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Using A New Statistical Metric to Classify of Osteoporosis Diseases in the Erbil City

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Abstract:
Osteoporosis is characterized by weak, fragile, sponge-like bones because the body can no longer produce new bone as rapidly as it eliminates old bone. A fall or even a minor stressor, such as coughing, can cause bones to break due to increased brittleness. This typically affects the hip, wrist, or spine. This study explores the use of measurement distance between two variables to assess their Likeness or difference. The primary is comprinig between three methodes of distance the first one is the Euclidean distance, The second is the Pearson correlation distance., and a new proposed is the distance Weighted Correlation, which is depended on minimum distances is the third one. The Data assembled for this research were Komari Hospital and the Media Laboratory between 1/12/2024 and 1/3/2025, encompassing 150 female cases. It means that the lowest value was achieved between years of menopause and weight. This indicates that the proposed method outperforms the Pearson correlation distance calculation method.

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أستخدام مقياس إحصائي جديد لتصنيف مرض هشاشة العظام في محافظة أربيل

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المستخلص

يُوصف مرض هشاشة العظام بضعف العظام وهشاشتها وتحوّلها إلى مادة إسفنجية، لأن الجسم لم يعد قادرًا على إنتاج عظام جديدة بنفس سرعة التخلص من العظام القديمة. يمكن أن يتسبب السقوط أو حتى عامل ضغط بسيط مثل: السعال في تكسر العظام بسبب زيادة هشاشتها. يؤثر هذا عادةً على الورك أو الرسغ أو العمود الفقري. وقد اعتمدت في هذا البحث على قياس المسافة بين متغيرين لتقييم تشابههما أو اختلافهما. إنّ الهدف الرئيس هو مقارنة بين ثلاث طرق مختلفة لحساب المسافة: الاولي هي المسافة الإقليدية، ومسافة ارتباط بيرسون الثانية، والطريقة الثالثة هي مسافة الارتباط الموزونة - والذي يعتمد على الحد الأدنى من المسافات. تم جمع بيانات هذه الدراسة في مستشفى أربيل التعليمي كوماري ومختبر ميديا بين 2024/12/1 و2025/3/1، وشملت 150 حالة أنثوية. توصلت نتائج التحليل الى ان أقل قيمة للمسافة عند استخدام الطريقتين الاولى واالثالثة بين المتغيرين العمر وسنوات انقطاع الطمث. أمّا بالنسبة للطريقة الثانية يختلف عند استخدام حساب المسافة بين المتغيرين أي أقل قيمة بين سنوات انقطاع الطمث والوزن. هذا يدل على ان الطريقة المقترحة قد تفوقت على طريقة حساب مسافة ارتباط بيرسون.

الكلمات المفتاحية: التصنيف، المسافات، مصفوفة اللتقارب، مسافة الارتباط المرجحة.

1.Introduction

Typically causing little pain, osteoporosis can go undiagnosed for years until a bone breaks. Pain is the most typical sign of a fracture, or broken bone, and the position of the pain varies depending on where the break occurs. Its fractured bones result in disability, reduced productivity at work, and a marked decline in quality of life. Weakened bones do not heal well, therefore some bone breaks, such as hip fractures, may heal slowly or badly and may need surgery to fix. They could lead to a reduction in movement, a loss of autonomy, and in certain cases, care in a nursing home. There is a higher chance of death after a broken bone, and people who have one may become weak. (Balligand and Jakovljevic,1987:93).

2.Types of Osteoporosis:

Three different kinds of osteoporosis Your osteoporosis is considered one of three types, based on what is causing your bone loss.

a. Primary: it is the most common form of natural bone loss with aging. Both men and women with low estrogen are prone to bone loss.

b. Secondary: With secondary osteoporosis, another health condition or medication decreases your bone density. Some of the possible health problems that can lead to this kind of thing can include:

- Autoimmunity in MS and RA
- Diabetes

- Eating disorders
- Gastrointestinal (GI) complaints (for example, celiac disease and inflammatory bowel disease [IBD])
- Hormone disorders
- Blood diseases, including multiple myeloma and human immunodeficiency virus (HIV)

c. Idiopathic: osteoporosis is uncommon among premenopausal individuals, men who are younger than 50, teenagers, and children. Idiopathic means that condition is not caused by a known source.

