

Ingredient Mining Techniques for Understanding Non-Communicable Diseases

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Abstract_ It has been widely acknowledged that healthy diets are important for controlling and preventing non-communicable diseases (NCDs). However, there is currently little research on the nutritional components of food that can aid in the recovery from NCDs. Utilizing data mining techniques, the relationship between nutritional ingredients and diseases was thoroughly examined here. In this project, the number of diseases was first gathered, and then the materials for food that are rich in particular nutritional ingredients that are related to Indian food nutrition were gathered. Now, predict the likelihood of a particular disease based on how much of the food's nutritional ingredient is consumed. The Decision Tree algorithm, Nave-Baye's algorithm, which increases accuracy, and the kNN algorithm, which classifies new cases based on similarity measure, are the data mining algorithms used in this case to extract the data from the data set. Our data mining-based method outperforms the conventional statistical approach, as demonstrated by experiments on

actual data. Also, for a few normal sicknesses, for example, Diabetes, Hypertension and Coronary illness, this work can distinguish accurately the initial a few wholesome fixings in food that can help the recovery of those illnesses. The selection of the quantity of nutritional ingredients in food to be taken in order to analyze the disease is demonstrated by these experimental results.

1.INTRODUCTION

NCDS are ongoing illnesses, which are predominantly brought about by word related and ecological variables, ways of life and ways of behaving, including Weight, Diabetes, Hypertension, Growths and different infections. The World Health Organization's (WHO) Global Status Report on Non-Communicable Diseases states that the annual death toll from NCDs continues to rise, putting a significant strain on the global economy. Each year, about 40 million people died from noncommunicable diseases, or 70% of all deaths worldwide. The prevalence rate of noncommunicable diseases (NCDs)

in China has exploded, surpassing that of any other nation, according to statistics from the Chinese Resident Chronic Disease and Nutrition Survey. Furthermore, the populace matured 60 or over in China has arrived at 230 million and around 66% of them are experiencing NCDs as per the authority measurements. As a result, NCDs are a concern for all relevant departments in every nation, particularly in China, including medical schools, hospitals, and disease research centers. When it comes to preserving one's health and preventing the development of noncommunicable diseases (NCDs), nutritious diets are crucial. With the continuous acknowledgment of this idea, China has likewise repositioned the effect of food on wellbeing. Notwithstanding, research on dietary fixings in food by means of information mining, which are helpful for the restoration of sicknesses is as yet uncommon in China. China has just begun the construction of smart health care using information technology. The majority of studies on the connection between nutritional ingredients in food and diseases still use expensive precision instruments or clinical trials that last a long time. There are also a lot of prevention reports, but they only look at one or two diseases. Data mining is still in its infancy in China for studying the link between diseases and nutritional

components. The majority of doctors only recommend a specific food to NCD patients without providing pertinent nutrition information, particularly regarding food's nutritional components. Interdisciplinary expertise is required to find solutions to NCDs. Data mining has emerged as an essential method for uncovering new information in a variety of fields, particularly accurate health care and disease prediction (AHC). Preventive medicine, basic medicine, and clinical medicine research all rely heavily on it.

2.LITERATURE SURVEY

Different processes to identification and quantification of plant sickness are in exercise and leaf image-based identification of plant sickness is one of them [11-17]. It is by way of a ways the best way to mechanically become aware of plant sickness and can be used for identification of quite a number illnesses [12]. The incidence of plant disorder reasons precise modifications in the texture and shade of the leaf and consequently leaf imagery can be used to extract shade and texturebased elements to instruct a classifier. Some of the full-size literature in the area of

plant leaf-based sickness identification is furnished below.

