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Analysis of correlation between food consumption habits and COVID-19 outbreak

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Abstract

The outbreak of COVID-19 sparked a massive movement among the world's people to control this dangerous and unknown disease. So many nutritionists have made many medical recommendations to control this disease by using special nutrients. In this regard, we decided to examine the effect of two nutrients, protein and fat, which are the main ingredient in many nutrients, on the rate of death and recovery of patients' covid-19. Available data from 170 countries worldwide have been examined to discover this effect. Linear and non-linear relationships and the correlation coefficient between response variables and different nutrients have been calculated and analyzed in detail. According to the results, these two elements cannot be considered influential in predicting the current rate with high reliability. Protein and fat have a high nutritional value and play an essential role in human health, but the amount of this need for humans is different, which in turn contradicts the results obtained from patients. Although correlation coefficients are not high, the existence of this correlation still requires further studies in this field. We have also used models such as Decision tree, Rule introduction, and Naive Bayes in our research to predict future results, which will give us an understanding of the results obtained.

Keywords: COVID-19, data analysis, decision tree, rule introduction, naive Bayes

1- Introduction

The COVID-19 epidemic has affected the entire food system and exposed its fragility. Closing borders, trade restrictions, and restrictive measures prevent farmers from accessing markets, buying agricultural inputs (a set of factors used in the production process to produce products), selling their products, and avoiding agricultural workers from harvesting. It disrupts domestic and international food supply chains and reduces access to healthy, safe, and varied diets. This epidemic has destroyed jobs and endangered millions of livelihoods. As breadwinners lose their jobs, they get sick and die, the food security and nutrition of millions of men and women are threatened, and in low-income countries, marginalized people, including small farmers and natives, suffer the most.

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While providing the world with food, millions of farmers - day laborers and self-employed workers - are constantly faced with poverty, malnutrition, and poor health. They are suffering a lack of safety and labor protection and other forms of abuse. The Corona outbreak has posed a major challenge to the importance of the body's security system to all citizens. In this regard, a lot of research has been done on discovering nutrients and their effectiveness in improving the immune system's functioning worldwide. F. BourBour et al. (2020) have divided these influential elements into 'innate response cells' & 'adaptive response cells' and describe each one's importance in the immune system, the proposed classification of which is attached below.

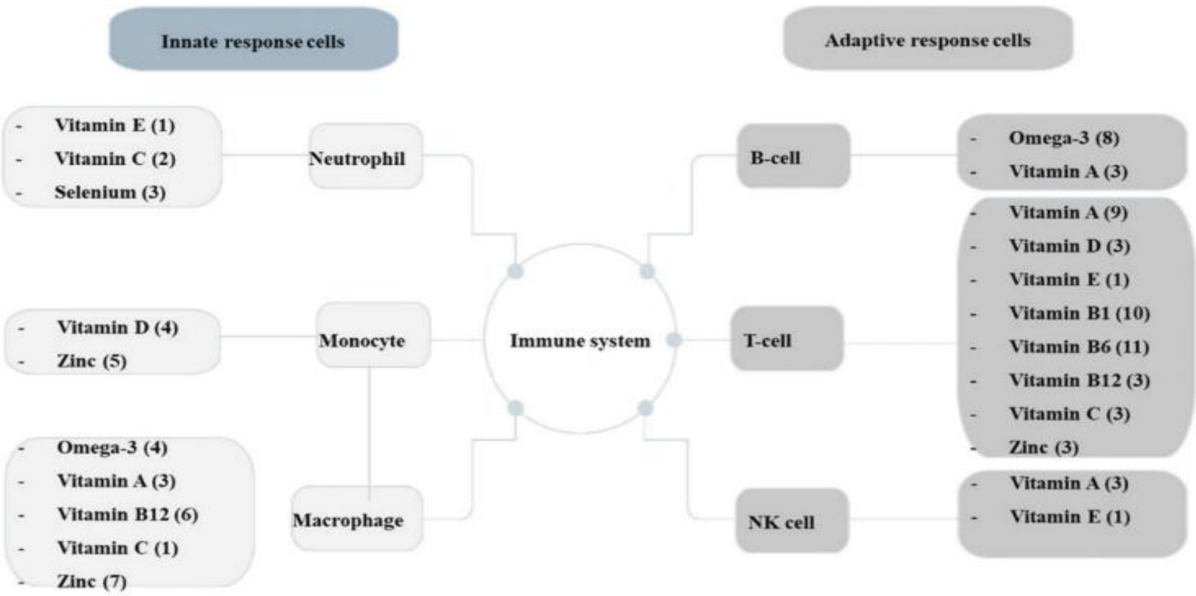

Fig. 1. Immune system supporting nutrients (BourBour et al., 2020).

Hussain, Mahawar, Xia, Yang, and Shamsi (2020) have also specifically examined the relationship between overweight and coronary heart disease. Their research concluded that because the problem of overweight has become very common in the new age, it is necessary to pay attention to the fact that these people are much more susceptible to COVID-19 disease than others. According to available data, these people are more resistant to recovery and vaccination than others (Alipour Vaezi & Tavakkoli-Moghaddam, 2020). In this article, we considered the impact of underlying factors. Factors such as Obesity, Alcoholic Beverages consumption rate, Undernourishment, Sugar and Sweeteners consumption rate (which concludes in diabetes), and having the underlying disease are considered in the dataset. In this regard, different people with various diets have taken in to account for identification of correlation between food consumption habits and having Covid-19 positive test. While various categories of people investigated, practitioners highlighted factors such as Undernourishment, Sugar and Sweeteners consumption rate (which concludes in diabetes), and having the underlying disease in them and announced the results. Having data gathered, the process of identification of Covid19 and consumption habits began. The ultimate goal of the present study is to investigate the impression of nutrition on coronavirus. In this work, we will load, clean, label data, and finally, predict the consumption of different food on recovered and death rates.

2- Literature review

This section will focus on some problems related to COVID-19 that researchers have reviewed. A healthy food program can aid in the recovered rate. With the incidence of coronavirus, food insecurity has been increased. Besides, people try to change their food habits because of the risk of using unhealthy food. Food security is defined as a means of measuring the amount of food available in a country and the extent to which a community has access to food. It can also be acknowledged that food security means access to food at any time and place we need to be able to maintain our physical and mental health (IFPRI, 2013). The Agriculture Department defines food insecurity as "limited or uncertain availability of nutritionally adequate and safe foods or limited or uncertain ability to acquire acceptable foods in socially acceptable ways". In the definition of eating habits in general, it can be said that eating habits are a set of customs, beliefs, and thoughts that are available and effective in how to use food resources. These differences can be in cooking, food storage, food choice, and how they are distributed in age groups. Eating habits are very closely related to specific geographical conditions, economic status, level of cultural and religious beliefs, and the degree of influence of the foreign societies' culture. Food waste and waste management are the series of tasks done from the beginning to the formation and disposal of waste. But in general, all strategies to reduce waste production and minimize waste production are recycling and reuse. Also, in the technology and data section, we tried to review the articles written in recent years based on collected data. These articles, which use up-to-date software to explore the data collected, give readers a broader perspective to anticipate and understand the problem's mechanism ahead. Finally, we mentioned a few articles covering pharmaceutical science and health basics in the pharmaceutical section. The categorization has been done only for readers' easier understanding and thematic separation. We will refer to the articles related to the mentioned titles in the following.

2-1- Food insecurity

Neff (2020) mentioned the key phrase "hidden hunger". He points out that food insecurity existed before the outbreak of COVID-19 but has not received much attention before. The emergence of the disease has highlighted the importance of addressing this issue. Erokhin and Gao (2020) have categorized citizens in terms of family income and mentioned the crises during the virus outbreak and their effects on the food supply. They have divided families into three categories: low income, middle income, and above-average income. They believe that although this crisis has affected all families varies depending on which group they belong to. For example, in high-income families, this crisis manifests itself in the type of food transaction or restrictions on the import of some food, while in low-income families, this manifests itself in the form of a lack of vital nutrients that can endanger their health. Leddy, Weiser, Palar, and Seligman (2020) proposed a model for the impact of COVID-19 on food insecurity and public health. The bulk of this article addresses the importance of providing food for a section of the generally considered low-income population. Because a person with type 2 diabetes has severe diabetes if they are unable to get adequate food, or a person with high blood pressure will suffer from a severe physical disability. All of this has prompted senior officials to consider measures to provide food for society's low-income segment. Adams, Caccavale, Smith, and Bean (2020) have studied the effects of this disease on American families' eating habits. They found that due to citizens' stress and nervousness that has occurred due to the endangerment of their job position, citizens are more inclined to consume fatty foods that have no nutritional value. According to an online questionnaire they published, they found that the number of children suffering from malnutrition and overweight has increased significantly due to living at home and consuming unhealthy substances. Carroll et al. (2020) also examined the impact of COVID-19 on the health habits, stress level, financial status, and food security of Canadian families. They found that more than half of households changed their eating habits significantly, some turning more to organic foods and some to unhealthy foods. They also found that electronic devices have dramatically increased, which has dramatically reduced the amount of physical activity. It was also observed that families endured a lot of stress due to working conditions and endangering their position. Monitoring children's education at home and balancing their work inside and outside the home with educating children has increased this level of stress among Canadian families. In their study of Chinese citizens, Zhao et al. (2020) surveyed the level of stress on different segments of society during the outbreak of COVID-19. Citizens who live in more prevalent places have more stress than people who live in less common places, divorced people have a significantly higher level of stress than single or married people, and finally, young and adolescent citizens experience a lot of stress compared to the elderly in society. Fitzpatrick and Willis (2020) also found that more than 600,000 people in the United States are homeless, sometimes without access to food for several days. The statistics published in this article are important because we face a large population that is prone to severe physical weakness due to lack of food security and is therefore prone to covid-19 disease. That this is just a small statistic of reality.

2-2- Food habits

Laguna, Fiszman, Puerta, Chaya, and Tárrega (2020) examined the effect of coronavirus on consumer habits before and after the epidemic. According to an online questionnaire and a case study of the United Kingdom and Spain, they found that with the spread of COVID-19, people pay more attention to their consumables. Their tendency is more towards using essential and useful substances for the immune system. The data also show that consumers try as much as possible to avoid cold and preservative foods and substances such as Desserts, Chocolate, etc., that cause obesity and loss of body shape. Consumption data pattern shows that people have turned to foods such as Dairy products, Bananas, Wheat, Fresh fruits, etc. However, it should be noted that they have avoided buying the perishable materials due to the traffic restriction for the out breaking of the disease. In general, the food consumption pattern has undergone a huge change before and after, which shows the importance of examining it. Xie, Huang, Li, and Zhu (2020) have surveyed the level of awareness of Chinese citizens about the health of food and the level of observance of nutritional tips at different ages. Based on a questionnaire collected from citizens, older citizens are more aware of the health and unhealthiness of food than younger people. But they are still reluctant to avoid high-risk foods such as animal meat because of their old beliefs, and they believe that animal meat has many benefits, so they continue to eat it. Peter and Xavier (2020) examine different eating habits, parameters affecting eating habits, and the effect of these effects on different ages' physical and mental health. They note that each person’s eating habits are influenced by his or her self-esteem and emotions; Citizens have been asked to value their health more by maintaining their morale. Finally, given the current global situation in which citizens have become less active due to staying at home; Provide minimum time for physical activity at different ages.

2-3- Food waste management

Ben Hassen, El Bilali, and S Allahyari (2020) surveyed Qatari consumer behavior using an online questionnaire published in the United States. It can be said that they achieved similar results, with the difference that due to the existing policies, the fear of losing their jobs was less seen for the citizens of this country. Due to the public’s preference for eating at home, food waste rates have dropped dramatically. Aldaco et al. (2020) examined the impact of COVID-19 on the food supply chain in Spain; they found that healthy food disposal was significantly reduced compared to before, and they also found that people’s willingness to buy goods exported from other countries had sharply decreased. Also, after the disease outbreak, since most citizens buy their goods online, the need to store products has decreased a lot, and all these changes have made a big difference in the supply chain of products.
Zhang, Diao, Chen, Robinson, and Fan (2020) are among those who study the destructive effects that covid_19 has on the agricultural industry and try to help develop the industry in the current critical situation by providing solutions. They found that COVID-19 hits both the macro economy and agri-food systems. Amicarelli and Bux (2020) examined changes in people's eating habits after the outbreak of covid-19. They found that people reduced their food loss after the outbreak due to awareness of staying home. They use more homemade food. They also noted the importance of reviewing food logistics.

2-4- Technology and data

Kang, Rohlof, Yuan, and Yang (2020) allude to the changes that have taken place since COVID-19. Noting that the government has shown more support for virtual health services such as virtual pharmacies and virtual communication with doctors, etc., they predict that we will see the unprecedented growth of virtual health services in a short time. Funayama, Kurose, Kudo, Shimizu, and Takata (2020) pointed out that the number of people suspected of having the disease has been drastically reduced because they are afraid of being exposed to carriers. They do not go to the hospital even if they have some symptoms. Also, according to health instruction, not to communicate directly with others, even families have very little control over each other. Most communication takes place in the form of video calls. Therefore, in such situations, the best way is to create an accurate and, at the same time, simple information system that can collect and analyze useful data from citizens. Sarkar, Mishra, and Padhy (2020) while pointing to the negative mental effects that COVID-19 has had on people, including stress, feeling of loneliness, etc. The importance of gathering information and tools and problems in collecting and processing information and the opportunities ahead. Trade and travel and, in general, globalization affect the outbreak of the disease. Shrestha et al. (2020) have investigated the effect of COVID-19 on the phenomenon of globalization. They calculated a pandemic vulnerability index (PVI) by creating a quantitative measure of the potential global health and technique for order of preference by similarity to ideal solution (TOPSIS). (Mamoudan, Forouzanfar, Mohammadnazari, Aghsami, & Jolai, 2021; Mohammadnazari & Ghannadpour, 2018, 2021; Tavakkoli-Moghaddam, Alipour-Vaezi, & Mohammad-Nazari, 2020) applied the Best-Worst method as a novel Multi-Criteria Decision-Making approach. Throughout the result, certain countries are more exposed to damage. D. Li, Chaudhary, and Zhang (2020) proposed a CorExQ9 algorithm that integrates a Correlation Explanation (CorEx) learning algorithm and clinical Patient Health Questionnaire (PHQ) lexicon to detect COVID-19 related stress symptoms in the United States. Their study results show a strong correlation between stress symptoms and the number of increased COVID-19 cases. It is also observed that people feel the risk of public news on coronavirus. This algorithm observed the spatiotemporal pattern of the stress and responded to concerns about this infected disease in different geographical areas. J. Li, Xu, Cuomo, Purushothaman, and Mackey (2020) conduct a quantitative and qualitative assessment of Chinese social media posts originating in Wuhan City on the Chinese microblogging platform Weibo during the early stages of the COVID-19 outbreak. Albahri and Hamid (2020) obtained an overview of this critical virus, addressed the limitations of utilizing data mining and ML algorithms, and provided the health sector with the benefits of this technique.

