619	2018	summer	onion	seasonal	Tamil Nadu
660	2019	summer	coffee	seasonal	Tamil Nadu
672	2020	summer	urad	seasonal	Tamil Nadu
673	2020	summer	sunflower	seasonal	Tamil Nadu

Fig.5.3

The Fig.5.3 shows that the seasonal disaster that occurred in Tamil Nadu in summer season with the year and also with the affected crop.

SEASONAL DISASTER IN SPRING:

	year	season	crops_affected	nature_of_disaster
9	1995	spring	jute	seasonal
11	1995	spring	chillies	seasonal
72	1997	spring	paddy	seasonal
73	1997	spring	coriander	seasonal
74	1998	spring	urad	seasonal
75	1998	spring	sunflower	seasonal
101	1998	spring	onion	seasonal
102	1998	spring	banana	seasonal
103	1998	spring	paddy	seasonal
110	1998	spring	coriander	seasonal
141	1999	spring	tea	seasonal
142	1999	spring	arhar	seasonal
176	2001	spring	maize	seasonal
214	2003	spring	cardamon	seasonal
215	2003	spring	black pepper	seasonal
229	2003	spring	groundnut	seasonal
230	2004	spring	milletts	seasonal
321	2007	spring	milletts	seasonal
329	2007	spring	cardamon	seasonal
331	2007	spring	barley	seasonal
391	2009	spring	tea	seasonal
392	2009	spring	arhar	seasonal
403	2009	spring	black pepper	seasonal

Fig.5.4

The Fig.5.4 shows the seasonal disaster that occurred in Tamil Nadu in spring season with the year and also with the affected crop.

SEASONAL DISASTER IN MONSOON:

	year	season	crops_affected	nature_of_disaster	state_name
109	1998	monsoon	paddy	seasonal	Tamil Nadu
112	1998	monsoon	sunflower	seasonal	Tamil Nadu
118	1999	monsoon	cardamon	seasonal	Tamil Nadu
149	2000	monsoon	chillies	seasonal	Tamil Nadu
150	2000	monsoon	groundnut	seasonal	Tamil Nadu
152	2000	monsoon	onion	seasonal	Tamil Nadu
173	2001	monsoon	chillies	seasonal	Tamil Nadu
196	2002	monsoon	ragi	seasonal	Tamil Nadu
291	2005	monsoon	tea	seasonal	Tamil Nadu
303	2006	monsoon	maize	seasonal	Tamil Nadu
308	2006	monsoon	mesta	seasonal	Tamil Nadu
377	2009	monsoon	maize	seasonal	Tamil Nadu
410	2010	monsoon	cotton	seasonal	Tamil Nadu
412	2010	monsoon	cardamon	seasonal	Tamil Nadu
520	2014	monsoon	moong	seasonal	Tamil Nadu
524	2014	monsoon	maize	seasonal	Tamil Nadu
547	2015	monsoon	mesta	seasonal	Tamil Nadu
591	2017	monsoon	ginger (dry)	seasonal	Tamil Nadu
638	2018	monsoon	cotton	seasonal	Tamil Nadu
644	2019	monsoon	sugarcane	seasonal	Tamil Nadu
682	2020	monsoon	banana	seasonal	Tamil Nadu
684	2020	monsoon	sugarcane	seasonal	Tamil Nadu

Fig.5.5

The Fig.5.5 shows the seasonal disaster that occurred in Tamil Nadu in monsoon season with the year and also with the affected crop.