There are two tactics for leaf picture primarily based plant sickness identification: (i) deep gaining knowledge of based, which use complicated architectures to routinely examine facets (ii) feature-based, which extract home made facets such as shade and texture facets to teach a traditional laptop gaining knowledge of algorithm. The deep mastering primarily based techniques has supplied greater accuracies however they require greater computation and consequently now not appropriate for cellular or handheld gadgets with confined reminiscence and computations. Some of the designed structures are focused one-of-a-kind illnesses of some unique plant, whereas the different procedures goal a couple of plant diseases. Phadikar et al. [18] has introduced a function primarily based strategy to ailment identification of rice plant. They have used Fermi strength primarily based technique for segmentation observed by way of color, contour

and locality mapping. Rough set principle is used for determination of essential facets and rule mining with 10-fold cross-validation is used for gadget testing. Baquero et al. [19] has introduced a Content-Based Image Retrieval (CBIR) device which makes use of coloration shape descriptors and nearest neighbors to classify vital ailments or sickness signs and symptoms such as chlorosis, sooty molds and early blight. Similarly, Patil et al. [20] has additionally introduced a CBIR and extracted color, structure and texture based totally features. Sandika et al. [21] has proposed a feature-based strategy for ailment identification of grapes leaves. They have additionally carried out the evaluation of texture feature's performance. of Their Oberti et al. [22] has focused the fungal ailment of grapevine plant (powdery mildew) due to its damaging outcomes on the crop yield and great of produce. They have used multi-spectral imaging and captured grapevines leaf pictures at a vary of angles (0 to seventy five degrees). They have additionally highlighted

that the detection sensitivity will increase with the expand in perspective and very best fee is bought at 60 tiers and for early center a long time the sensitivity improves from 9-75% with trade in perspective from 0-60 degrees. Similarly, Zhang et al. [15] has introduced a feature-based strategy which radically change the photo into superpixel illustration and then section the favored place the usage of k-means and extract pyramid of histogram of orientation gradient (PHOG). Sharif et al. [23] has introduced a feature-based method for citrus fruit plant disease. They have used a hybrid characteristic decision method based totally on fundamental factor evaluation and function statistics. Singh et al. [24] has additionally introduced a function primarily based method for pine trees. Bai et al.[25] has centered cucumber plant sickness and proposed an accelerated fuzzy c-mean primarily based clustering method to section the diseased leaf area. Hlaing et al. has introduced a function primarily based strategy and used PlantVillage dataset. The have extracted SIFT points and

utilized generalized pareto distributions to calculate density function. Support vector machines is used to teach on these points and furnished a 10-fold cross-validation accuracy of 84.7%.

Recently deep mastering based totally procedures are used for leaf picture based totally plant ailment identification. Picon et al. [26] has used CNN for classification of plant ailments and claimed that deep studying based totally strategies has supplied absolute best performance. They have used Deep Residual Neural Networks and by and large focused septoria, tan spot and rust. Ferentinos et al. [12] has additionally introduced a deep gaining knowledge of primarily based answer the use of prolonged PlantVillage dataset with fifty eight classes. They have used pre-trained VGG for switch mastering and supplied an accuracy of 99.53%. The cross-dataset comparison has supplied sharp minimize of 25-35% in accuracy indicating bad generalization. Mohanty et al. [14] and Yuan et al. [27] has proposed deep studying based totally options

the use of PlantVillage dataset. They have used pre-trained CNN and utilized switch studying to classify plant life into 38 classes. Zeng et al. [28] has introduced a high-order residual CNN structure which extracts low stage small print as properly as high-level summary illustration concurrently to enhance classification overall performance and supplied 91.3% classification accuracy with true generalization performance

