ANALYSING VARIOUS OCCASIONAL DISASTERS ON CROP CULTIVATION USING PREDICTIVE ANALYSIS

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ABSTRACT

Agriculture is the primary source of livelihood for about 58% of India's population. Due to variations in climatic conditions, there exists bottlenecks for increasing the crop production in India. It has become a challenging task to achieve desired targets in agri based crop yield. Crop Yield prediction is one of the important factors in agriculture practices. Farmers need information regarding crop yield before sowing seeds in their fields to achieve enhanced crop yield. The use of technology in agriculture in recent year and data analytics is one such trend that has penetrated into the agriculture field. Occasional disasters like earthquakes, floods, droughts, cyclones, tsunami, landslides, avalanches can deliver massive destruction and loss of life. Analysis of these various related attributes are used in prediction analysis. The results show that the Random forest algorithm is convenient for analysing and internal laws of disaster risk and has good applicability.

Keyword : Agriculture, Occasional disasters, Random forest algorithm

I. INTRODUCTION

Every year disasters, such as hurricanes, floods, earthquakes and tornadoes challenge agricultural production. Because agriculture relies on the weather, climate and water availability to thrive, it is easily impacted by natural events and disasters. Predictive data analytics uses powerful algorithm models to analyse past data to predict future trends. It can be used to improvedisaster relief efforts, thus reducing the economic impact of natural calamities on agriculture. Vulnerability associated with the hazards of natural disasters can be controlled to some extent by accurate and timely prediction and by taking counter-measures to reduce their impacts on agriculture.

II. RELATED WORK

Crop yield maps are important for both the implementation and evaluation of site-specific crop management strategies. Management decisions and evaluations based on yield maps must take into consideration the accuracy and resolution of the maps.[8] The accuracy of DNN model was very stable, despite the increases in the duration of the heatwave. It indicates that the optimized DNN model can provide robust predictions for corn yield under conditions of extreme weather and can be extended to other prediction models for various crops in future work.[4]

Machine learning makes agricultural applications incredibly efficient and simple. Data acquisition, model building, and generalization are the three stages of the machine learning process. The majority of cases, machine learning algorithms are used to deal with complex problems when human competence is insufficient. Machine learning may be used in agriculture to forecast soil parameters like organic carbon and moisture content, as well as crop yield prediction, disease and weed identification in crops, and species detection.[7]

Plant diseases can have a devastating influence on food safety, as well as a considerable loss in both the quality and quantity of agricultural goods. Plant diseases can potentially prevent grain harvesting entirely in severe circumstances. As a result, in the field of agricultural information, computerized identification and diagnosis of plant diseases is widely needed. Many approaches for doing this problem have been offered, with deep learning emerging as the preferred method because to its excellent performance.[2]

Over the past several decades, Information Technology (IT) has been the disruptive force in industries by driving out market inefficiencies through automation and better decision support tools that require the inclusion of both the citizens and consumers in the process. Like all industries, agriculture has not been immune to the constant disruptions over the past century. However, recent advances in computing infrastructure, sensor technology, big data, and advanced algorithms (e.g., Deep Learning)[1] Using precision conservation to increase the sustainability of agricultural systems will contribute to adaptation to a changing climate and maintaining long-term productivity. In other words, sustainability in agriculture is increasingly becoming a necessary component of today's agricultural practices.[5]

The successful application of deep learning to account for the complex nonlinear relationships between crop yields and remote sensing and weather-related covariates has motivated us to apply this approach to predicting the area of flood damage to crops, which affects the food supply,

market prices, and import and export planning. If accurate, such prediction can minimize the socioeconomical impact of crop loss.[6] In precision farming, IoT based smart sensors are deployed in the agriculture land for collecting data related to soil nutrients, fertilizers, and water requirements as well as for analysing the crop growth. Autonomous and semi-autonomous devices such as an unmanned aerial vehicle (UAV). There is an urgent need to mitigate the effects hydro-meteorological disasters through improved use of climate and weather information and forecasts, early warning systems, and appropriate methods of management of land and natural resources.[7]

III. METHODOLOGY

RANDOM FOREST

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. 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 Random forest machine learning algorithm is used to find accuracy and it is displayed with the respective attributes.

STEP 1 : Imported the dataset, modified the dataset and saved in Excel.csv format.