Sonbhadra, Agarwal, and Nagabhushan (2020) extracted the trends of coronavirus. They proposed a novel approach for mining COVID-19 articles using parallel one-class support vector machines which are trained on the clusters of related articles generated with the help of clustering approaches such ask-means, DBSCAN, and HAC. Wang et al. (2020) investigated the GBJW (the general belief in a just world) to protect individuals' emotions when facing a major social disaster such as the COVID-19 epidemic. The GBJW can reduce the individual negative emotions evoked by an epidemic focus and increase the positive emotions diminished by the epidemic. Ayyoubzadeh, Ayyoubzadeh, Zahedi, Ahmadi, and Kalhori (2020) proposed the use of prediction models for COVID-19 incidence in Iran using Google Trends data. The features' effect of the linear regression model shows that besides new cases in the previous day, hand sanitizer, hand washing, and antiseptic topics were the focus of the population.

2-5- Pharmacology

Antibody-dependent enhancement (ADE) negatively influences antibody therapy for viral infection. This effect was first identified in the dengue virus and has since also been described as coronavirus. Wen et al. (2020) summarized antibody-dependent enhancements in the dengue virus and two kinds of coronavirus. Possible solutions for the effects are reported. They speculate that ADE may exist in SARS-CoV-2. Pharmaceutical compounds such as antiretroviral drugs, anti-malaria and antibiotics show the improvement of COVID-19 clinical condition. Using the silico toxicogenic data-mining approach Baralić et al. (2020) assessed both risks and benefits of the COVID19 treatment with the promising candidate drug combinations. According to the results, these drug combinations should be administrated with caution to patients suffering from cardiovascular problems. As there are no vaccines or approved effective treatments at present against COVID-19, governments use mitigation strategies to prevent coronavirus deaths. Dey, Das, Misra, and Uppal (2020) described the present status of therapeutics and vaccine development and the different ways in which the disease is being managed at the global level. Sun, Jiang, Wang, and Liu (2020) conducted a study exploring the TCM formulae that have been used for the prevention and treatment of pneumonia or 'pestilence' to investigate their compatibility with the Chinese material medical (CMM). Also, they recognized their potential mechanisms in the treatment of COVID-19. Alves et al. (2021) have provided a solution based on machine learning and decision trees to respond more quickly to diagnose COVID-19 disease and to help physicians to diagnose it more accurately. Also, Burdick et al. (2020) investigated the role of a machine-learning algorithm to anticipate ventilation systems between COVID-19 patients. They found this algorithm perform effectively to triage patients. Using the available time-series data, Kareem Kamal et al. (2020) focused on research and applying Artificial Intelligence (AI) algorithms to predict COVID-19 propagation. Alballa and Al-Turaiki (2021) utilized Machine learning for COVID-19 diagnosis and prediction of mortality/severity.

As can be deduced from the review of previous studies, although in the short time since the outbreak of COVID-19, many articles have been written in the field of pandemic management. But very few articles have been written on the role of food in human health. There are several reasons for this because in addition to the COVID-19 being unknown, collecting and testing the vital body mass of an infected and untreated population in a country requires a lot of time and money. But enough time has passed since the emergence of this unknown disease. Appropriate data have been collected from sick and healthy people, which has led us to study two useful nutrients, namely iron, and protein, based on these valuable data. Because, as you know, from the beginning of the epidemic of this disease, there was a lot of publicity about the great role of these two essential elements of the body; In this study, we are going to find out whether these two elements in food play a decisive role in the death or life of humans during the corona outbreak, or is it just a baseless hypothesis for the market to thrive.

3- Methodology

In our research, we want to focus specifically on the role of protein and fat in food in the rate of improvement and mortality during the coronavirus and answer the question of the role of protein and fat in strengthening or weakening the immune system in the face of COVID-19? We examined data collected from 170 countries on GitHub (2020) to answer this question. These data examine the amount of protein and fat in various foods consumed in these countries. We intend to answer our main question by considering these countries' mortality and improvement rate. Because we have monitored data from 170 countries, we can measure these two nutrients' effects on recovery and mortality rates more accurately. All the data used are calculated as the percentage of protein and fat in each country's total amount of food consumed. Also, the data obtained for mortality and recovery rates are based on the percentage of each country's current population. Data for different food group supply quantities, nutrition values, obesity, and undernourished percentages are obtained from the food and Agriculture Organization of the United Nations (FAO) website. Data for each country's population count comes from the Population Reference Bureau (PRB) website, and data for COVID-19 confirmed deaths, recovered, and active cases are obtained from Johns Hopkins Center for Systems Science and Engineering (CSSE) website. Also, the data used in this article has been continuously updated since 12/02/2020 and is valid on the date of the compilation of this research. In this regard, we intend to monitor the collected data using Minitab software. Indeed, we investigate the output diagrams of the relationships between each of its main variables: the amount of protein and fat in different types of different foods consumed by different countries.

In the end, we can reach the final answer to the problem. The foods and the contents used in this research are defined in table 1. First, we have calculated the correlation coefficient to discover the linear relationships between response variables (mortality rate and recovery rate) with food sources. However, since the relationships between data will not necessarily be linear, we have used a scatter matrix to examine the existence of nonlinear relationships between variables. You will see the results and analysis related to each in section 4. It should be noted that the numbers obtained from the correlation coefficient will always be in the range [-1, 1]. The closer the number is to 1, the higher the direct correlation with the problem's defined response variable. And the closer the number -1, then it will still have a high correlation with the response variable, but inversely. Finally, the closer the correlation coefficient to 0, the less linear the relationship with the problem variable. Some foods are not recommended only for overweight people due to their special conditions. Therefore, data on the number of overweight people is included in the data analysis to determine if there is a significant relationship between the data bits.

Table 1. Categories and Items of the food GitHub (2020)

Categories	Items
Alcoholic Beverages	Alcohol, Non-Food; Beer; Beverages, Alcoholic; Beverages, Fermented; Wine
Animal fats	Butter, Ghee; Cream; Fats, Animals, Raw; Fish, Body Oil; Fish, Liver Oil
Animal Products	Aquatic Animals, Others; Aquatic Plants; Bovine Meat; Butter, Ghee; Cephalopods; Cream; Crustaceans; Demersal Fish; Eggs; Fats, Animals, Raw; Fish, Body Oil; Fish, Liver Oil; Freshwater Fish; Marine Fish, Other; Meat, Aquatic Mammals; Meat, Other; Milk - Excluding Butter; Molluscs, Other; Mutton & Goat Meat; Offals, Edible; Pelagic Fish; Pigmeat; Poultry Meat
Aquatic Products, Other	Aquatic Animals, Others; Aquatic Plants; Meat, Aquatic Mammals
Cereals - Excluding Beer	Barley and products; Cereals, Other; Maize and products; Millet and products; Oats; Rice (Milled Equivalent); Rye and products; Sorghum and products; Wheat and products
Eggs	Eggs
Fish, Seafood	Cephalopods; Crustaceans; Demersal Fish; Freshwater Fish; Marine Fish, Other; Molluscs, Other; Pelagic Fish
Fruits - Excluding Wine	Apples and products; Bananas; Citrus, Other; Dates; Fruits, Other; Grapefruit and products; Grapes and products (excl wine); Lemons, Limes and products; Oranges, Mandarines; Pineapples and products; Plantains
Meat	Bovine Meat; Meat, Other; Mutton & Goat Meat; Pigmeat; Poultry Meat
Milk - Excluding Butter	Milk - Excluding Butter
Miscellaneous	Infant food; Miscellaneous
Offals	Offals, Edible
Oil crops	Coconuts - Incl Copra; Cottonseed; Groundnuts (Shelled Eq); Oilcrops, Other; Olives (including preserved); Palm kernels; Rape and Mustardseed; Sesame seed; Soybeans; Sunflower seed
Pulses	Beans; Peas; Pulses, Other and products
Spices	Cloves; Pepper; Pimento; Spices, Other
Starchy Roots	Cassava and products; Potatoes and products; Roots, Other; Sweet potatoes; Yams
Stimulants	Cocoa Beans and products; Coffee and products; Tea (including mate)
Sugar & Sweeteners	Honey; Sugar (Raw Equivalent); Sugar non-centrifugal; Sweeteners, Other
Sugar Crops	Sugar beet; Sugar cane
Tree nuts	Nuts and products
Vegetable Oils	Coconut Oil; Cottonseed Oil; Groundnut Oil; Maize-Germ Oil; Oilcrops Oil, Other; Olive Oil; Palm Oil; Palm kernel Oil; Rape and Mustard Oil; Ricebran Oil; Sesame seed Oil; Soyabean Oil; Sunflowerseed Oil
Vegetables	Onions; Tomatoes and products; Vegetables, Other
Vegetal Products	Alcohol, Non-Food; Apples and products; Bananas; Barley and products; Beans; Beer; Beverages, Alcoholic; Beverages, Fermented; Cassava and products; Cereals, Other; Citrus, Other; Cloves; Cocoa Beans and products; Coconut Oil; Coconuts - Incl Copra; Coffee and products; Cottonseed; Cottonseed Oil; Dates; Fruits, Other; Grapefruit and products; Grapes and products (excl wine); Groundnut Oil; Groundnuts (Shelled Eq); Honey; Infant food; Lemons, Limes and products; Maize and products; Maize Germ Oil; Millet and products; Miscellaneous; Nuts and products; Oats; Oilcrops Oil, Other; Oilcrops, Other; Olive Oil; Olives (including preserved); Onions; Oranges, Mandarines; Palm kernels; Palm Oil; Palmkernel Oil; Peas; Pepper; Pimento; Pineapples and products; Plantains; Potatoes and products; Pulses, Other and products; Rape and Mustard Oil; Rape and Mustardseed; Rice (Milled Equivalent); Ricebran Oil; Roots, Other; Rye and products; Sesame seed; Sesameseed Oil; Sorghum and products; Soyabean Oil; Soyabeans; Spices, Other; Sugar (Raw Equivalent); Sugar beet; Sugar cane; Sugar non-centrifugal; Sunflower seed; Sunflowerseed Oil; Sweet potatoes; Sweeteners, Other; Tea (including mate); Tomatoes and products; Vegetables, Other; Wheat and products; Wine; Yams

We have also used models such as Decision Tree, Rule Induction, and Naive Bayes in our study, which we will mention briefly to understand better. The decision tree consists of several nodes and branches in which it classifies the specimens so that it grows from the root downwards and eventually reaches the leaf nodes (Alipour-Vaezi, Tavakkoli-Moghadaam, & Samieinasab, 2021). An attribute identifies each internal or non-leaf node. In this study, we use this algorithm for classification as separate values depending on different classes. Rule Induction is expressed with "if-then statements". This rule evaluates each attribute's possible value and opts for the position with the greatest information gain. The rule learning algorithm takes training data as input and existing rules by dividing the table with cluster analysis. Finally, Naive Bayes' essential supposition given the value of the label (the class), the value of any attribute is autonomous of the value of any other attribute.

4- Results and discussion

To better understand the trend and effects of food categories on mortality and recovery rates in the data in the datasets in section 4.1, the results of fat data are analyzed, in section 4.2, the results of protein data that can be Inferred graphs and correlation coefficients have been examined, in section 4.3 prediction models have been used, and in the last section, the accuracy and performance of prediction models have been evaluated.

4-1- The effect of fat in various food categories on mortality and recovery rates

As mentioned in section 3, we first extracted the correlation coefficient between the variables, the results of which can be seen in table 2 and table 3.

Table 2. Correlation rates between death rates and different food categories in fat data

Deaths	1.000000
Obesity	0.425477
Animal Fats	0.384024
Animal Products	0.366625
Eggs	0.323065
Milk-Excluding Butter	0.311430
Stimulants	0.199298
Treenuts	0.145182
Meat	0.132455
Vegetables	0.010786
Population	-0.026218
Vegetable Oils	-0.050779
Fruits-Excluding Wine	-0.061038
Sugar & Sweeteners	-0.064233
Alcoholic Beverages	-0.077970
Aquatic Products, Other	-0.078184
Sugar Crops	-0.098432
Offals	-0.143194
Spices	-0.150737
Miscellaneous	-0.153383
Fish, Seafood	-0.199872
Starchy Roots	-0.238257
Pulses	-0.251954
Oil Crops	-0.312325
Cereals-Excluding Beer	-0.338442
Vegetable Products	-0.366664

As you can see in figures 2 and 3, there is no nonlinear relationship between the data, and the numbers in tables 2 and 3 can be used to conclude. According to the results of table 2, among the mentioned food categories, animal fats, animal products, and eggs had the most direct relationship, and cereals-excluding beer and oil crops had the most inverse relationship with mortality. And other categories have little or no correlation with mortality. It should be noted that, as shown in tables 2, 3, 4, and 5, no logical correlation can be found between vegetal products and mortality and recovery rates, either in fat-related or protein-related data. The inclusion of a wide range of different nutrients in this category has led to an uncoordinated relationship, so we will avoid analyzing this category from now on.

