ANALYSISING CROP CULTIVATION BASED ON OCCASIONAL DISASTER

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ABSTRACT

India being an agriculture country, its economy predominantly depends on agriculture yield growth and agro industry products. Data analysis is an emerging research field in crop yield analysis. Yield prediction is a very important issue in agricultural. 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, landslips and avalanches. The disasters are classified based on the type: Seasonal and Occasional Disasters. The Seasonal disasters like weather climatic changes like rainfall causes a regular issues to farmers across India. The Occasional Disasters like tsunamis make a dramatic change in the agriculture sectors. Any farmer is interested in knowing how much yield he is about to expect in all type of climatic and disasters. Analyze the various related attributes like earthquakes, floods, droughts, cyclones, tsunamis, landslips and avalanches are used in prediction analysis along with the weather and temperature, type of soil, nutrient value of the soil in that region, amount of rainfall in the region, soil composition can be determined. All these attributes of data will be analyzed, train the data with various suitable machine learning algorithms for creating a model. The system comes with a model to be precise and accurate in predicting crop yield and deliver the end user with proper recommendations about required fertilizer ratio based on atmospheric and soil parameters of the land which enhance to increase the crop yield and increase farmer revenue.

Keyword: Agriculture, Natural Disaster, Occasional Disaster, Decision Tree

I. INTRODUCTION

Indian agriculture, like India's landscape, is vulnerable to multiple disasters of natural and anthropogenic nature, and is also aggravated by the impact of climate change. Unlike anytime in the past, challenges to agriculture sector in India have to be understood concurrently in many dimensions. The increased frequency and severity of climate related hazards and risks induced by climate change are adding a new dimension to the existing disaster risk profile of India. Though, there are visible improvement brought by adoption of management practices through on-farm and off-farm operations in this sector, there is also growing risk of disaster related damages and losses to the agriculture systems.

II. RELATED WORK

Disaster response and recovery operations from a project management perspective. In disaster response and recovery projects, characterized by uncertainty and time pressure, inter-organizational collaboration among disaster management organizations is essential.[5] A study was conducted to understand if the disaster death in Odisha, India across five categories, viz. tropical cyclone, lightning, heat wave, cold wave and extreme precipitation events underwent any significant change during 2001–14. It was based on timeseries data available at the National Data Portal of India.[6] In all areas of academic or practical work related to disaster risk, climate change and development more generally, *community* and its adjunct *community-based* have become the default terminology when referring to the local level or working ‘with the people’. The terms are applied extensively to highlight what is believed to be a people-centred, participatory, or grassroot-level approach.[1]

Those living in informal settlements lacking basic infrastructure and services are often disproportionately affected by such impacts. Moreover, while most attention has traditionally been paid to large disasters, available evidence suggests that the cumulative impacts of everyday hazards and small disasters may be considerably greater. [7] In modern times, the divide between natural, man-made and man-accelerated is quite difficult to draw with human choices like architecture fire resource management or even climate change[10] potentially playing a role. Under the Convention on the Rights of Persons with Disabilities, "States Parties shall take, in accordance with their obligations under international law, including international humanitarian law and international human rights law, all necessary measures to ensure the protection and safety of persons with disabilities in situations of risk, including situations of armed conflict, humanitarian emergencies and the occurrence of natural disasters." [2] According to the UN, Asia-Pacific is the world's most disaster prone region. According to ReliefWeb, a person in Asia-Pacific is five times more likely to be hit by a natural disaster than someone living in other regions. [3]

During emergencies such as natural disasters and armed conflicts more waste may be produced, while waste management is given low priority compared with other services. Existing waste management services and infrastructures can be disrupted, leaving communities with unmanaged waste and increased littering. Under these circumstances human health and the environment are often negatively impacted. [5] Disasters stress government capacity, as the government tries to conduct routine as well as emergency operations.[4]