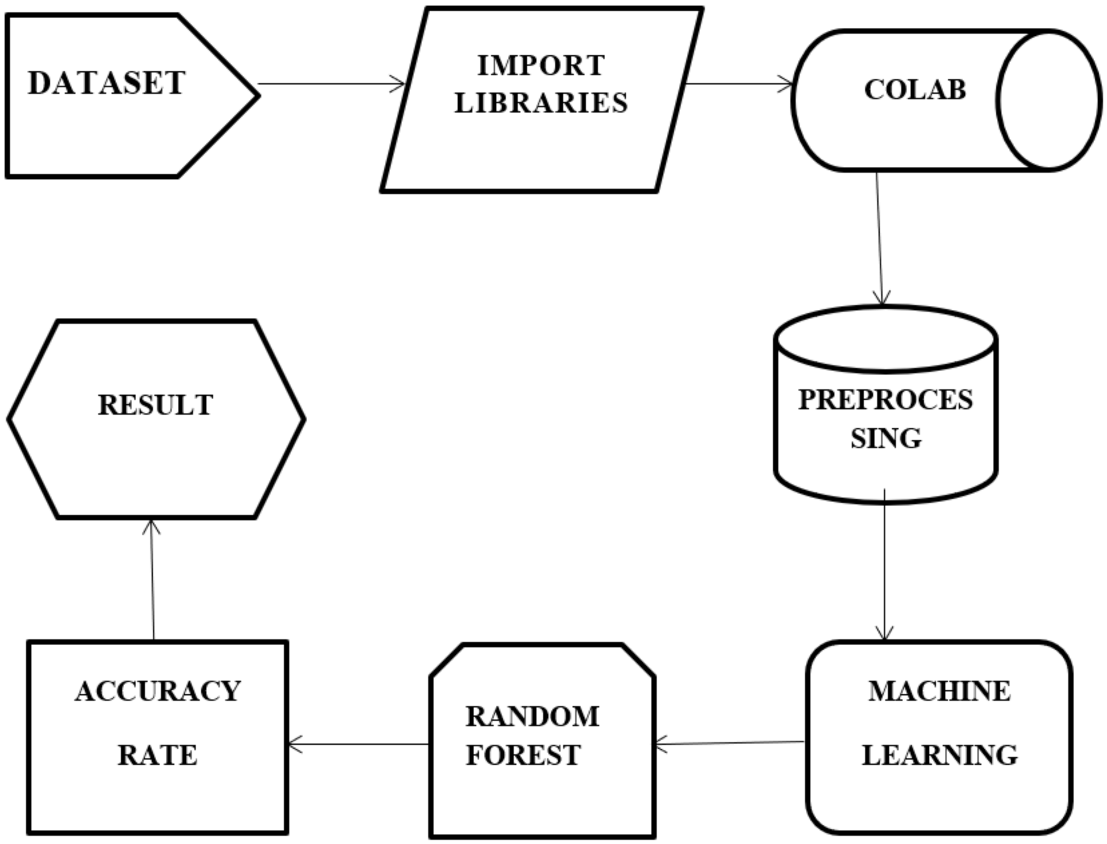
STEP 2 : Used Google colab for executing python coding and removed all unwanted data from dataset.

STEP 3 : Then dataset is splitted into training dataset and testing dataset.

STEP 4 : Visualization are made in Google colab foe better understanding of dataset.

STEP 5 : Analysing the crop cultivation based on Occasional disaster.