Table 3. Correlation rates between recovered rates and different food categories in fat data

Recovered	1.000000
Stimulants	0.439024
Obesity	0.379917
Animal Products	0.345611
Eggs	0.322374
Milk-Excluding Butter	0.320457
Animal Fats	0.320171
Treenuts	0.169697
Meat	0.114419
Vegetables	0.060749
Miscellaneous	0.022815
Fruits-Excluding Wine	-0.037000
Sugar & Sweeteners	-0.056180
Population	-0.062480
Sugar Crops	-0.072643
Alcoholic Beverages	-0.075246
Aquatic Products, Other	-0.076626
Spices	-0.094597
Fish, Seafood	-0.097210
Vegetables Oils	-0.112150
Offals	-0.125645
Pulses	-0.221833
Starchy Roots	-0.243610
Cereals-Excluding Beer	-0.279876
Oilcrops	-0.284449
Vegetal Products	-0.345645

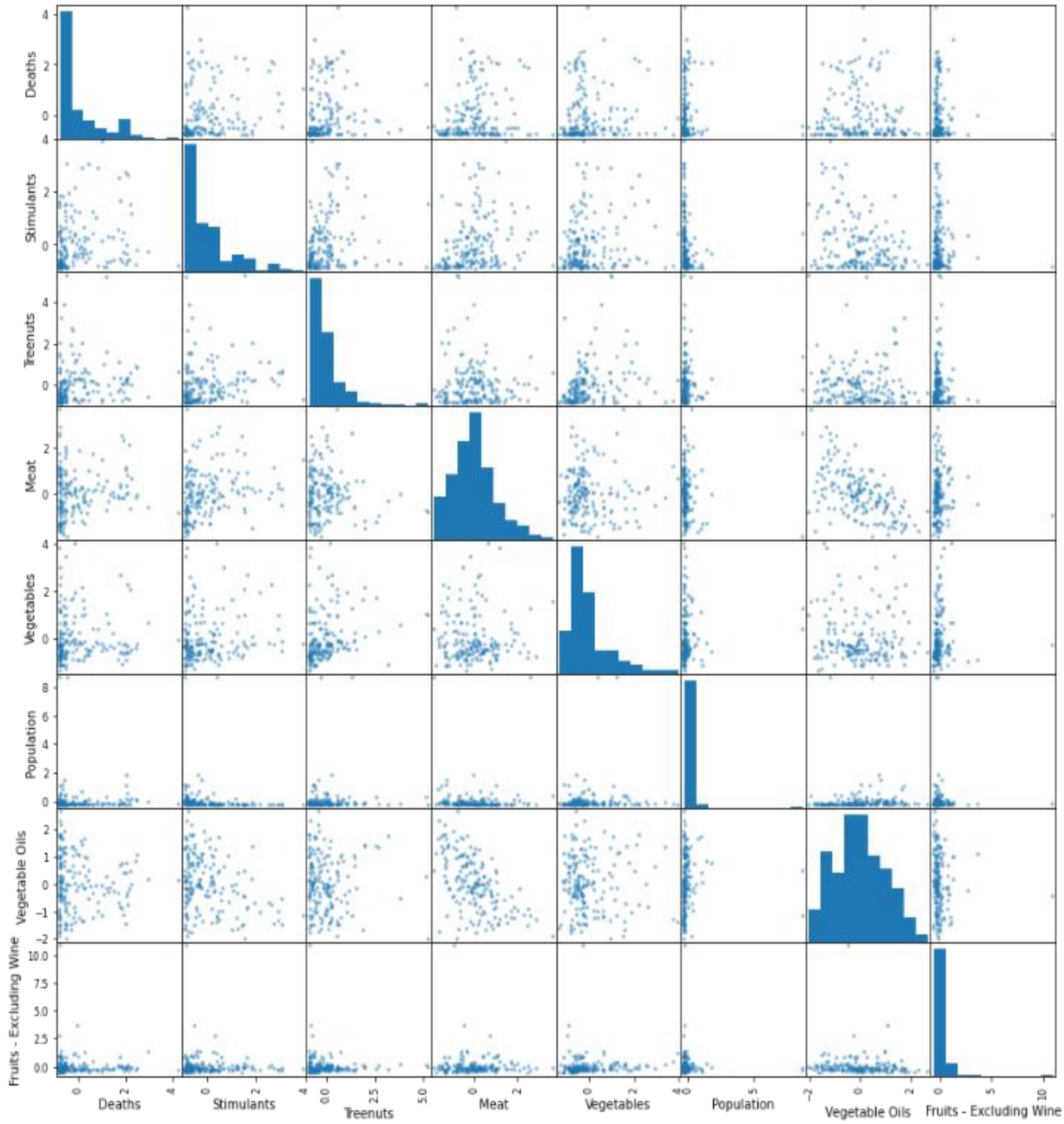

Fig. 2 a. Charts related to the discovery of nonlinear death rate relationships with food categories in fat data (Stimulants, tree nuts, meat, vegetables,...)

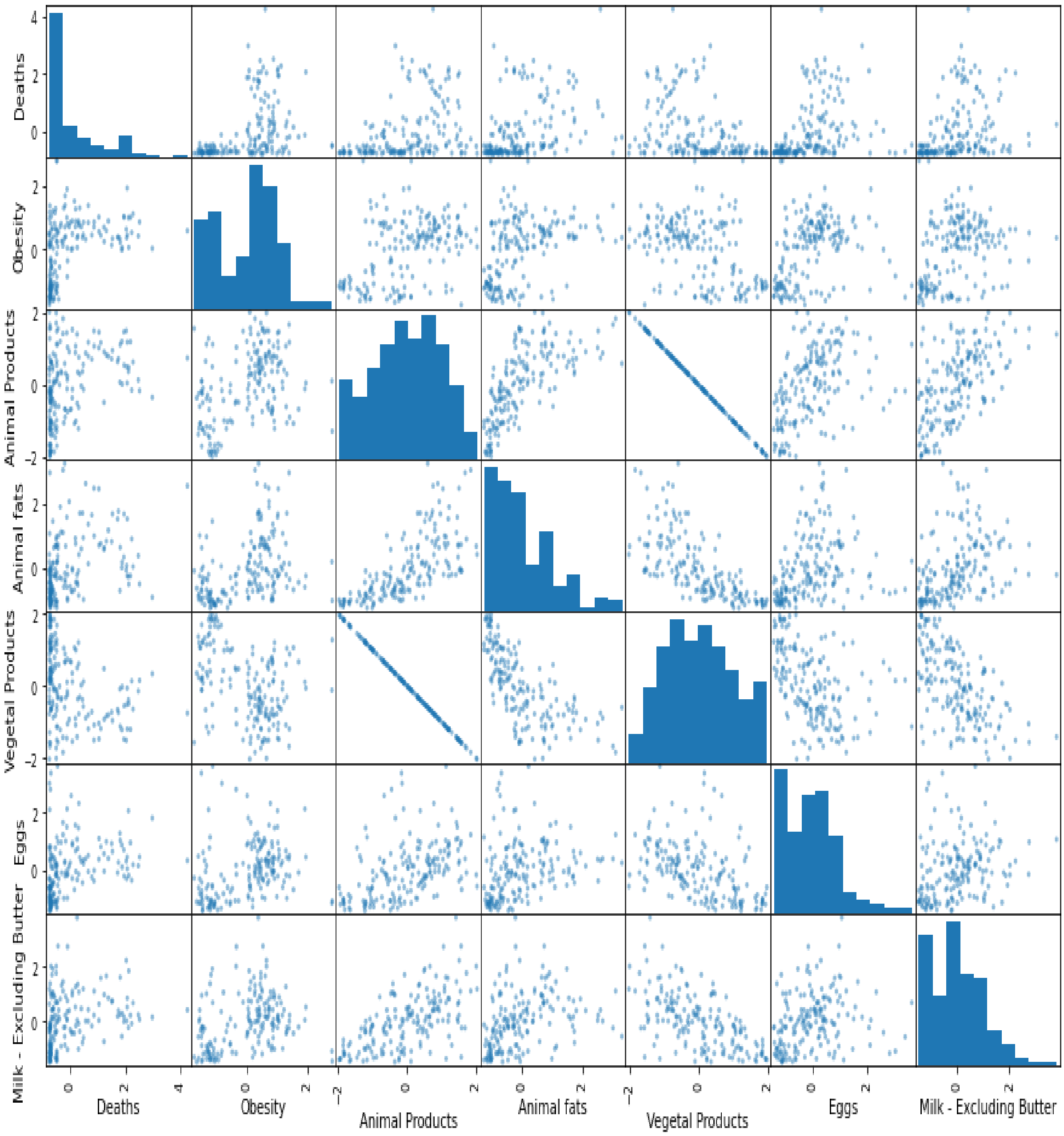

Fig. 2b. Charts related to the discovery of nonlinear death rate relationships with food categories in fat data (Obesity, animal products, animal fats…)

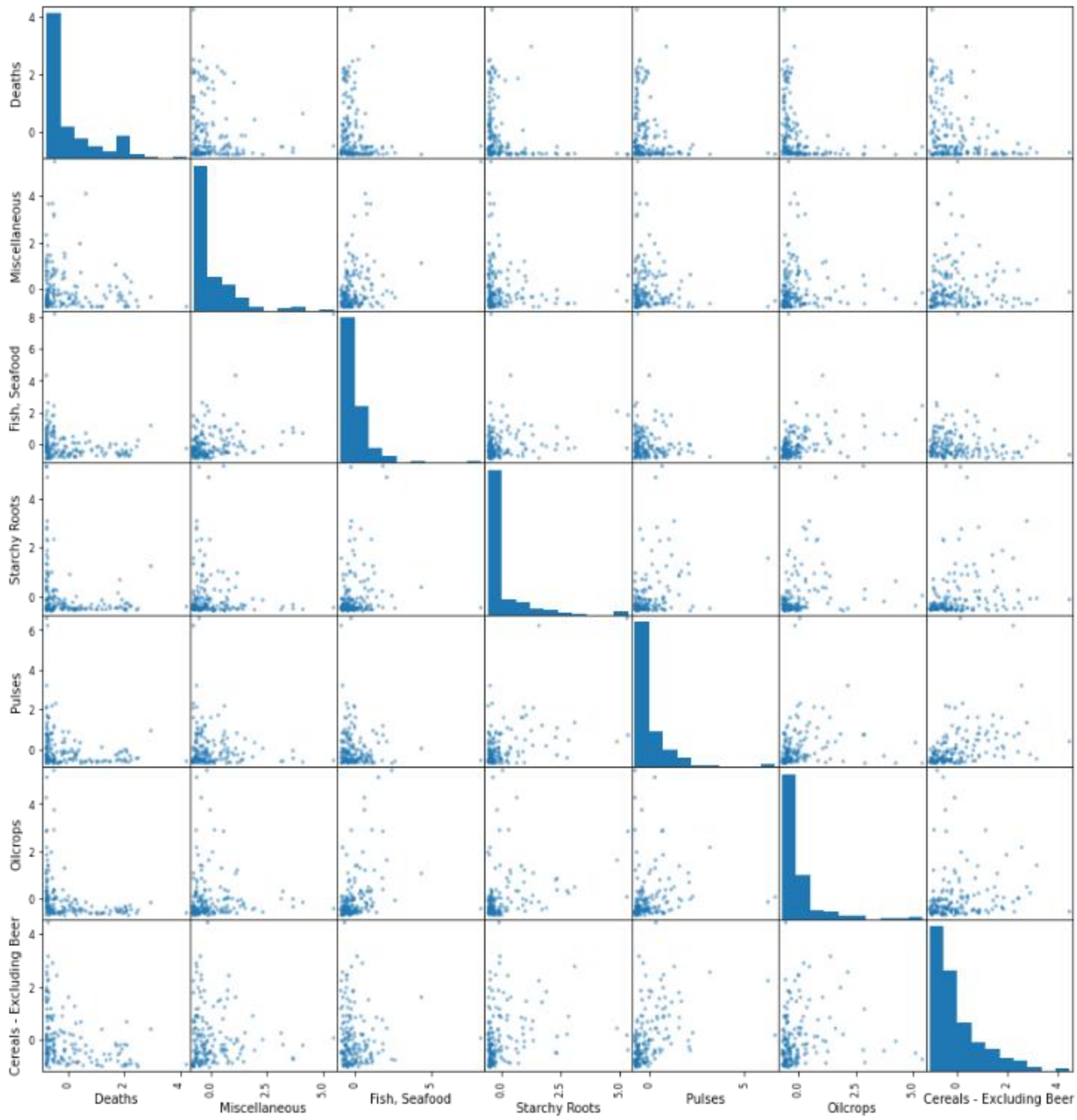

Fig. 2c. Charts related to the discovery of nonlinear death rate relationships with food categories in fat data (Fish, starchy roots, pulses, …)