1) Family history of osteoporosis
2) Low calcium and vitamin D in the diet
3) Sedentary lifestyle
4) Early menopause
5) Cigarette smoking
6) Excessive alcohol consumption .(Balligand and Jakovljevic,1987:93).

cluster analysis is assigning observations to groups is the goal of cluster analysis; the observations within each group are comparable in terms of variables or characteristics of curiosity, and the groupings themselves are distinct from one another. To put it another way, the goal is separate the results are divided into distinct and uniform groupings. (Gábor et al ,2013:1251; Hardle and Simer, 2014:393).

1. **Distance:** is study and control of symmetry between elements. It has a number of characteristics, reciprocal and a positive distance being the most crucial. (Richard, 2007:674).
2. **Kineds of Distances: three kindes are used**

a) Euclidean Distance

differed formulae yield varied clustering outcomes, which is the consequence of the distance's way are integrated mathematically used the numerous components of the data feature vectors into a single clustering-useful distance metric. The design of an appropriate distance metric for any application must be guided by domain expertise. Distance measurements are essential in machine learning, as illustrated by the equation (1). While the varabiles *x, y* are equale to $(x_1, x_2,\ldots,x_n)$, $(y_1,y_2,\ldots,y_n)$. (Kahwachi and Hasan, 2022: 53; Hardle and Simer, 2014:393).

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad (1)$$

b) The Pearson Correlation Distance

This method is usually used to data analysis to gauge how similar a group is, since it helps find similarities between data items. It is a simple and extensively used metric for evaluating similarity. A notion under

consideration concerns the measurement of the strength, direction with linear relationship betweenmore than one variable with probability continuous distributions. This approach aims to assess the extent of the problem. According to (Bates,1995:541; Dillon et al. ,1997:90), equation (2) is showen that, While the varabiles *x*, y are equale to $(x_1, x_2,\ldots,x_n)$, $(y_1,y_2,\ldots,y_n)$.(macqueen,1967:283;kosorok,2009:6).

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \qquad \bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}$$

c) Weighted Distance Correlation

The Weighted Dice Coefficient (WDC) has been applied in a variety of domains, including computer science, medicine, and finance. It has been used, for example, in finance to predict the relationship between stock returns while accounting for the weights of various companies. development presented the idea of WDC. By taking into account each gene's relative relevance, it has helped identify co-expressed genes in biology. Which takes into account the relative importance of various pixels, has been used in computer science to evaluate how similar images are. It's crucial to remember that distance correlation may not accurately reflect the degree of dependency between variables when they have different levels of importance, even though it has received significant recognition across a variety of academic areas for measuring interdependence. The idea of WDC was recently developed as a solution to this constraint. The goal of this research is provided a thorough examination of this approach, emphasizing its characteristics, uses and comparison to other methods. (bickel and peter, 2009:2; belanger et al., 2000: 9). in equation (3), it is visible. While the varabiles *x*, y are equale to $(x_1, x_2,\ldots,x_n)$. , $(y_1,y_2,\ldots,y_n)$,

$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$, $\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}$ and $0 \prec \alpha \prec 1$

$$Wdcorr(x,y) = \frac{\sum_{i=1}^{n} [\{\alpha(x_i - \bar{x})\}\{(1-\alpha)(y_i - \bar{y})\}]}{\sqrt{\left[\sum_{i=1}^{n} \alpha(x_i - \bar{x})^2\right]\left[\sum_{i=1}^{n} (1-\alpha)(y_i - \bar{y})^2\right]}} \qquad (3)$$

3. Proximity Matrices

The square matrix is one in which each cell measures the separation between the objects in row and column (j, j). A simple illustration might be a distance chart, in which the closer two objects are, the smaller the entry. Through the use of proximity matrices, Multifaceted scaling data is

created. The proximity is represented using one element at a time. (Timm, 2002:420; klebanov,2005:43).

4. Hierarchical Clustering

cluster analyses used most widely techniques because founded for straightforward ideas, gathers sample items in a sequential manner within m clusters. every n cluster is the most intricate and comprehensive. Convergent vocabulary is then combined into connected groups called clusters, with the cluster one being the simple cluster and the final cluster being most thorough and complex since it contains every element in the sample. Because it encompasses everyone, each cluster is the most intricate and complete. Numerous techniques are used to measure the distance between clusters. The nearest clusters with similarities were aplied for this research. (al-miklafi, 2012:8; XU and Wunsch, 2005:646).