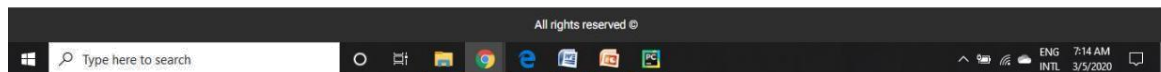
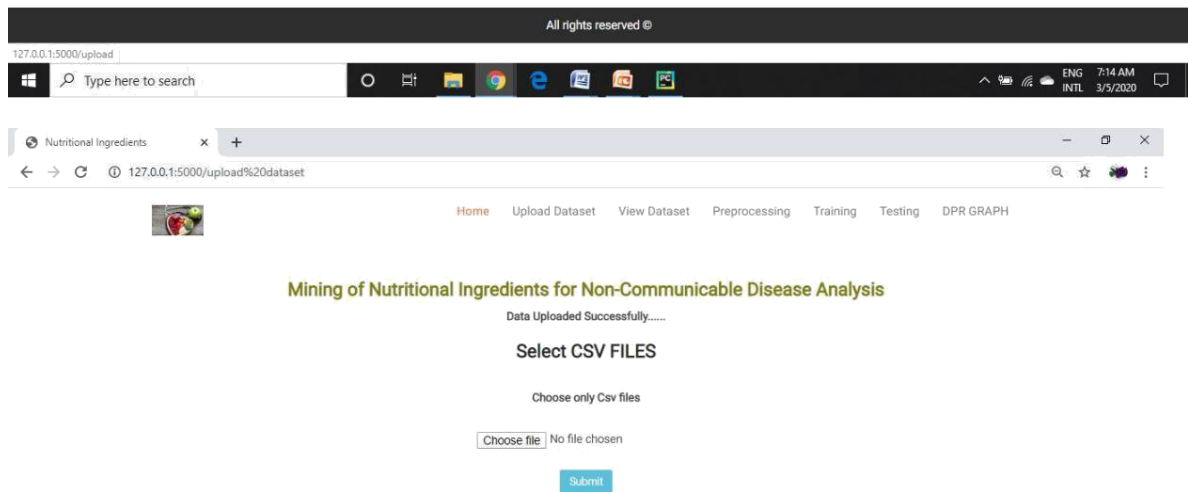
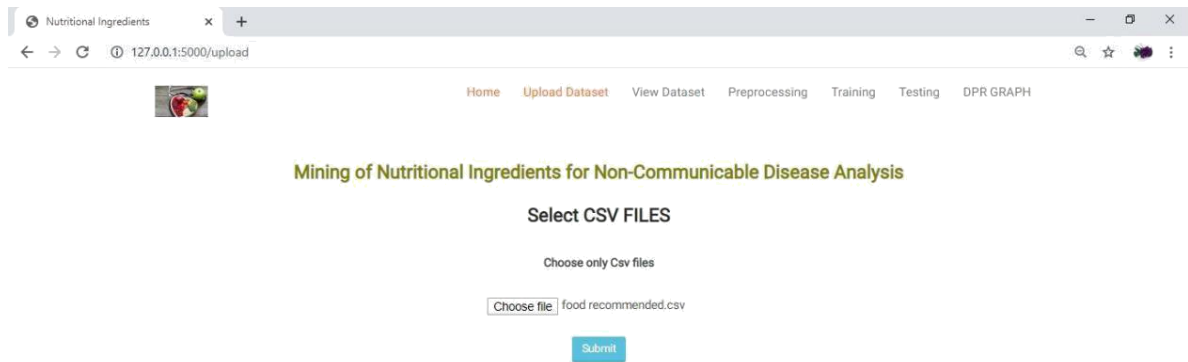
3.PROPOSED SYSTEM

The aforementioned studies, however, are primarily long-term clinical trials that merely recommend food for certain specific diseases and infrequently use data mining techniques to investigate the connection between dietary components and illnesses. According to the proposed system, the amount of nutritional ingredients present in a food item determines the likelihood that a given disease will manifest itself.