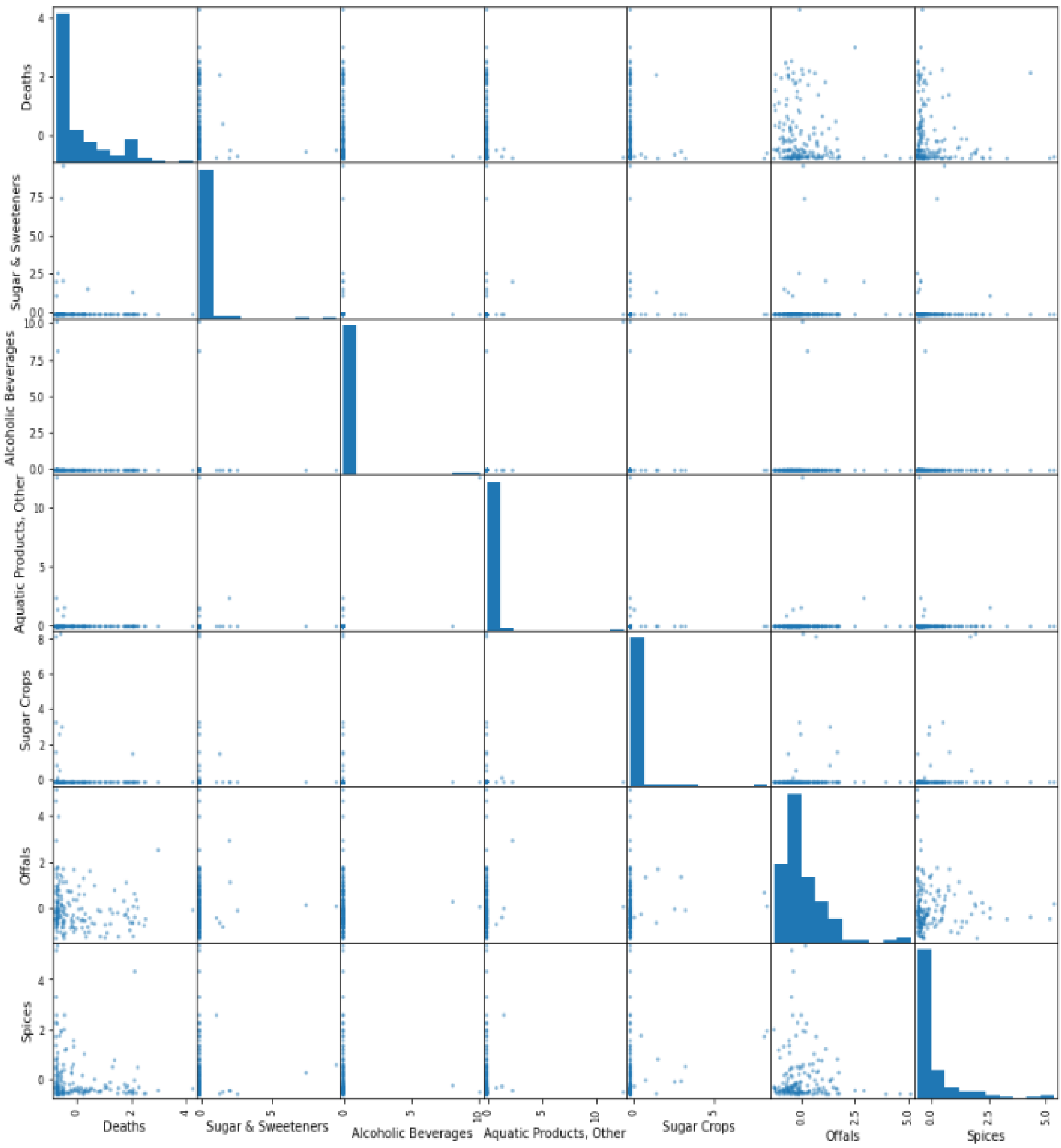

Fig. 2d. Charts related to the discovery of nonlinear death rate relationships with food categories in fat data (Sugar & sweeteners, alcoholic beverages, …)

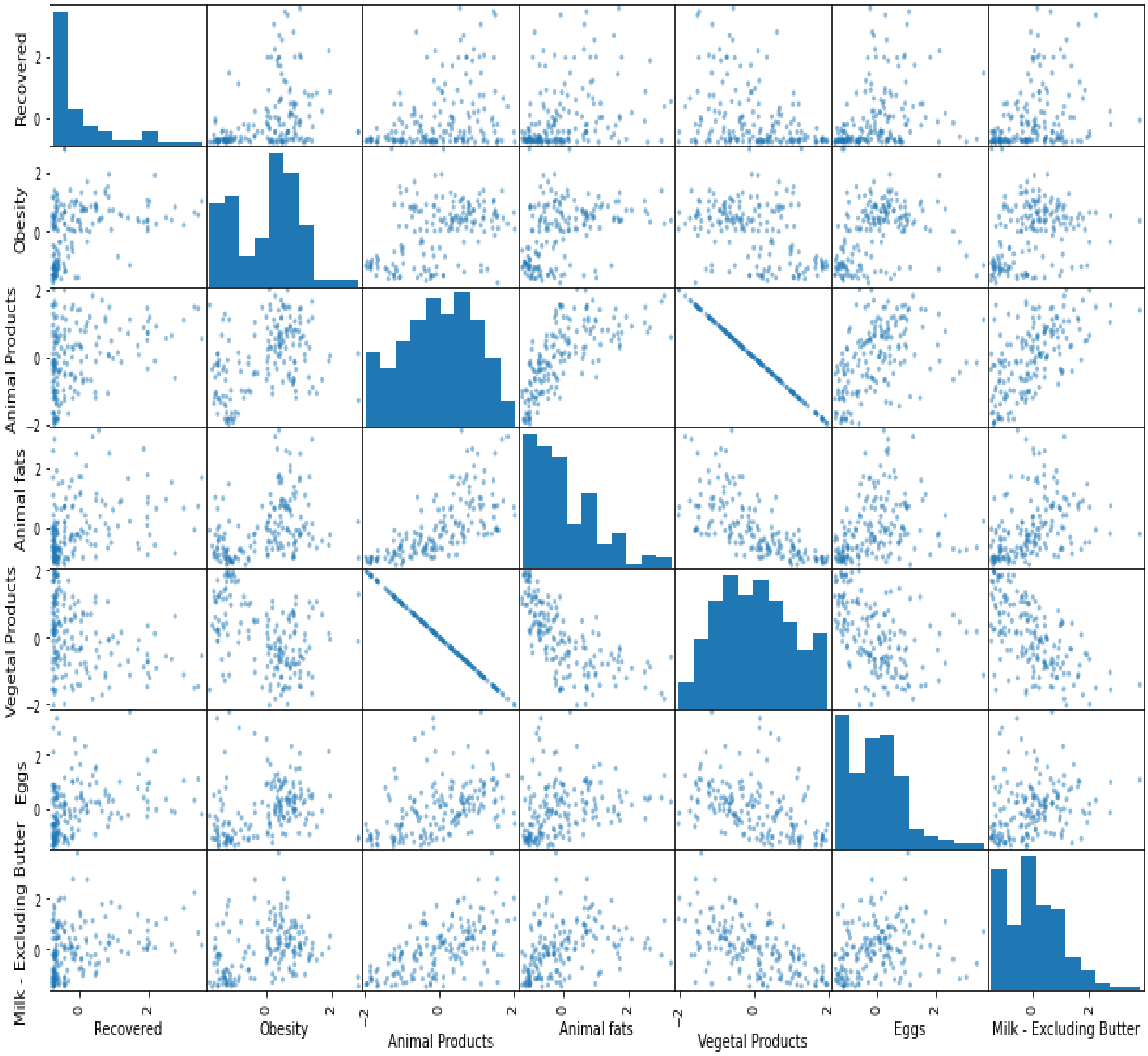

Fig. 3a. Charts related to the discovery of nonlinear recovered rate relationships with food categories (Obesity, animal products, …)

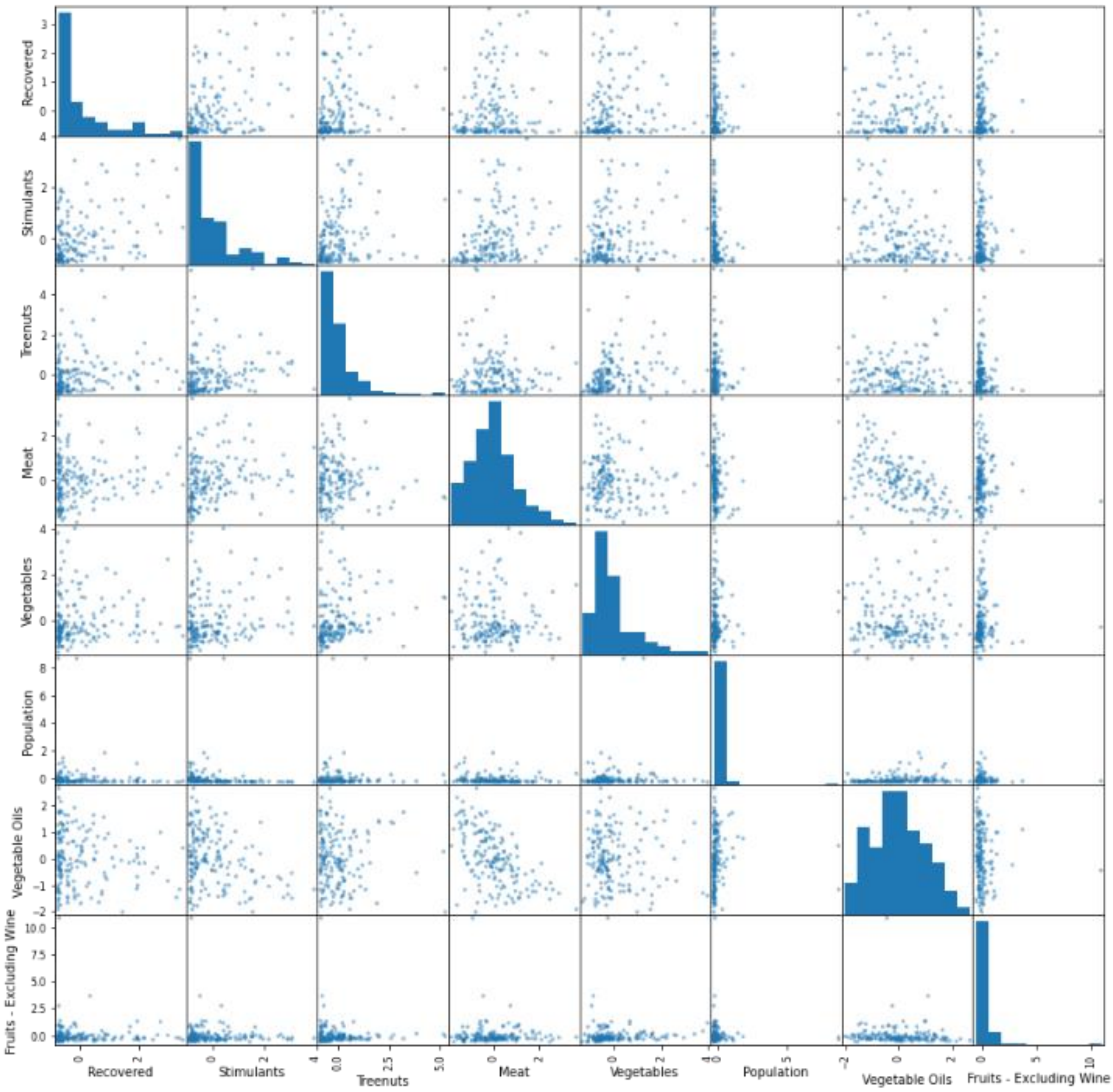

Fig. 3b. Charts related to the discovery of nonlinear recovered rate relationships with food categories (Stimulants, tree nuts, …)

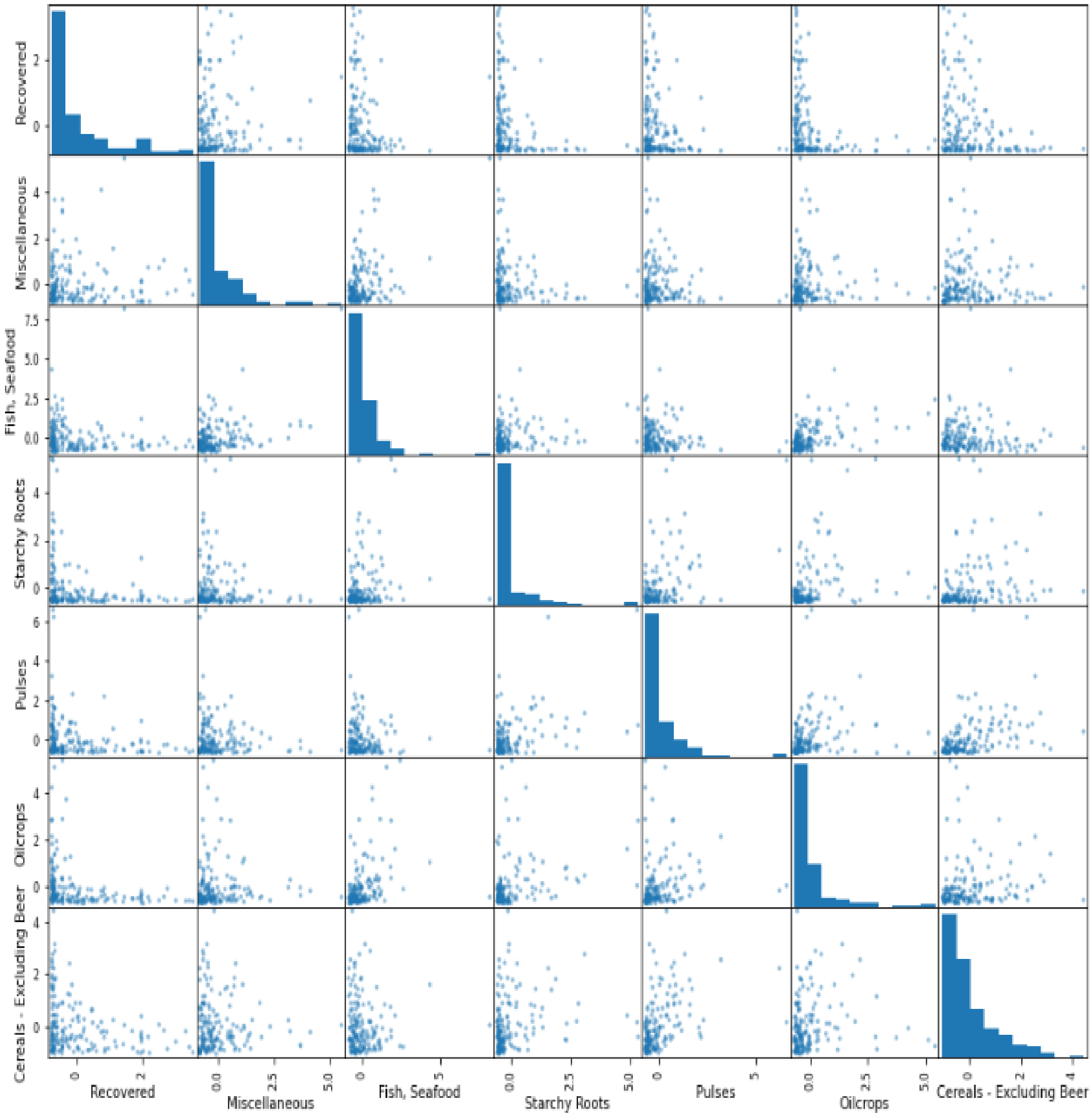

Fig. 3c. Charts related to the discovery of nonlinear recovered rate relationships with food categories (Fish and seafood, …)