- **Single-Link (Nearest Neighbor):** Given that there are multiple methods to measure the likeness between two observations, the distance between them is good indicator of convergence. The appropriate measure of convergence is the distance between pear of observations. (Giorgio, 2000:7; majeed and abdel aziz,2008 :403).

$$d(A,B) = \min\{d(y_i, y_j)\} \qquad (4)$$

where A and B are the first and second clusters, respectively, and the estimated distance is denoted by the elements of the first and second clusters, i and j, respectively. (al-Mikhlafi, 2012:18; kahwachi & hasan, 2022:56).

5. Application Part

In this part of the research is to analyziz data to classify the reason of Osteoporosis. It is depended of result on the programs SPSS (Version 28) and Matlab (R2013a). The variables to be standardized the value is between (0,1), while the variables in this research is defined on: X1: Age, X2: Menopause years, X3: Weight, X4: Height, X5: Calcium, X6: total count measures the number of white blood cells (TC), X7: Diabetic, X8: Ca Supplement, X9: Vitamin D, X10: Family History (in families), X11: Sun exp, X12: Previous fracture, X13: smoking, X14: Caffeine In, X15: Soft drink, X16: Salt intake, X17: Malnutrition, X18: Physical Activity.

Table 1: the result of Proximity Matrix by using Euclidean Distance

case	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X1`7	X18
X1	0	7.311	19.57	19.64	17.1	15.95	17.48	17.28	17.23	18.32	18.48	17.08	17.31	17.46	15.25	16.47	15.79	16.77
X2	7.311	0	19.74	19.37	17.1	15.89	17.13	17.04	17.23	17.79	17.85	17.3	18.07	17.99	15.96	17.35	16.17	16.94
X3	19.57	19.74	0	12.69	18.32	17.82	17.43	17.01	17.32	15.88	17.3	16.63	17.02	17.22	17.26	16.59	16.97	16.79
X4	19.64	19.37	12.69	0	17.69	16.72	17.22	16.78	17.06	16.69	17.06	16.21	18.2	17.48	17.43	17.95	18.28	16.85
X5	17.1	17.1	18.32	17.69	0	17.7	17.77	18.54	18.02	17.06	16.87	17.71	16.59	17.71	17.38	15.62	17.27	17.43
X6	15.95	15.89	17.82	16.72	17.7	0	17.09	17.13	17.22	16.39	17.22	16.85	16.83	17.72	16.91	17.16	17.26	16.73
X7	17.48	17.13	17.43	17.22	17.77	17.09	0	17.04	17.31	16.84	16.64	16.94	17.67	17.55	17.8	17.33	17.61	17.89
X8	17.28	17.04	17.01	16.78	18.54	17.13	17.04	0	9.032	16.91	16.2	16.03	17.38	16.03	16.08	16.83	17.64	16.03
X9	17.23	17.23	17.32	17.06	18.02	17.22	17.31	9.032	0	16.02	17.05	16.25	16.97	16.99	16.8	16.85	17.65	17.71
X10	18.32	17.79	15.88	16.69	17.06	16.39	16.84	16.91	16.02	0	19.08	17.37	16.72	17.39	17.88	17.32	17.02	18.03
X11	18.48	17.85	17.3	17.06	16.87	17.22	16.64	16.2	17.05	19.08	0	17.62	17.04	16.33	17.39	17.09	17.11	16.04
X12	17.08	17.3	16.63	16.21	17.71	16.85	16.94	16.03	16.25	17.37	17.62	0	16.8	17.42	17.04	18.74	17.21	16.61
X13	17.31	18.07	17.02	18.2	16.59	16.83	17.67	17.38	16.97	16.72	17.04	16.8	0	15.26	17.35	17.01	17.34	17.73
X14	17.46	17.99	17.22	17.48	17.71	17.72	17.55	16.03	16.99	17.39	16.33	17.42	15.26	0	18.19	17.44	17.45	16.69
X15	15.25	15.96	17.26	17.43	17.38	16.91	17.8	16.08	16.8	17.88	17.39	17.04	17.35	18.19	0	16.06	15.57	16.4
X16	16.47	17.35	16.59	17.95	15.62	17.16	17.33	16.83	16.85	17.32	17.09	18.74	17.01	17.44	16.06	0	15.98	17.2
X17	15.79	16.17	16.97	18.28	17.27	17.26	17.61	17.64	17.65	17.02	17.11	17.21	17.34	17.45	15.57	15.98	0	16.57
X18	16.77	16.94	16.79	16.85	17.43	16.73	17.89	16.03	17.71	18.03	16.04	16.61	17.73	16.69	16.4	17.2	16.57	0