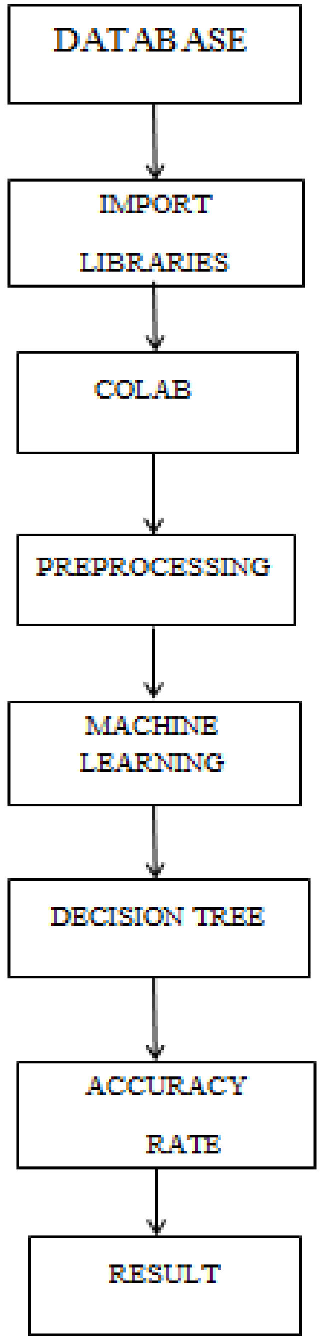
III. METHODOLOGY

A. DECISION TREE

Decision Tree algorithm belongs to the family of supervised learning algorithms. Unlike other supervised learning algorithms, the decision tree algorithm can be used for solving regression and classification problems too. A decision tree is a flowchart-like tree structure where an internal node represents feature(or attribute), the branch represents a decision rule, and each leaf node represents the outcome. This algorithm is used in this case to forecast a occasional disaster in India with appropriate attributes.Once, the dataset is imposed into colab. The decision tree machine learning algorithm is used to find accuracy and the decision tree is displayed with the respective attributes and the result is also displayed

STEP 1: Imported the dataset, modified the dataset and saved in Excel.csv format.
STEP 2: Used Google colab for executing python coding and removed all unwanted data from dataset.
STEP 3: Then dataset is splitted into training dataset and testing dataset.
STEP 4: Visualization are made in Google colab for better understanding of dataset.
STEP 5: Analysising the crop cultivation based on Occasional Disaster

B.WORK FLOW


DATABASE
IMPORT LIBRARIES
COLAB
PREPROCESSING
MACHINE LEARNING
DECISION TREE
ACCURACY RATE
RESULT

IV. RESULT

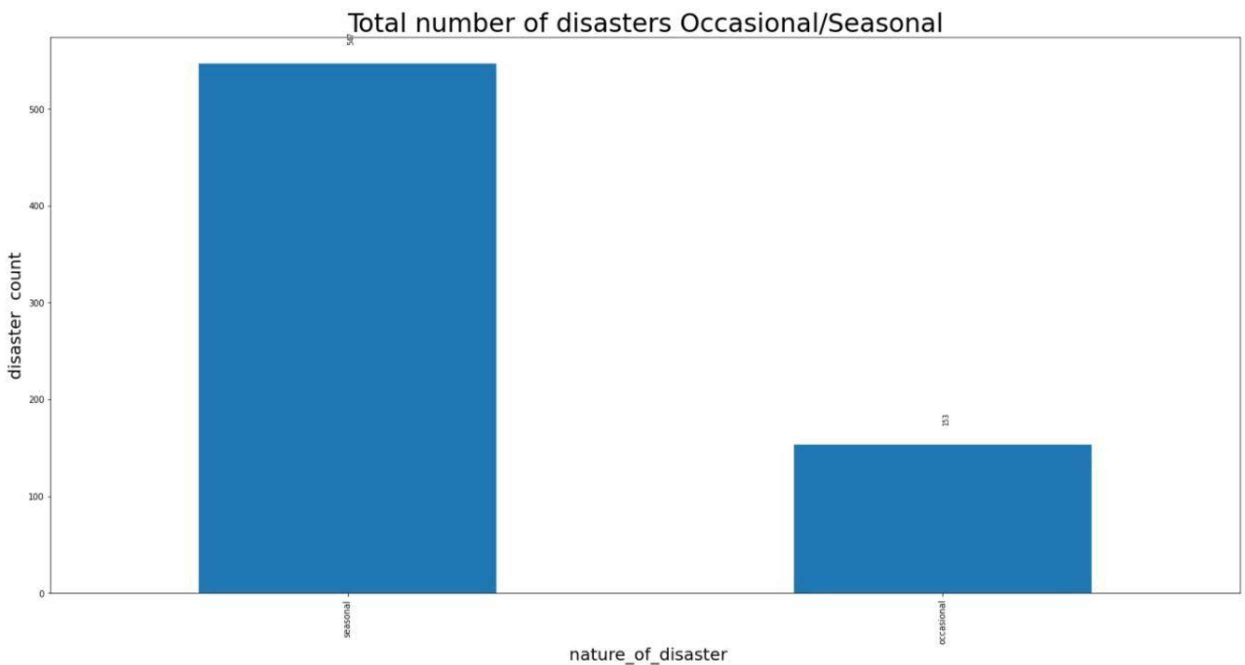


Fig1.1

This fig1.1 has tht analyzed that seasonal disaster has occurred 547 times and Occasional Disaster has occurred 153 times