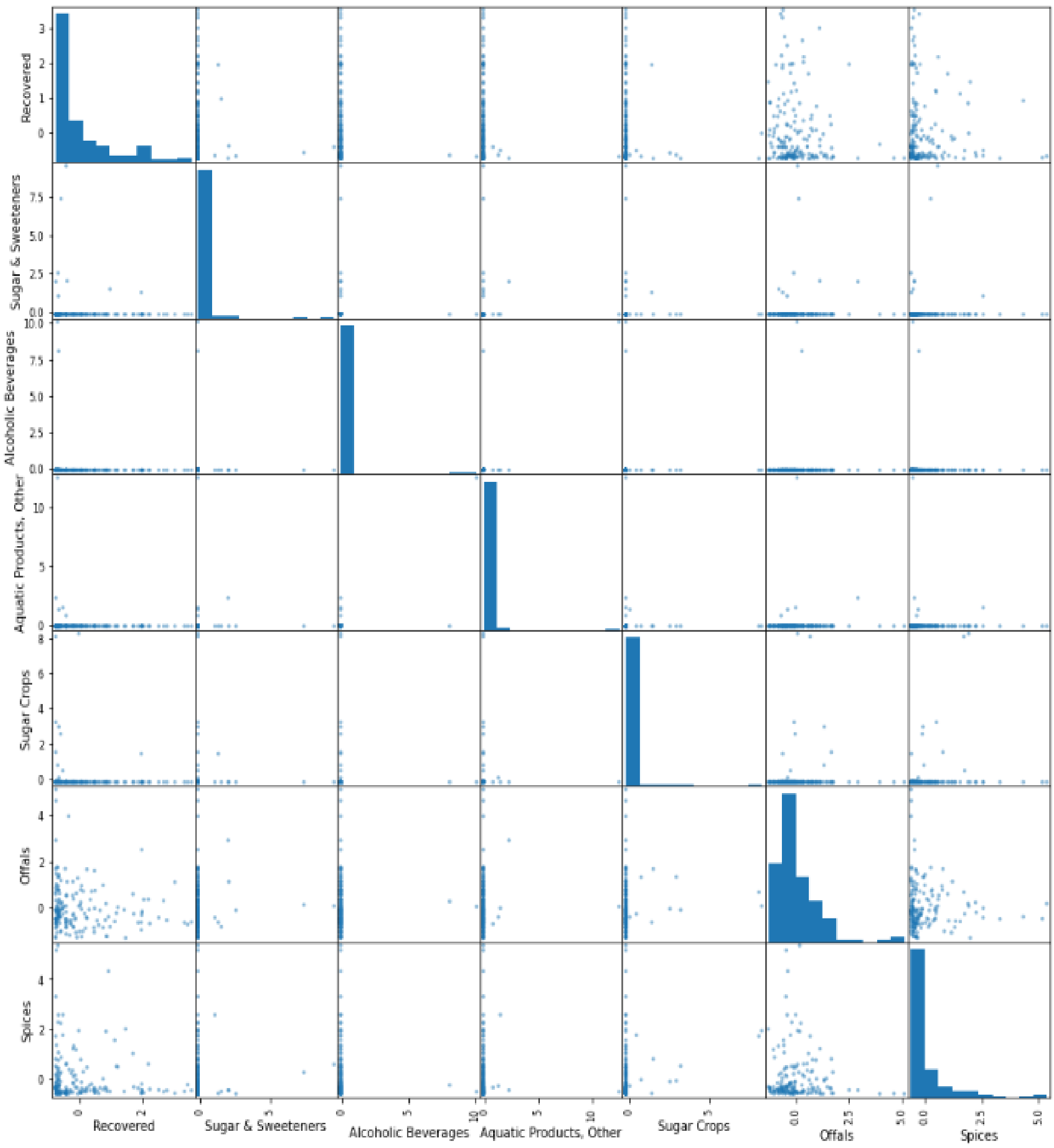

Fig. 3d. Charts related to the discovery of nonlinear recovered rate relationships with food categories (Sugar & Sweetened, alcoholic beverages, …)

According to the results extracted from table 2 and table 3, the amount of fat contained in Stimulants, Eggs, and Animal Products has the most direct effect on improvement. And oil crops, Cereals-Excluding Beer has the highest inverse effect with recovery rate. Obesity is also highly correlated with the recovery rate. Although the correlation between obesity and death rate is somewhat higher than this correlation with recovery rate, this difference is negligible. It can be said that we cannot conclude the impact of obesity at present.

4-2- The effect of protein in different food categories on mortality and recovery rates

Tables 4 and 5 show the protein in Milk-Excluding Butter, Eggs, and Animal Products has the most direct linear relationship with death rate and recovery rate. And oil crops and Cereal-Excluding Beer have the most inverse linear correlation with death rate and recovery rate. Examining tables 4 and 5, we still see a slight difference in the correlation coefficient between obesity and our two response variables, namely death and recovery rate. This value is ignored due to inadequacy. We also reviewed the available data to conclude that the rate of obesity in different countries is relative to the rate of recovery and death rate. And by referring to the rate of obesity, it is impossible to reach a significant relationship with the rate of death or the rate of improvement in Covid-19 conditions. Although obesity endangers a person's health, it cannot be generally concluded that overweight people are more vulnerable to coronary heart disease.

Table 4. Correlation rates between death rates and different food categories in protein data

Deaths	1.000000
Milk-Excluding Butter	0.449048
Eggs	0.426272
Obesity	0.425477
Animal Products	0.397139
Meat	0.343925
Vegetable Oils	0.305021
Animal Fats	0.264761
stimulants	0.239271
Alcoholic Beverages	0.201811
Tree nuts	0.163770
Sugar & Sweeteners	0.138855
Vegetables	0.093613
Offal	-0.019091
Fruits-Excluding Wine	-0.023005
Population	-0.026218
Aquatic Products, Other	-0.067290
Spices	-0.104315
Miscellaneous	-0.111133
Sugar Crops	-0.135539
Starchy Roots	-0.166110
Fish, Seafood	-0.208237
Pulses	-0.263647
Cereals- Excluding Beer	-0.274714
Oil crops	-0.345104
Vegetal Products	-0.397087

Table 5. Correlation rates between recovery rates and different food categories in protein data

Recovered	1.000000
Milk-Excluding Butter	0.421809
Obesity	0.379917
Animal Products	0.368109
Eggs	0.355945
Meat	0.292005
Stimulants	0.286456
Animal Fats	0.190026
Alcoholic Beverages	0.135384
Vegetable Oils	0.129732
Sugar & Sweeteners	0.125408
Tree nuts	0.124262
Vegetables	0.096043
Miscellaneous	0.034565
Fruits-Excluding Wine	0.001065
Offal	-0.026219
Population	-0.062480
Aquatic Products, Other	-0.067152
Spices	-0.091425
Sugar Crops	-0.101739
Fish, Seafood	-0.141361
Starchy Roots	-0.194673
Cereals- Excluding Beer	-0.247460
Pulses	-0.249817
Oil Crops	-0.326731
Vegetal Products	-0.368100

As can be deduced from the results of sections 4.1 and 4.2, the relationship between different food categories and mortality rates and recovery rates has been interrelated both in food fat content data and in food protein content data, and in other words, they are related to both response variables. However, the correlation rate of response variables with the available data is very low, even for categories with a high correlation with response variables. It does not have a high citation rate. But these results are a very reliable source for claiming that each person's body needs a variety of nutrients to play a significant role in determining the impact of personal health and thus in determining the rate of death and the rate of recovery of a country.

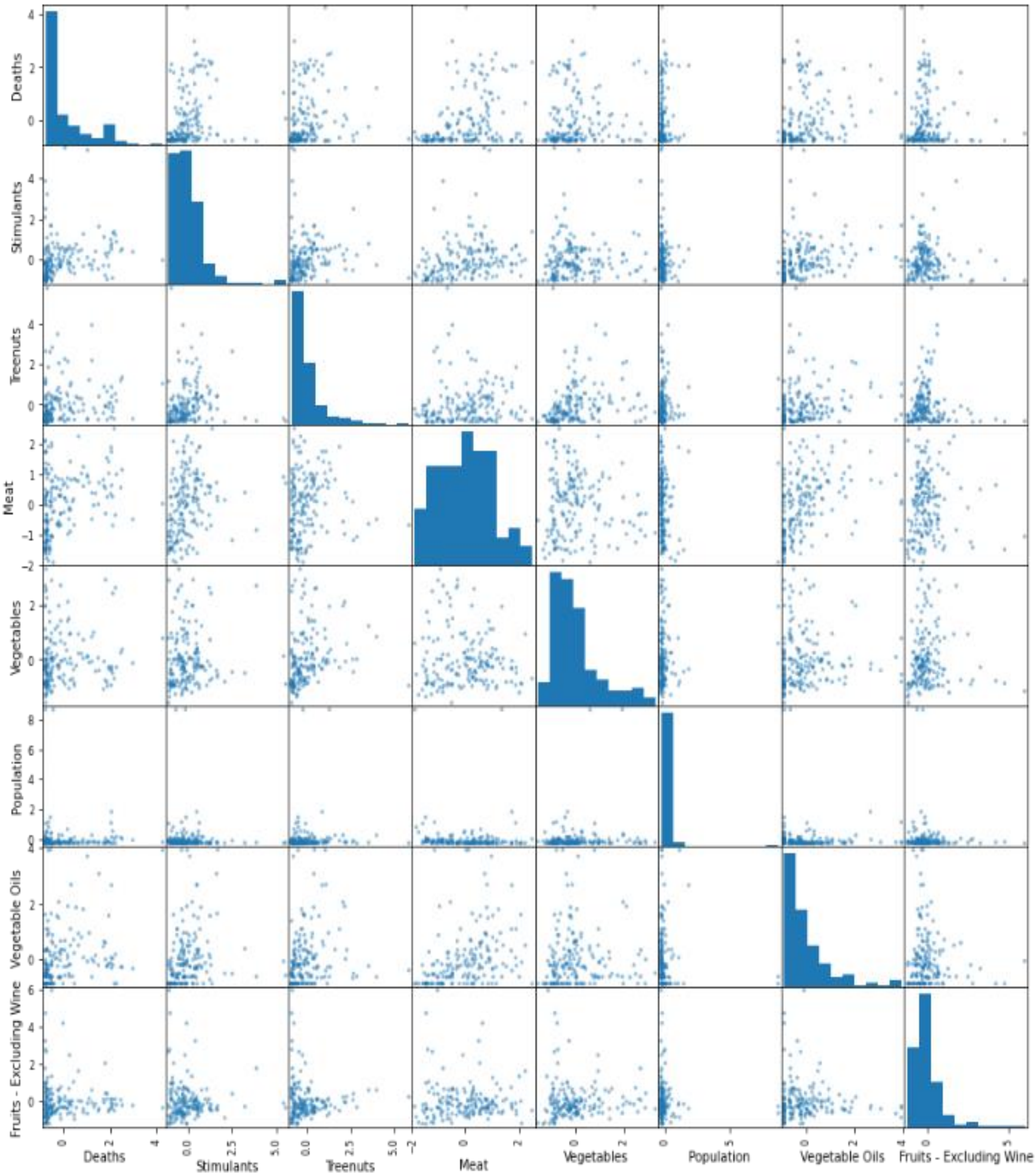

Fig. 4a. Charts related to the discovery of nonlinear death rate relationships with food categories in protein data (Stimulants, tree nuts, …)

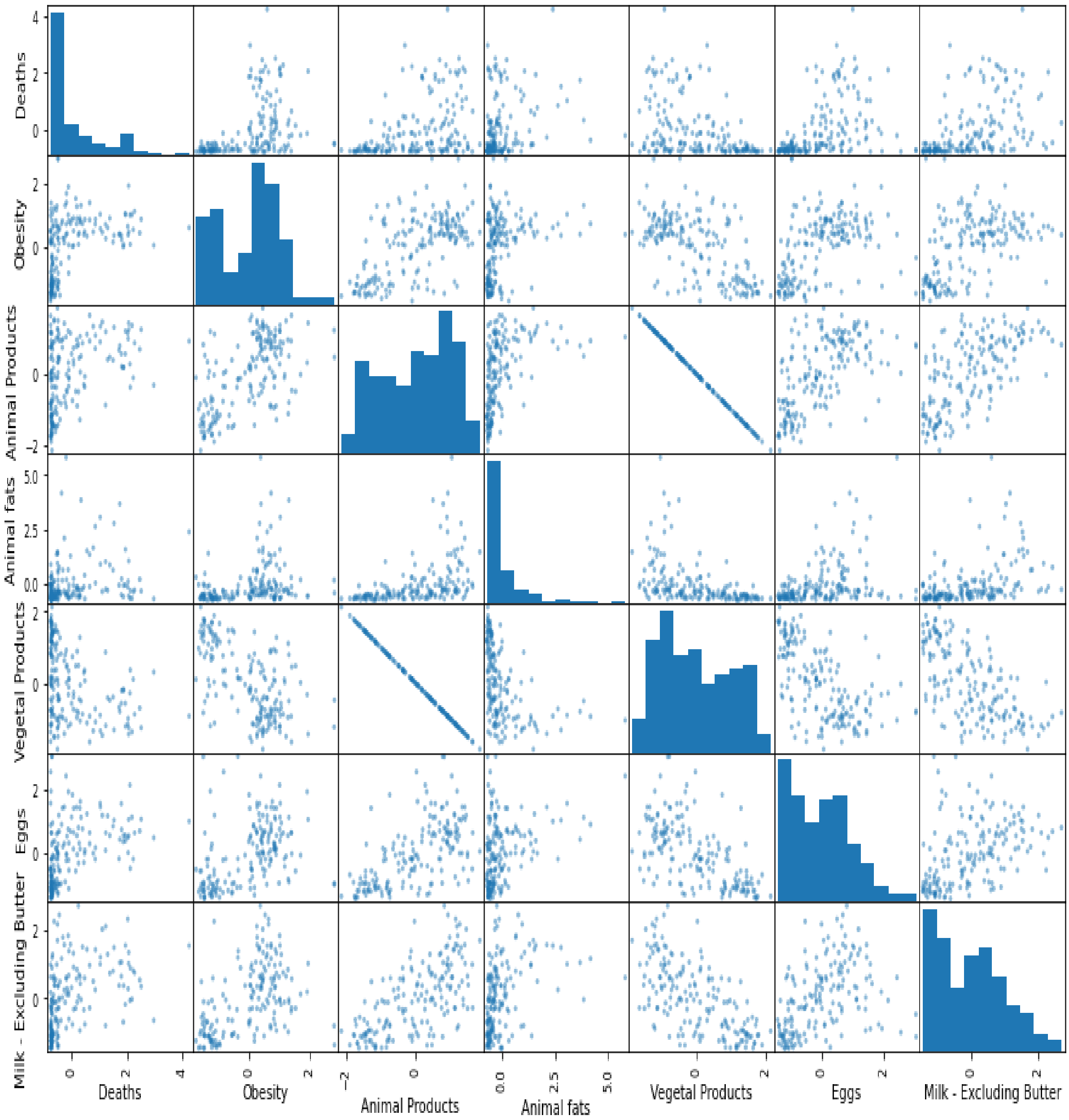

Fig. 4b. Charts related to the discovery of nonlinear death rate relationships with food categories in protein data (Obesity, animal products, …)