Source: Compiled by the researchers, using SPSS outputs,Version 28

where apply this method to showen the result is depending on the proximity matrix by applying the equation (1), inTable1 shown that. The smallest separation between Age, Menopause years equal 7.311 convergence while, the maximum distance between Weight and Menopaus.

Table2: Agglomeration Schedule used by Nearest Distance of Osteoporosis

Stage	Cluster Combined		Distance	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	1	2	7.311	0	0	7
2	8	9	9.032	0	0	9
3	3	4	12.69	0	0	10
4	13	14	15.258	0	0	13
5	15	17	15.571	0	0	7
6	5	16	15.622	0	0	14
7	1	15	15.792	1	5	11
8	11	18	16.043	0	0	13
9	8	12	16.139	2	0	12
10	3	10	16.284	3	0	12
11	1	6	16.5	7	0	14
12	3	8	16.812	10	9	15
13	11	13	16.947	8	4	16
14	1	5	16.956	11	6	17
15	3	7	17.129	12	0	16
16	3	11	17.204	15	13	17
17	1	3	17.471	14	16	0

Source: Compiled by the researchers, using SPSS outputs, Version 28

Cluster 1: Includes the following variables: Age, Ca Supplement, Weight, Smoking, Soft drink, Calcium, Sun Exp; cluster 2: Includes the following variables: Menopause years, Height, TC, Diabetic, Vitamin D, Family History, Salt intake and Malnutrition. From Table2 cluster membership shows the building of clustering from the aggregation stages is connecting used by the nearest method distance clustre one in first stage comprises between Age and Menopause years in clustre two with a 7.311 distance, it has the minimum value, the stage two comprening between Ca Supplement and Vitamin D, with a distance of 9.032, and so on. For last stage betweeen Age and wegiht, with a distance of 17.471.

Table3: Cluster Membership used Euclidean Distance

Case	3 Clusters	2 Clusters
X1	1	1
X2	1	1
X3	2	2
X4	2	2
X5	1	1
X6	1	1
X7	2	2
X8	2	2

X9	2	2
X10	2	2
X11	3	2
X12	2	2
X13	3	2
X14	3	2
X15	1	1
X16	1	1
X17	1	1
X18	3	2

Source: Compiled by the researchers, using SPSS outputs, Version 28

In Table3 the distributed of the variable is the Osteoporosis in two or three clusters' memberships, it was divided into three clusters Sun Exp, smoking, Caffeine in and Physical Activity in cluster three, Weight, Height, Diabetic, Ca Supplement, Vitamin D, Family History and Previous fracture in cluster 2, the other in cluster 1. When divided into 2 clusters Weight, Height, Diabetic, Ca Supplement, Vitamin D, Family History, Sun Exp, Previous fracture smoking, Caffeine in and Physical Activity in cluster two, and in clustre one the other varabils. the reason of Osteoporosis in proximity matrix Equation (2) is used to demonstrate how similar the elements are, as shown in Table4. The smallest separation between Menopause years, Weight is equivalent to -0.307 and the maximum distance between Age, Menopause years is equal to 0.821.

Table4: Proximity Matrix of the result data by using Person Correlation Distance

Case	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18
X1	1	0.821	-0.29	-0.29	0.019	0.147	-0.03	-0	0.004	-0.13	-0.15	0.021	-0.01	-0.02	0.22	0.09	0.163	0.056
X2	0.821	1	-0.30	-0.26	0.019	0.153	0.015	0.026	0.004	-0.06	-0.07	-0	-0.1	-0.09	0.146	-0.01	0.122	0.037
X3	-0.29	-0.30	1	0.46	-0.13	-0.07	-0.02	0.029	-0.01	0.154	-0.01	0.072	0.028	0.005	0	0.076	0.033	0.054
X4	-0.29	-0.26	0.46	1	-0.05	0.061	0.005	0.055	0.024	0.065	0.023	0.119	-0.11	-0.03	-0.02	-0.08	-0.12	0.047
X5	0.019	0.019	-0.13	-0.05	1	-0.05	-0.06	-0.15	-0.09	0.023	0.045	-0.05	0.076	-0.05	-0.01	0.181	-0	-0.02
X6	0.147	0.153	-0.07	0.061	-0.05	1	0.02	0.015	0.005	0.099	0.005	0.048	0.049	-0.05	0.041	0.012	0.001	0.061