	year	season	crops_affected	nature_of_disaster
0	1995	winter	ginger (dry)	occasional
1	1995	winter	cardamon	occasional
2	1995	winter	black pepper	occasional
3	1995	autumn	maize	occasional
4	1995	autumn	chillies	occasional
...	...	...	...	...
691	2020	monsoon	urad	occasional
693	2020	monsoon	tea	occasional
694	2020	spring	arhar	occasional
695	2020	winter	chillies (dry)	occasional
699	2021	spring	tea	occasional

153 rows × 4 columns

Fig1.2

This fig 1.2 has visualizes the Occasional Disaster that affected crops in year 1995 - 2021.

Result of crops affected basedon Disaaster: occasional and Season : Summer

	year	season	crops_affected	nature_of_disaster
42	1996	summer	paddy	occasional
43	1996	summer	sugarcane	occasional
86	1998	summer	wheat	occasional
116	1999	summer	chillies (dry)	occasional
118	1999	summer	urad	occasional
123	1999	summer	chilles	occasional
158	2000	summer	rape-seed & mustard	occasional
181	2002	summer	sugarcane	occasional
211	2003	summer	chillies (dry)	occasional
233	2004	summer	peas & beans	occasional
264	2004	summer	jute	occasional
271	2005	summer	cashewnut	occasional
274	2005	summer	peas & beans	occasional
290	2005	summer	sunflower	occasional
300	2006	summer	ginger (dry)	occasional
301	2006	summer	cardamon	occasional
302	2006	summer	black pepper	occasional
320	2007	summer	barley	occasional
326	2007	summer	gram	occasional
370	2008	summer	moong	occasional
382	2009	summer	castor seed	occasional
388	2009	summer	barley	occasional
418	2010	summer	coffee	occasional
423	2010	summer	barley	occasional
506	2014	summer	chilles	occasional
514	2014	summer	jute	occasional
529	2015	summer	onion	occasional
531	2015	summer	paddy	occasional
532	2015	summer	sugarcane	occasional
553	2016	summer	coriander	occasional

Fig1.3

result of crops affected basedon Disaaster: Occasioanl and Season : Spring

	year	season	crops_affected	nature_of_disaster
114	1998	spring	arhar	occasional
153	2000	spring	banana	occasional
213	2003	spring	ginger (dry)	occasional
216	2003	spring	barley	occasional
279	2005	spring	onion	occasional
368	2008	spring	millets	occasional
507	2014	spring	peas & beans	occasional
540	2015	spring	onion	occasional
633	2018	spring	millets	occasional
694	2020	spring	arhar	occasional
699	2021	spring	tea	occasional

Fig1.4

	year	season	crops_affected	nature_of_disaster
0	1995	winter	ginger (dry)	occasional
1	1995	winter	cardamon	occasional
2	1995	winter	black pepper	occasional
8	1995	winter	gram	occasional
121	1999	winter	chillies	occasional
128	1999	winter	ragi	occasional
144	2000	winter	moong	occasional
176	2001	winter	jute	occasional
182	2002	winter	groundnut	occasional
193	2002	winter	sunflower	occasional
206	2003	winter	paddy	occasional
280	2005	winter	millets (small)	occasional
281	2005	winter	potato	occasional
296	2006	winter	sunflower	occasional
346	2007	winter	arhar	occasional
381	2008	winter	arhar	occasional
420	2010	winter	jute	occasional
429	2011	winter	groundnut	occasional
442	2011	winter	jute	occasional
451	2012	winter	potato	occasional
486	2012	winter	banana	occasional
517	2014	winter	barley	occasional
525	2015	winter	millets (small)	occasional
613	2018	winter	ragi	occasional
628	2018	winter	arhar	occasional
696	2020	winter	chillies (dry)	occasional

Fig1.5

result of crops affected basedon Disaaster: occasional and Winter in State Tamilnadu

	year	season	crops_affected	nature_of_disaster	state_name
420	2010	winter	jute	occasional	Tamil Nadu
525	2015	winter	millets (small)	occasional	Tamil Nadu

Fig1.6

Atlast fig1.6 it is results of affected crops in Tamilnadu .