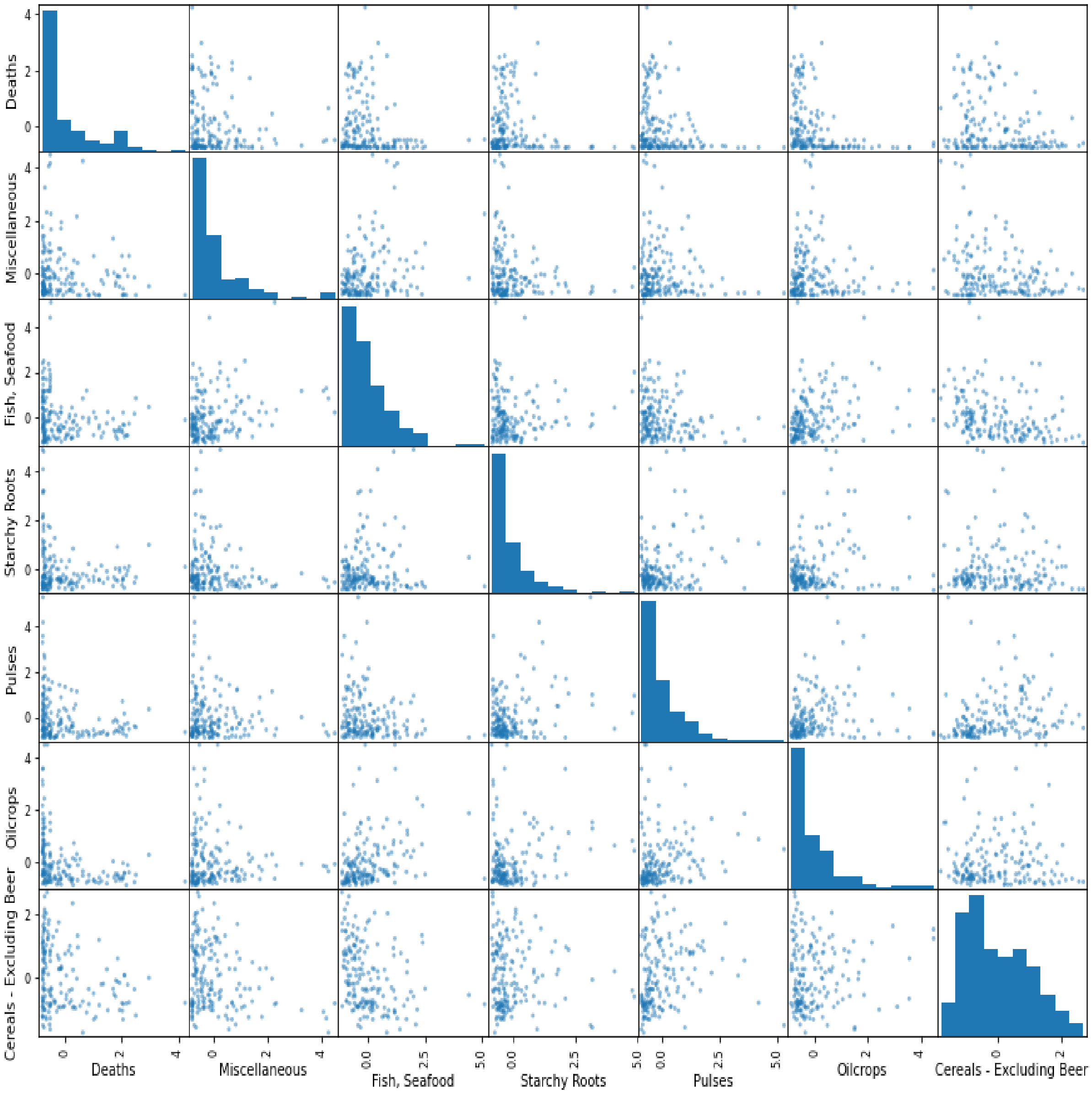

Fig. 4c. Charts related to the discovery of nonlinear death rate relationships with food categories in protein data (Fish and seafood, starchy roots, …)

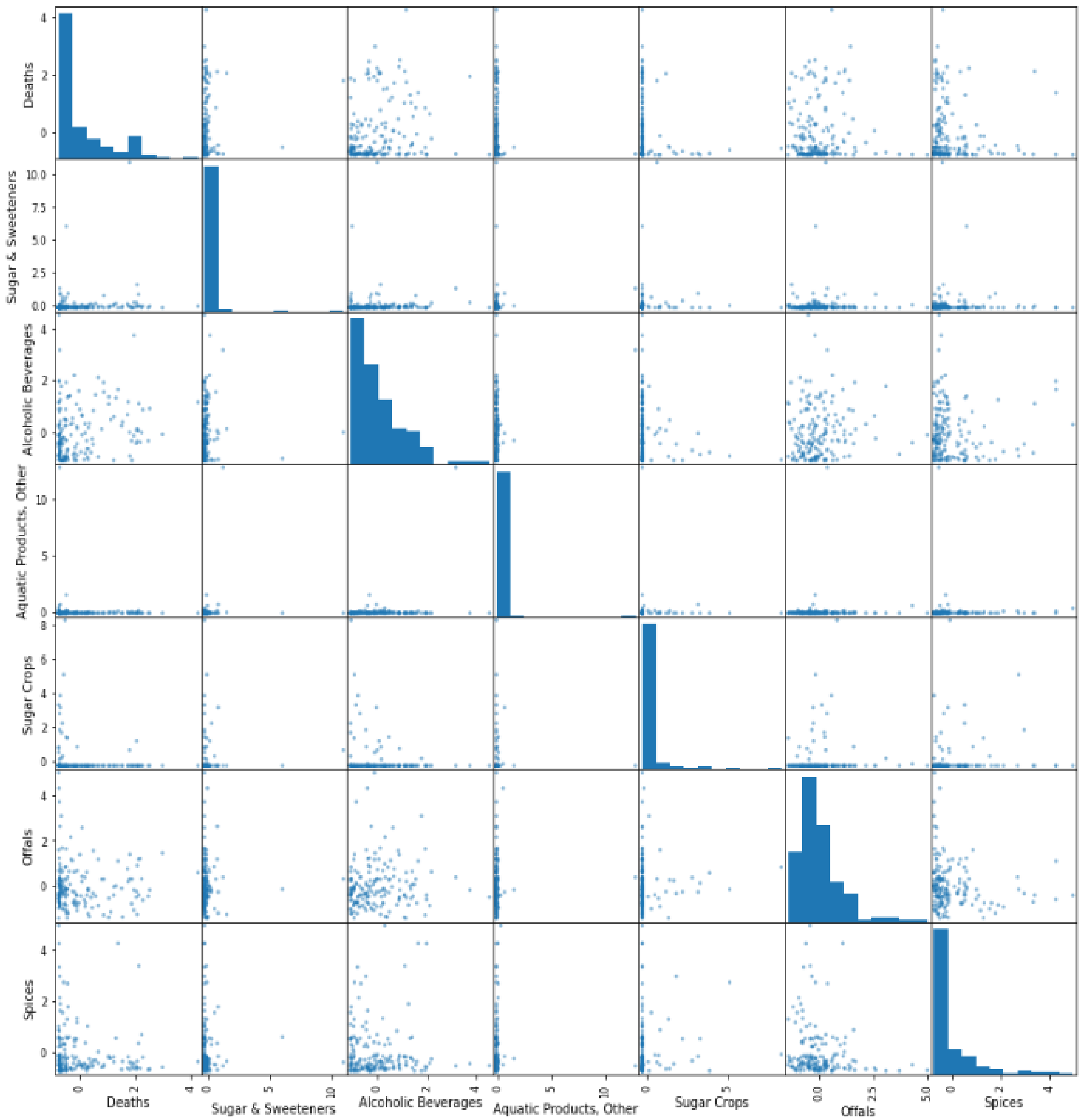

Fig. 4d. Charts related to the discovery of nonlinear death rate relationships with food categories in protein data (Sugar & sweeteners, alcoholic beverages, …)

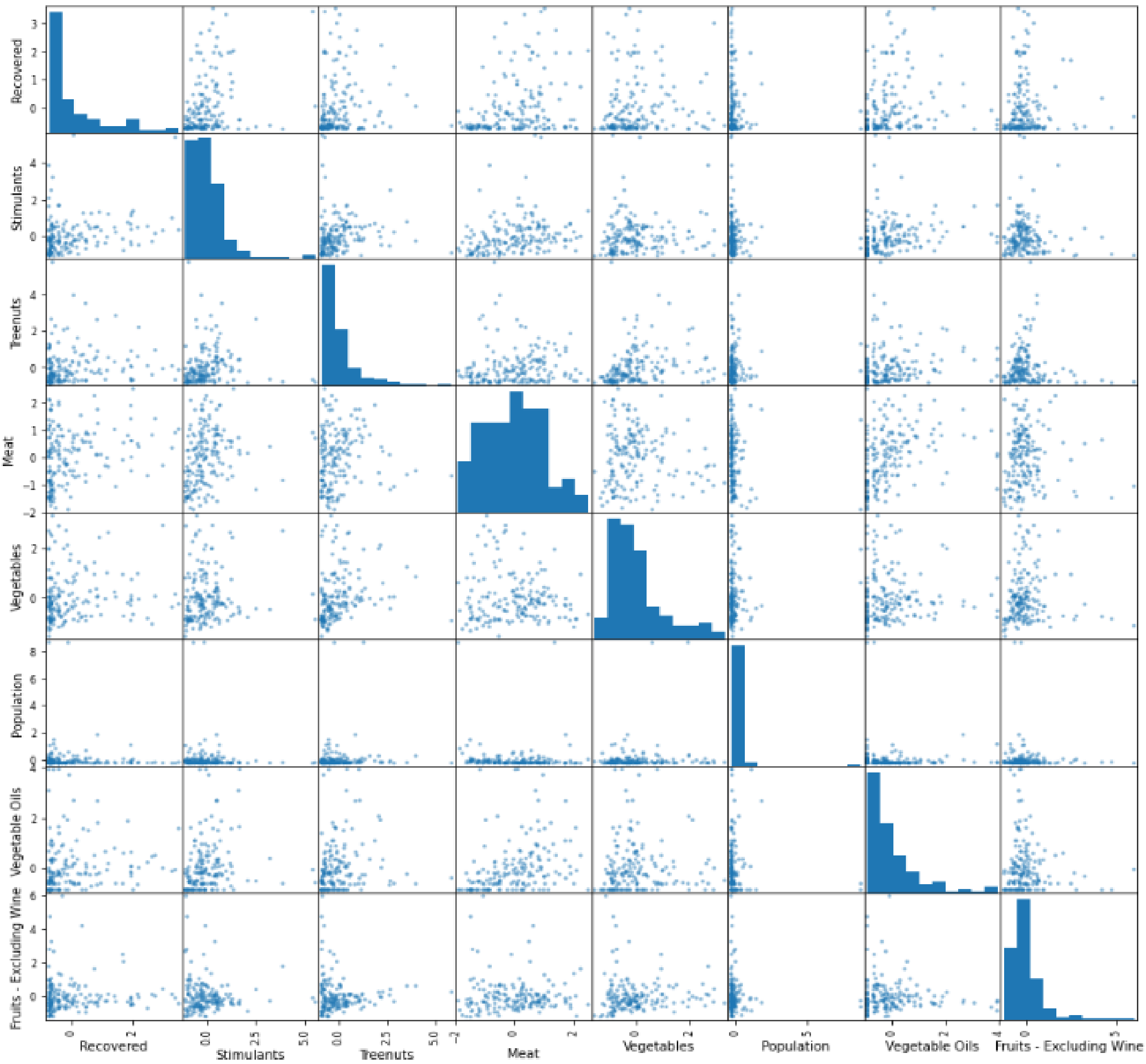

Fig. 5a. Charts related to the discovery of nonlinear recovery rate relationships with food categories in protein data (Stimulants, meat, tree nuts, …)