B. WORK FLOW



IV. RESULT

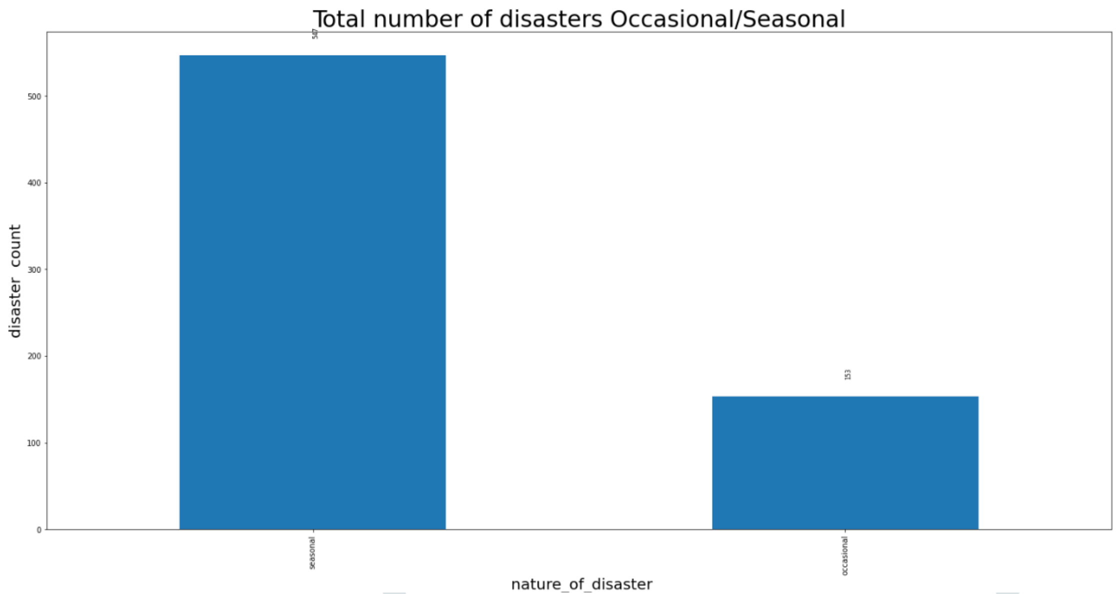


Fig1.1

The fig1.1 shows 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

Fig1.2

The fig1.2 shows the visualization of occasional disaster that affected crops in the year 1995 -2021.

result of crops affected basedon Disaster: 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

Fig1.3

esult of crops affected basedon Disaaster: occasional and Season : Winter

	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
175	2001	winter	jute	occasional
182	2002	winter	groundnut	occasional
193	2002	winter	sunflower	occasional
193	2002	winter	sunflower	occasional
205	2003	winter	paddy	occasional
260	2005	winter	millets (small)	occasional
261	2005	winter	potato	occasional

Fig1.4

295	2006	winter	sunflower	occasional
345	2007	winter	arhar	occasional
361	2008	winter	arhar	occasional
420	2010	winter	jute	occasional
429	2011	winter	groundnut	occasional
442	2011	winter	jute	occasional
451	2012	winter	potato	occasional
465	2012	winter	banana	occasional
517	2014	winter	barley	occasional
525	2015	winter	millets (small)	occasional
618	2018	winter	ragi	occasional
626	2018	winter	arhar	occasional
695	2020	winter	chillies (dry)	occasional

Fig1.5

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
85	1998	summer	wheat	occasional
115	1999	summer	chillies (dry)	occasional
116	1999	summer	urad	occasional
123	1999	summer	chillies	occasional
158	2000	summer	rape-seed & mustard	occasional
191	2002	summer	sugarcane	occasional
211	2003	summer	chillies (dry)	occasional

Fig1.6

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Result of crops affected basedon Disaaster: occasional and Season : summ
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	year	season	crops_affected	nature_of_disaster
42	1996	summer	paddy	occasional
43	1996	summer	sugarcane	occasional
85	1998	summer	wheat	occasional
115	1999	summer	chillies (dry)	occasional
116	1999	summer	urad	occasional
123	1999	summer	chillies	occasional
158	2000	summer	rape-seed & mustard	occasional
191	2002	summer	sugarcane	occasional
211	2003	summer	chillies (dry)	occasional
238	2004	summer	peas & beans	occasional
254	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
325	2007	summer	gram	occasional
370	2008	summer	moong	occasional
382	2009	summer	castor seed	occasional
398	2009	summer	barley	occasional
418	2010	summer	coffee	occasional
423	2010	summer	barley	occasional
506	2014	summer	chillies	occasional
514	2014	summer	jute	occasional
529	2015	summer	onion	occasional

Fig1.7

529	2015	summer	onion	occasional
531	2015	summer	paddy	occasional
532	2015	summer	sugarcane	occasional
553	2016	summer	coriander	occasional
554	2016	summer	urad	occasional
613	2018	summer	chillies	occasional
646	2019	summer	sunflower	occasional
659	2019	summer	moong	occasional
679	2020	summer	barley	occasional
690	2020	summer	coriander	occasional

Fig1.8

```
There are 700 rows and 11 columns passed as Input Data of natural_disaster_dataset
There are 772 rows and 7 columns passed as Training Data cropdetails
Natural disaster on crop  Randomly Generated Weights:
[[-0.16595599]
 [ 0.44064899]
 [-0.99977125]]
Natural disaster on crop  Analysis and prediction  Ending Weights After Training:
[[-6.11442809]
 [ 3.13531908]
 [ 6.3262046 ]]
Considering New Situation of Natural disaster on crop of years :  2000 2015 2021
New Output data of Accuracy level:
Accuracy in percentage % [75.6]
```

Fig1.9

The fig1.9 shows the result obtained using Random forest algorithm

V. CONCLUSION

Predicting and increasing agricultural plant yield from occasional disasters using big data technology and Random forest algorithm is relatively suitable. Different results can be obtained by adjusting various parameters. The Random forest algorithm was utilized to obtain the required result. Considering the new situation of natural disaster on crop of years 2000 2015 2021 the obtained accuracy level is 75.6%

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