4.RESULTS AND DISCUSSION

Fig: Home Page



Nutritional Ingredients x +
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Home Upload Dataset View Dataset Preprocessing Training Testing DPR GRAPH

Mining of Nutritional Ingredients for Non-Communicable Disease Analysis

Rows :: 998

LABLES	FOOD TYPE	FOOD DISEASE	MINERALS	RAMS
A	vegetables	Angina	vitamins A	400
B	meat	Acne	C	0.8
C	fruits	cardiovascular	E	400
D	Dairy Foods	ovarian	Vitamin B12	1
E	Grains	Stroke	magnesium	3
F	Beans and Nuts	tooth decay	potassium	m
G	Fish and Seafood	Asthma	iron	μ
H	liquid drinks	liver disease	copper	NaN
I	tobacco food	oral cancers	Vitamin A	2
J	potato chips	Hypertension	Sodium	100
K	vegetables	Kidney stone	maleate	400
L	meat	NaN	NaN	0.8
M	fruits	Angina	vitamins A	400
N	Dairy Foods	Acne	C	1
O	Grains	cardiovascular	E	3
P	Beans and Nuts	ovarian	Vitamin B12	m
Q	Fish and Seafood	Stroke	magnesium	μ
R	liquid drinks	tooth decay	potassium	NaN
S	tobacco food	Asthma	iron	2
T	potato chips	liver disease	copper	100

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Nutritional Ingredients x +
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Home Upload Dataset View Dataset Preprocessing Training Testing DPR GRAPH

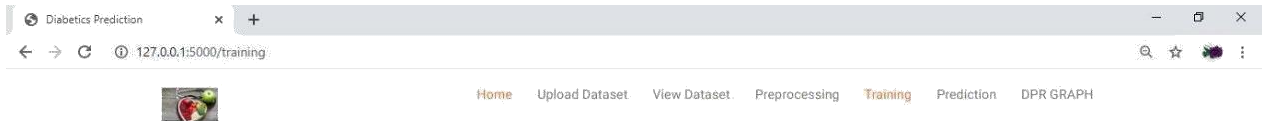
Mining of Nutritional Ingredients for Non-Communicable Disease Analysis

Rows after Preprocessing :: 833

FOOD TYPE	FOOD DISEASE	MINERALS	RAMS
0	10	10	400
1	0	0	0.8
2	1	2	400
3	2	9	1
4	3	4	3
5	4	6	0.1
6	5	3	0.2
8	7	8	2
9	8	7	100
0	9	5	400
2	10	10	400
3	0	0	1
4	1	2	3
5	2	9	0.1
6	3	4	0.2
8	5	3	2
9	6	1	100
0	7	8	400
1	8	7	0.8
2	9	5	400

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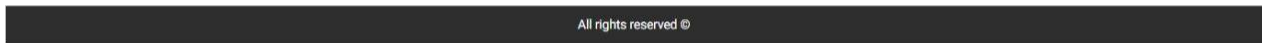
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Mining of Nutritional Ingredients for Non-Communicable Disease Analysis

Select model

Select an option ▼
Select an option
Decision Tree
Logistic Regression
Naive Bayes
KNN

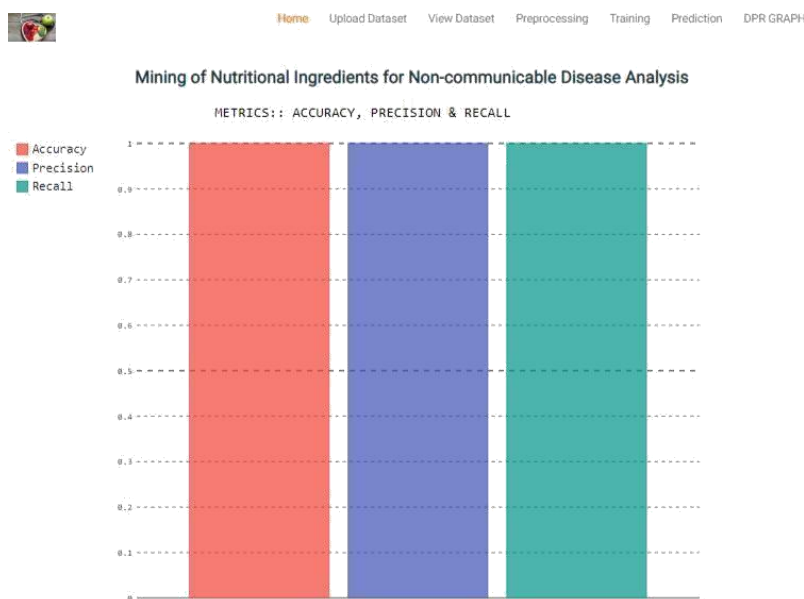


Mining of Nutritional Ingredients for Non-Communicable Disease Analysis

Disease Predicted :: ANGINIA

Food Type:
Minerals:
Grams:





5. CONCLUSION

The main task of this paper can be broken down into two parts: first, we collected and organised some diseases and associated nutritional ingredients from official and medical websites; second, we discussed the relationship between nutritional ingredients and diseases, with the main goal of predicting the disease based on the amount of nutritional ingredients present in the food. Here, data mining technology is used to identify the link between dietary components of food and diseases. This website allows users to forecast the likelihood of a disease based on the food and nutrition quantity consumed during the disease. As a result, this aids in the most accurate rehabilitation of diseases.

REFERENCES

[1] CNS, "2016 Global Nutrition Report," in Chinese Nutrition Society, 2016.

[2] WHO, "Global Status Report on Noncommunicable Diseases (2014)," in World Health Organization, 2014.

[3] S. Balsari, P. Vemulapalli, M. Gofine et al., "A Retrospective Analysis of Hypertension Screening at a Mass Gathering in India: Implications for Non-communicable Disease Control Strategies," *Journal of Human Hypertension*, vol. 31, no. 11, pp. 750–753, 2017.

[4] DNHFPC of PRC, "Chinese Resident's Chronic Disease and Nutrition" (2015)," in National Health and Family Planning Commission of the People's Republic of China, 2015.

- [5] S. Tellier, A. KiabyLars, P. Nissen et al., “Basic Concepts and Current Challenges of Public Health in Humanitarian Action,” *International Humanitarian Action*, pp. 229–317, 2017.
- [6] F. Ara1, F. Saleh, S. J. Mumu, F. Afnan and L. Ali, “Awareness Among Bangladeshi Type 2 Diabetic Subjects Regarding Diabetes and Risk Factors of Non-communicable Diseases,” *Diabetologia*, pp. S379, 2011. DOI:10.1007/s00125-011-2276-4.
- [7] QIANZHAN, “Report of Market Prospective and Investment Strategy Planning on China Intelligent medical construction industry (2017-2022),” in *Qianzhan Intelligence CO.LTD*, 2017.
- [8] W. H. Ling, “Progress of Nutritional Prevention and Control on Noncommunicable Chronic Diseases in China,” *China J Dis Control Prev*, vol. 21, no. 3, pp. 215–218, 2017.
- [9] M. B. Margaret, B. K. Barbara and D. Colette, “Developing Health Promotion Workforce Capacity for Addressing Non-communicable Diseases Globally,” *Global Handbook on Noncommunicable Diseases and Health Promotion*, pp. 417–439, 2013.
- [10] M. Williams and H. Moore, “Lumping Versus Splitting: the Need for Biological Data Mining in Precision Medicine,” *BioData Mining*, vol. 8, no. 16, pp. 1–3, 2015.
- [11] G. M. Oppenheimer, “Framingham Heart Study: The First 20 Years,” *Progress in Cardiovascular Diseases*, vol. 53, no. 1, pp. 55–61, 2010.
- [12] W. Y. Jiao, Y. Xue, T. C. He, Y. M. Zhang and P. Y. Wang, “Association Between South Korean Dietary Pattern and Health,” *Food and Nutrition in China*, vol. 23, no. 5, pp. 81–84, 2017.
- [13] K. W. Lee and M. S. Cho, “The Traditional Korean Dietary Pattern Is Associated with Decreased Risk of Metabolic Syndrome: Findings from the Korean National Health and Nutrition Examination Survey 1998- 2009,” *Journal of Medicinal Food*, vol. 17, no. 1, pp. 43–56, 2014.