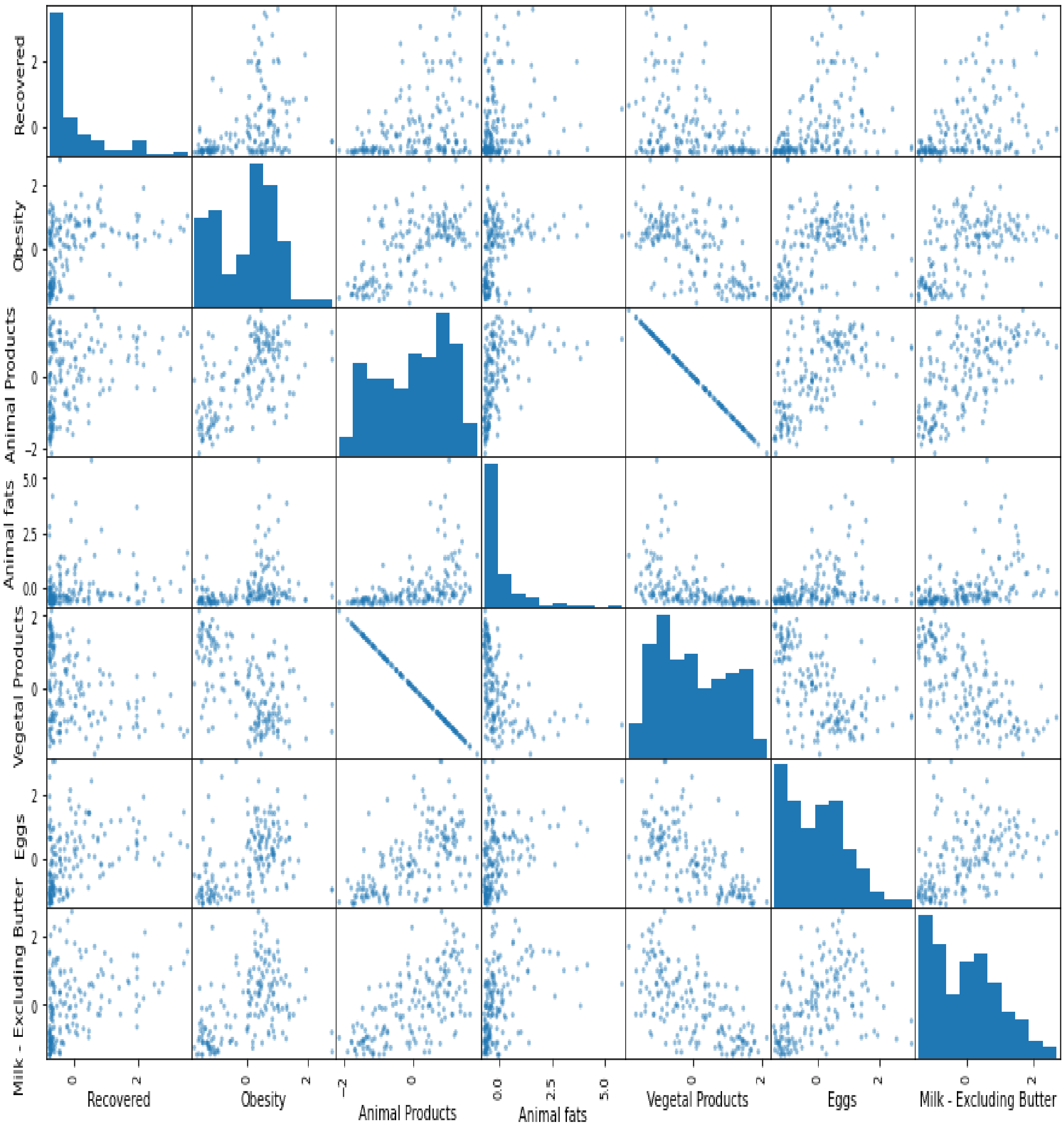

Fig. 5b. Charts related to the discovery of nonlinear recovery rate relationships with food categories in protein data (Animal products, animal fats, …)

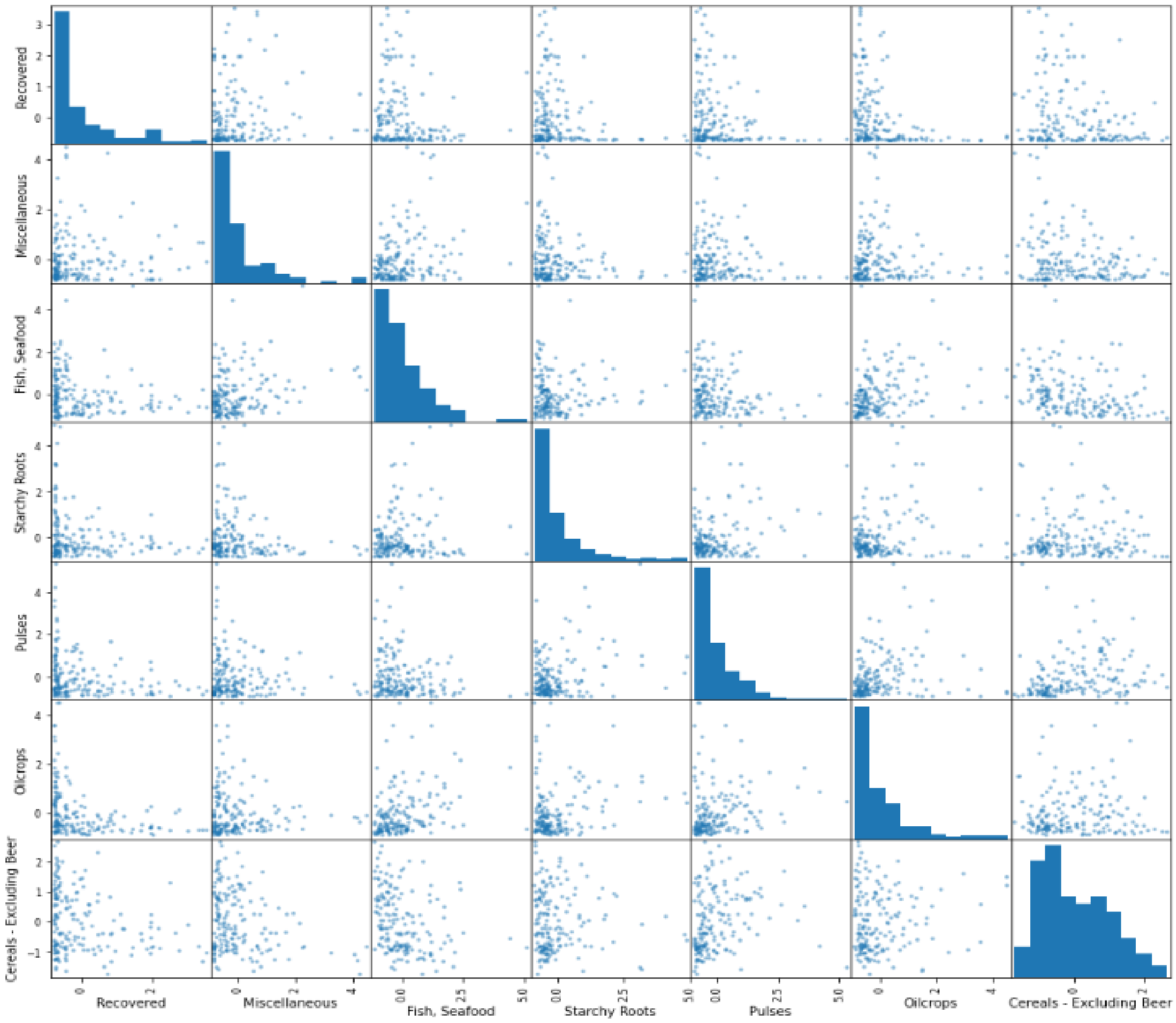

Fig. 5c. Charts related to the discovery of nonlinear recovery rate relationships with food categories in protein data (Fish, seafood, …)

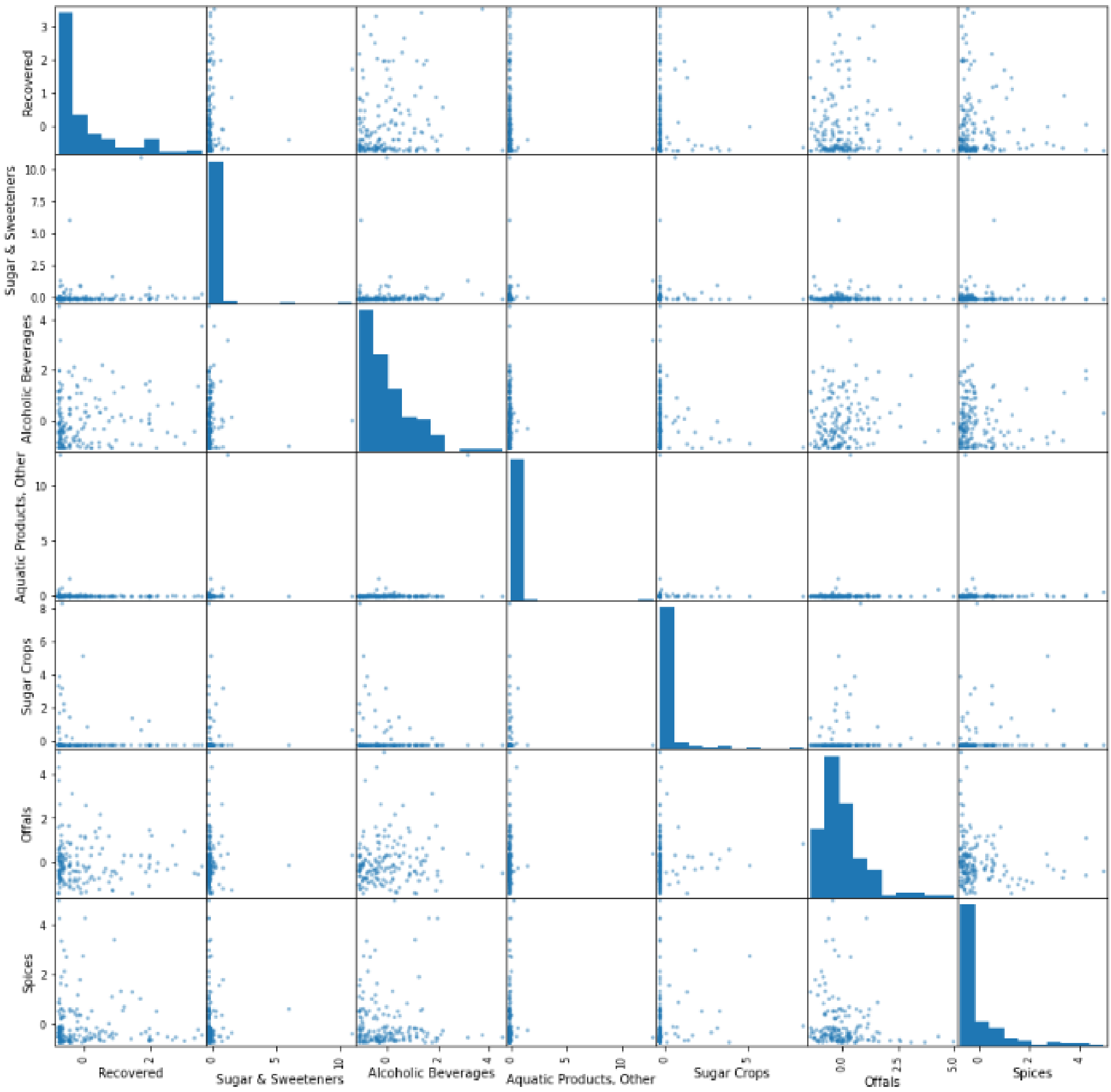

Fig. 5d. Charts related to the discovery of nonlinear recovery rate relationships with food categories in protein data (Sugar and sweeteners, alcoholic beverages, …)

4-3- Prediction models

We proceed from the preprocessing stage to integral modelling. First, we import our data into the RapidMiner environment. In the preprocessing stage, cleansing and blending data are done. Before modelling, we labelled recovered, and death attributes that are supposed to be predicted. Predictive models are a set of machine learning techniques, search data and discover patterns to do the best in new positions (Alipour-Vaezi, Aghsami, & Rabbani, 2021). Machine learning (ML) has become common to discover patterns from various datasets (Samieinasab et al., 2021). We use three classification models in this work: Decision Tree, Naive Bayes, and Rule Induction. The results of the foregoing models are attached below assumed that the death attribute was labelled.

We labelled death attribute and then, through Decision Tree, Naive Bayes, and Rule Induction models, predicted death rate belongs to different foods' value. Conditional commands of Rule Induction in table 6 represent the text form of the Decision Tree. These models express the mortality rate of fat based on the various food range. For example, if Animal Products > 29, then 0.082893 means when Animal Products rate is greater than 29, the death rate is 0.082893. This table shows 166 out of 169 training examples are correct.

Table 6. Description- rule Induction related to food categories in fat data

if Eggs ≤ 0.500 and Cereals - Excluding Beer ≤ 15.500 and oil crops ≤ 1.500 then 0.000000
if Recovered = NA(Not a Number), then NA(Not a Number)
if Milk - Excluding Butter ≤ 0.500 and Starchy Roots ≤ 2 then 0.000000
if Obesity = 20.2 then 0.000000
if Recovered = 0.09511 then 0.004680
if Milk - Excluding Butter > 15.500 then 0.029563
if Recovered = 0.12397 then 0.005555
if Obesity = 6.8 then 0.001079
if Meat > 20.500 then 0.086290
if Obesity = 20.9 then 0.075372
if Obesity = 30.4 then 0.003526
if Obesity = 21.9 then 0.038658
if Obesity = 19.9 then 0.014543
if Cereals - Excluding Beer ≤ 7.500 then 0.041476
if Recovered = 0.09511 then 0.004680
if Milk - Excluding Butter > 15.500 then 0.029563
if Recovered = 0.12397 then 0.005555
if Obesity = 6.8 then 0.001079
if Obesity = 3.4 then 0.003953
if Obesity = 24.5 and Animal Products > 26 then 0.146861
if Cereals - Excluding Beer ≤ 8.500 then 0.001304
if Offals > 2.500 then 0.000338
if Miscellaneous > 0.500 then 0.006516
if Fruits - Excluding Wine > 3 then 0.008095
if Obesity = 23.5 and Animal Products > 21.500 then 0.024493
if Milk - Excluding Butter > 12 then 0.058432
if Vegetables > 4 then 0.000923
if Eggs > 2.500 then 0.000090
if Animal Products ≤ 8, then 0.000035
if Animal Products > 29 then 0.082893
if Eggs > 0.500 then 0.001788
if Animal Products ≤ 10, then 0.001942
else 0.001864

Naive Bayes in table 7 describes the probability of occurrence of mortality based on different values. Class 0.004680 (0.006) express that with 0.006% probability mortality rate is 0.004680. One of the most important questions should be asked after building a predictive model: "How well is this model going to perform"? In the next section, we will answer this question.