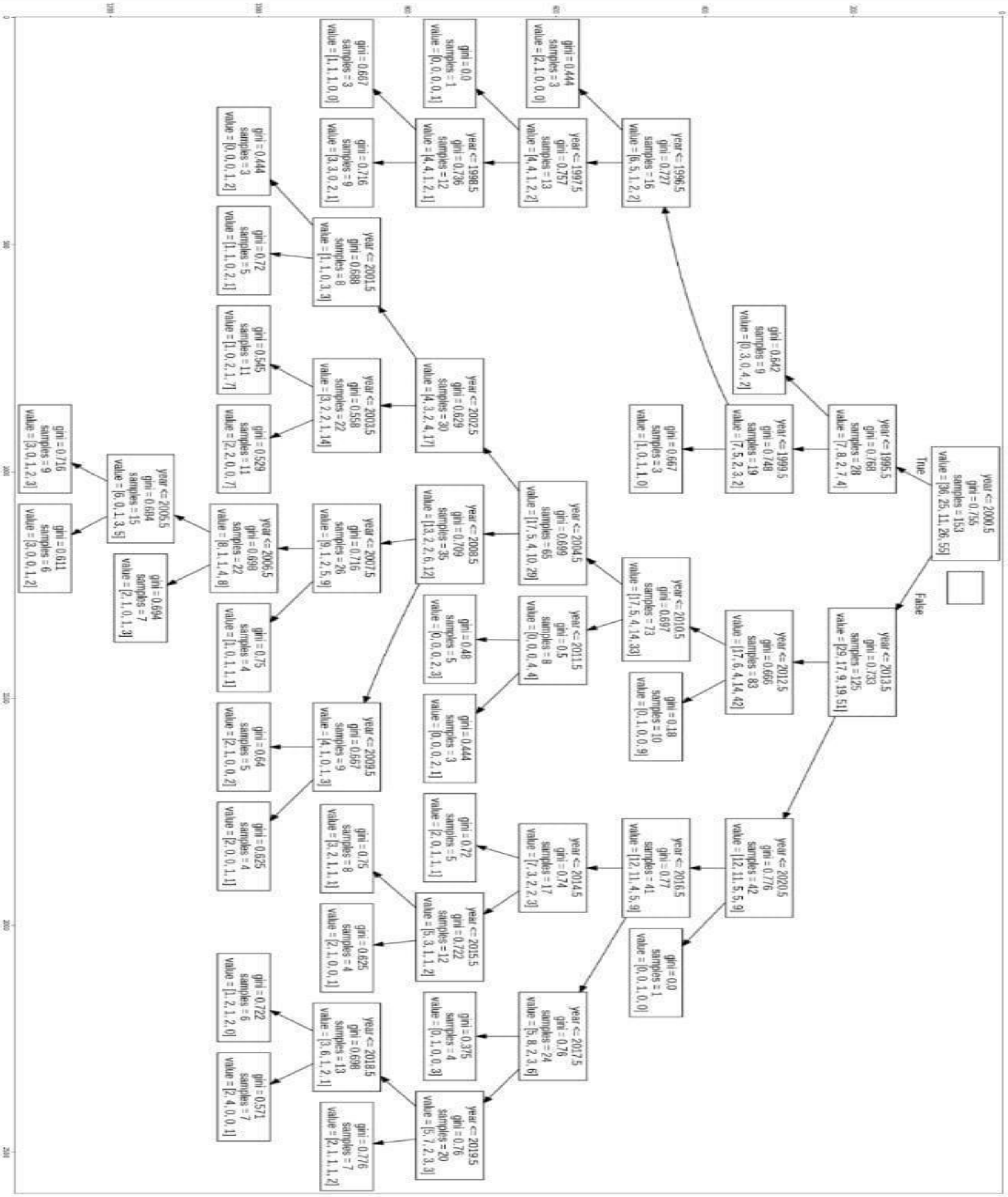


fig 1.7(Decision tree)

This fig1.7 is the decision tree which visualises the accuracy

V. CONCLUSION

The analysis is done through a decision tree machine learning algorithm and it displays that if the gini's value lies between 0 and 5 ,which means the classification showing better result with a big decision tree classification. If the seasonal climate does not change in future, then there will no occasional disaster affecting crop cultivation in agriculture. By these visualisation it shows prediction and precautions for further years of how to process crop cultivation according to the season.

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