DECISION TREE CLASSIFIER:

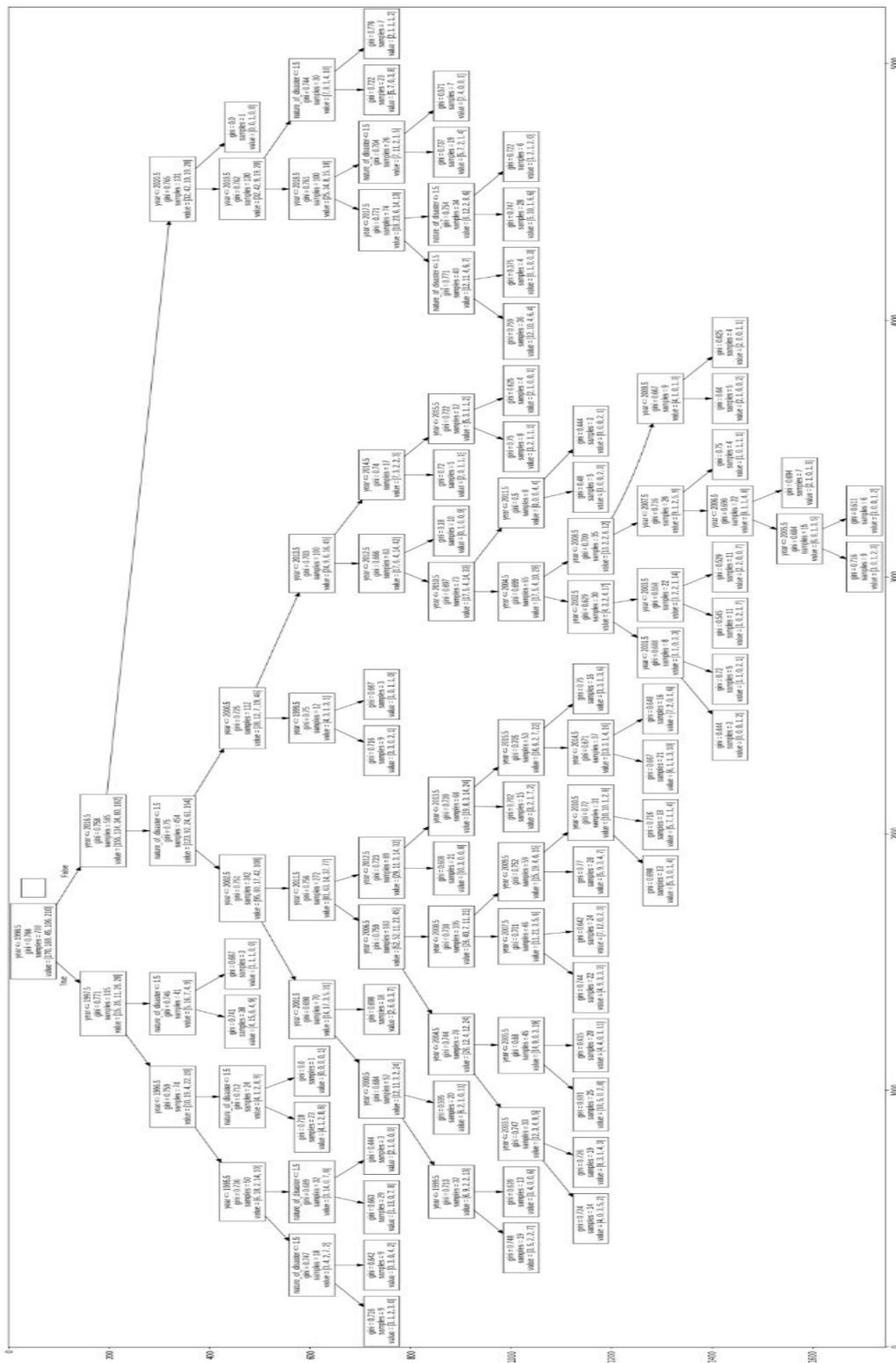


Fig.5.6

The Fig.5.6 shows the decision tree classification with the attributes of year, season, nature_of_disaster.

VI. CONCLUSION:

The analysis is done through a decision tree machine learning algorithm and it is found that if the gini's value lies between 0 and 5, which means that the classification of decision node and leaf node is showing the better result with a big decision tree classification with the year and the value taken from season and nature_of_disaster as the sample (i.e.: data) and the final value is also soon as a result. If the seasonal climate doesn't change in the future, there is more of a chance that the agriculture production will not be affected

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