Table 7. Description-naive Bayes related to food categories in fat data

Class 0.004680 (0.006) 21 distributions	Class 0.003526 (0.006) 21 distributions	Class 0.146861 (0.006) 21 distributions	Class 0.062754 (0.006) 21 distributions
Class 0.029563 (0.006) 21 distributions	Class 0.038658 (0.006) 21 distributions	Class 0.035322 (0.006) 21 distributions	Class 0.000325 (0.006) 21 distributions
Class 0.005555 (0.006) 21 distributions	Class 0.014543 (0.006) 21 distributions	Class 0.000360 (0.006) 21 distributions	Class 0.019065 (0.006) 21 distributions
Class 0.001079 (0.006) 21 distributions	Class 0.041476 (0.006) 21 distributions	Class 0.077125 (0.006) 21 distributions	Class 0.000000 (0.059) 21 distributions
Class 0.004082 (0.006) 21 distributions	Class 0.003953 (0.006) 21 distributions	Class 0.084517 (0.006) 21 distributions	Class 0.001658 (0.006) 21 distributions
Class 0.086290 (0.006) 21 distributions	Class 0.002439 (0.006) 21 distributions	Class 0.001467 (0.006) 21 distributions	Class 0.032317 (0.006) 21 distributions
Class 0.075372 (0.006) 21 distributions	Class 0.012523 (0.006) 21 distributions	Class 0.082391 (0.006) 21 distributions	Class 0.001304 (0.006) 21 distributions

4-4- Test splits and validation

Now we want to compare the predictions with the actual outcomes and calculate how often the model was right. In this section, first, we split labelled data into two partitions. We got two partitions with 70% of the data in one and 30% of the data in the other. Both sets are labelled. The 70% partition became the training set we built our model on. The remaining 30% became our test set against which we can compare our model's predictions. Second, we train and apply the model. The 30% test data have additional columns for the prediction of recovered together with confidence columns. Finally, we computed the accuracy of the models. The accuracy of protein data is 66.67% and tells how accurate the model is overall. This percentage of fat data is 50%.

Briefly, we have split our labelled data into two parts, one for training and one for testing, and used the performance operator to calculate how well the model does.

5- Conclusion and managerial insight

This study provided data about the amount of protein and fat in different foods and examined their relationships with death and recovered rate during the COVID-19 pandemic. We employ Decision Trees, Naive Bayes, and Rule Induction models to predict death rate fluctuations concerning various foods. The results show the calculated correlation coefficient between different variables was very low. Moreover, the accuracy of protein and fat data models is 66.67% and 50%, respectively. However, as the COVID-19 pandemic is ongoing, this new condition may endanger maintaining a healthy and varied diet. Adherence to healthy nutrition principles is one of the most essential and fundamental pillars in ensuring health and shortening this crisis period.

The findings show that the protein in Milk-Excluding Butter, Eggs and Animal Products has the most direct linear relationship with death and recovery rates. And Oil crops and Cereal-Excluding Beer have the most inverse linear correlation with death rate and recovery rate. Animal fats, Animal products, and Eggs had the most direct relationship, and Cereals-Excluding Beer and Oil crops had the most inverse relationship with mortality. The amount of fat contained in Stimulants, Eggs, and Animal Products directly affect improvement. And Oil crops, Cereals-Excluding Beer, has the highest inverse effect with recovery rate.

This research emphasizes to health managers that one of the main pillars of maintaining the health of the community's people is the supply of food they need. Although this has only been said to reduce malnutrition mortality in the past, we are facing a phenomenon called COVID-19, which despite being unknown, we know that many factors affect it. Hence, the best way for managers to deal with it is to prevent it from happening. And as we tried to address during this study, foods in addition to causing many diseases (such as blood sugar, blood lipids, etc.) and the best for the treatment and prevention of many diseases and even the only possible solutions. Therefore, we strongly advise the readers of this article not to neglect the role of food in treating COVID-19 and even other diseases. We will study more of other nutrients and even newer methods to examine the data in future research.

References

Adams, E. L., Caccavale, L. J., Smith, D., & Bean, M. K. (2020). Food insecurity, the home food environment, and parent feeding practices in the era of COVID-19. *Obesity, 28*(11), 2056-2063.

Albahri, A., & Hamid, R. A. (2020). Role of biological Data Mining and Machine Learning Techniques in Detecting and Diagnosing the Novel Coronavirus (COVID-19): A Systematic Review. *Journal of Medical Systems, 44*(7).

Alballa, N., & Al-Turaiki, I. (2021). Machine learning approaches in COVID-19 diagnosis, mortality, and severity risk prediction: A review. *Informatics in Medicine Unlocked*, *24*, 100564.

Aldaco, R., Hoehn, D., Laso, J., Margallo, M., Ruiz-Salmón, J., Cristobal, J., . . . Batlle-Bayer, L. (2020). Food waste management during the COVID-19 outbreak: a holistic climate, economic and nutritional approach. *Science of the Total Environment, 742*, 140524.

Alipour-Vaezi, M., Aghsami, A., & Rabbani, M. (2021). Introducing a Novel Revenue-Sharing Contract in Media Supply Chain Management using Data Mining and Multi-Criteria Decision-Making Methods.

Alipour-Vaezi, M., Tavakkoli-Moghadaam, R., & Samieinasab, M. (2021). Scheduling the COVID-19 vaccine distribution based on data-driven decision-making methods. *Journal of Industrial Engineering and Management Studies*, 1-11.

Alipour Vaezi, M., & Tavakkoli-Moghaddam, R. (2020). A new methodology for COVID-19 preparedness centers based on a location-allocation platform. *Journal of Industrial and Systems Engineering, 13*(1), 35-41.

Alves, M. A., de Castro, G. Z., Oliveira, B. A. S., Ferreira, L. A., Ramírez, J. A., Silva, R., & Guimarães, F. G. (2021). Explaining Machine Learning based Diagnosis of COVID-19 from Routine Blood Tests with Decision Trees and Criteria Graphs. *Computers in Biology and Medicine*, 104335.

Amicarelli, V., & Bux, C. (2020). Food waste in Italian households during the Covid-19 pandemic: a self-reporting approach. *Food Security*, 1-13.

Ayyoubzadeh, S. M., Ayyoubzadeh, S. M., Zahedi, H., Ahmadi, M., & Kalhori, S. R. N. (2020). Predicting COVID-19 incidence through analysis of google trends data in iran: data mining and deep learning pilot study. *JMIR Public Health and Surveillance, 6*(2), e18828.

Baralić, K., Jorgovanović, D., Živančević, K., Miljaković, E. A., Antonijević, B., Djordjevic, A. B., . . . Đukić-Ćosić, D. (2020). Safety assessment of drug combinations used in COVID-19 treatment: in silico toxicogenomic data-mining approach. *Toxicology and Applied Pharmacology, 406*, 115237.

Ben Hassen, T., El Bilali, H., & S Allahyari, M. (2020). Impact of COVID-19 on Food Behavior and Consumption in Qatar. *Sustainability, 12*(17), 6973.

BourBour, F., Mirzaei Dahka, S., Gholamalizadeh, M., Akbari, M. E., Shadnoush, M., Haghighi, M., . . . Doaei, S. (2020). Nutrients in prevention, treatment, and management of viral infections; special focus on Coronavirus. *Archives of Physiology and Biochemistry*, 1-10.

Burdick, H., Lam, C., Mataraso, S., Siefkas, A., Braden, G., Dellinger, R. P., . . . Barnes, G. (2020). Prediction of respiratory decompensation in Covid-19 patients using machine learning: The READY trial. *Computers in Biology and Medicine, 124*, 103949.

Carroll, N., Sadowski, A., Laila, A., Hruska, V., Nixon, M., Ma, D. W., & Haines, J. (2020). The impact of COVID-19 on health behavior, stress, financial and food security among middle to high income Canadian families with young children. *Nutrients, 12*(8), 2352.

Dey, A., Das, R., Misra, H. S., & Uppal, S. (2020). COVID-19: Scientific Overview of the global Pandemic. *New Microbes and New Infections*, 100800.

Erokhin, V., & Gao, T. (2020). Impacts of COVID-19 on trade and economic aspects of food security: Evidence from 45 developing countries. *International journal of environmental research and public health, 17*(16), 5775.

Fitzpatrick, K. M., & Willis, D. E. (2020). Homeless and hungry: food insecurity in the land of plenty. *Food Security*, 1-10.

Funayama, M., Kurose, S., Kudo, S., Shimizu, Y., & Takata, T. (2020). New information technology (IT)-related approaches could facilitate psychiatric treatments in general hospital psychiatry during the COVID-19 pandemic. *Asian Journal of Psychiatry*.

GitHub. (2020). COVID_19_Dataset_Challenge. Retrieved from https://github.com/mariarencode/COVID_19_Dataset_Challenge/blob/f22d3195ac1c69cd257ac9d45ec0b238426d6361/Cleaned_Datasets/Fat_Supply_Quantity_Data.csv

https://github.com/mariarencode/COVID_19_Dataset_Challenge/blob/f22d3195ac1c69cd257ac9d45ec0b238426d6361/Cleaned_Datasets/Protein_Supply_Quantity_Data.csv

Hussain, A., Mahawar, K., Xia, Z., Yang, W., & Shamsi, E.-H. (2020). Obesity and mortality of COVID-19. Meta-analysis. *Obesity research & clinical practice*.

IFPRI. (2013). Food security. Retrieved from https://www.ifpri.org/topic/food-security#:~:text=Food%20security,%20as%20defined%20by,an%20active%20and%20healthy%20life.

Kamal, M., Aljohani, A., & Alanazi, E. (2020). IoT meets COVID-19: Status, challenges, and opportunities. *arXiv preprint arXiv:2007.12268*.

Kang, C., Rohlof, H., Yuan, J., & Yang, J. (2020). Will the COVID-19 outbreak bring the health care system and health industry to a new era in China? *Asian Journal of Psychiatry*.

Laguna, L., Fiszman, S., Puerta, P., Chaya, C., & Tárrega, A. (2020). The impact of COVID-19 lockdown on food priorities. Results from a preliminary study using social media and an online survey with Spanish consumers. *Food Quality and Preference, 86*, 104028.

Leddy, A. M., Weiser, S. D., Palar, K., & Seligman, H. (2020). A conceptual model for understanding the rapid COVID-19–related increase in food insecurity and its impact on health and healthcare. *The American Journal of Clinical Nutrition, 112*(5), 1162-1169.

Li, D., Chaudhary, H., & Zhang, Z. (2020). Modeling spatiotemporal pattern of depressive symptoms caused by COVID-19 using social media data mining. *International Journal of Environmental Research and Public Health, 17*(14), 4988.

Li, J., Xu, Q., Cuomo, R., Purushothaman, V., & Mackey, T. (2020). Data mining and content analysis of the Chinese social media platform Weibo during the early COVID-19 outbreak: retrospective observational infoveillance study. *JMIR Public Health and Surveillance, 6*(2), e18700.

Mamoudan, M. M., Forouzanfar, D., Mohammadnazari, Z., Aghsami, A., & Jolai, F. (2021). Factor identification for insurance pricing mechanism using data mining and multi criteria decision making. *Journal of Ambient Intelligence and Humanized Computing*, 1-20.

Mohammadnazari, Z., & Ghannadpour, S. F. (2018). Employment of multi criteria decision making techniques and mathematical formulation for Construction of the sustainable hospital. *International Journal of Hospital Research, 7*(2), 112-127.

Mohammadnazari, Z., & Ghannadpour, S. F. (2021). Sustainable construction supply chain management with the spotlight of inventory optimization under uncertainty. *Environment, Development and Sustainability, 23*(7), 10937-10972.

Neff, L. M. (2020). Hidden hunger: food insecurity in the age of coronavirus. *The American Journal of Clinical Nutrition*.

Peter, D., & Xavier, P. (2020). A Review of the Possible Implication of COVID-19 Lockdown on Eating Habits. *Int J Cur Res Rev| Vol, 12*(19), 56.

Samieinasab, M., Torabzadeh, S.A., Behnam, A., Aghsami, A. and Jolai, F., 2022. Meta-Health Stack: A new approach for breast cancer prediction. Healthcare Analytics, 2, p.100010.

Sarkar, S., Mishra, S., & Padhy, S. K. (2020). How COVID-19 may impact mental health research conduct, interpretation and priorities? *Asian Journal of Psychiatry*.

Shrestha, N., Shad, M. Y., Ulvi, O., Khan, M. H., Karamehic-Muratovic, A., Nguyen, U.-S. D., . . . Cervantes, D. (2020). The impact of COVID-19 on globalization. *One Health*, 100180.

Sonbhadra, S. K., Agarwal, S., & Nagabhushan, P. (2020). Target specific mining of COVID-19 scholarly articles using one-class approach. *arXiv preprint arXiv:2004.11706*.

Sun, X., Jiang, J., Wang, Y., & Liu, S. (2020). Exploring the potential therapeutic effect of traditional Chinese medicine on coronavirus disease 2019 (COVID-19) through a combination of data mining and network pharmacology analysis. *European Journal of Integrative Medicine*, 101242.

Tavakkoli-Moghaddam, R., Alipour-Vaezi, M., & Mohammad-Nazari, Z. (2020). *A New Application of Coordination Contracts for Supplier Selection in a Cloud Environment.* Paper presented at the IFIP International Conference on Advances in Production Management Systems.

Wang, J., Wang, Z., Liu, X., Yang, X., Zheng, M., & Bai, X. (2020). The impacts of a COVID-19 epidemic focus and general belief in a just world on individual emotions. *Personality and Individual Differences, 168*, 110349.

Wen, J., Cheng, Y., Ling, R., Dai, Y., Huang, B., Huang, W., . . . Jiang, Y. (2020). Antibody-dependent enhancement of Coronavirus. *International Journal of Infectious Diseases*.

Xie, X., Huang, L., Li, J. J., & Zhu, H. (2020). Generational Differences in Perceptions of Food Health/Risk and Attitudes toward Organic Food and Game Meat: The Case of the COVID-19 Crisis in China. *International journal of environmental research and public health, 17*(9), 3148.

Zhang, Y., Diao, X., Chen, K. Z., Robinson, S., & Fan, S. (2020). Impact of COVID-19 on China's macroeconomy and agri-food system–an economy-wide multiplier model analysis. *China Agricultural Economic Review*.

Zhao, H., He, X., Fan, G., Li, L., Huang, Q., Qiu, Q., . . . Ding, L. (2020). COVID-19 infection outbreak increases anxiety level of general public in China: involved mechanisms and influencing factors. *Journal of affective disorders, 276*, 446-452.