X7	-0.03	0.015	-0.02	0.005	-0.06	0.02	1	0.026	-0.01	0.049	0.071	0.037	-0.05	-0.03	-0.06	-0.01	-0.04	-0.07
X8	-0	0.026	0.029	0.055	-0.15	0.015	0.026	1	0.726	0.041	0.119	0.138	-0.01	0.137	0.132	0.049	-0.04	0.138
X9	0.004	0.004	-0.01	0.024	-0.09	0.005	-0.01	0.726	1	0.139	0.025	0.114	0.034	0.031	0.053	0.047	-0.05	-0.05
X10	-0.13	-0.06	0.154	0.065	0.023	0.099	0.049	0.041	0.139	1	-0.22	-0.01	0.062	-0.02	-0.07	-0.01	0.027	-0.09
X11	-0.15	-0.07	-0.01	0.023	0.045	0.005	0.071	0.119	0.025	-0.22	1	-0.04	0.025	0.105	-0.02	0.02	0.018	0.136
X12	0.021	-0	0.072	0.119	-0.05	0.048	0.037	0.138	0.114	-0.01	-0.04	1	0.053	-0.02	0.026	-0.18	0.006	0.075
X13	-0.01	-0.1	0.028	-0.11	0.076	0.049	-0.05	-0.01	0.034	0.062	0.025	0.053	1	0.219	-0.01	0.03	-0.01	-0.05
X14	-0.02	-0.09	0.005	-0.03	-0.05	-0.05	-0.03	0.137	0.031	-0.02	0.105	-0.02	0.219	1	-0.11	-0.02	-0.02	0.065
X15	0.22	0.146	0	-0.02	-0.01	0.041	-0.06	0.132	0.053	-0.07	-0.02	0.026	-0.01	-0.11	1	0.134	0.186	0.098
X16	0.09	-0.01	0.076	-0.08	0.181	0.012	-0.01	0.049	0.047	-0.01	0.02	-0.18	0.03	-0.02	0.134	1	0.143	0.007
X17	0.163	0.122	0.033	-0.12	-0	0.001	-0.04	-0.04	-0.05	0.027	0.018	0.006	-0.01	-0.02	0.186	0.143	1	0.078
X18	0.056	0.037	0.054	0.047	-0.02	0.061	-0.07	0.138	-0.05	-0.09	0.136	0.075	-0.05	0.065	0.098	0.007	0.078	1

Source: Compiled by the researchers, using SPSS outputs, Version 28

Table 5: Agglomeration Schedule of the result data by using Preseason Correlation Distance

Stage	Cluster Combined		Distances	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	1	2	0.821	0	0	7
2	8	9	0.726	0	0	9
3	3	4	0.46	0	0	10
4	13	14	0.219	0	0	13
5	15	17	0.186	0	0	7
6	5	16	0.181	0	0	14

7	1	15	0.163	1	5	11
8	11	18	0.136	0	0	13
9	8	12	0.126	2	0	12
10	3	10	0.11	3	0	12
11	1	6	0.085	7	0	14
12	3	8	0.051	10	9	15
13	11	13	0.035	8	4	16
14	1	5	0.034	11	6	17
15	3	7	0.015	12	0	16
16	3	11	0.005	15	13	17
17	1	3	-0.026	14	16	0

Source: Compiled by the researchers, using SPSS outputs, Version 28

It can show in Table5 shown the connecting between clusters used by the nearest distance method. First cluster in stage one comprises between Age and Menopause years in cluster two, with a 0.821 distance, it has the maximum value. In the stage2 between Ca Supplement and Vitamin D, with a distance of 0.726, in the final stage between Age and weight, with a distance of -0.02.

Table 6: Cluster Membership Preseason Correlation Distance

Case	3 Clusters	2 Clusters
X1	1	1
X2	1	1
X3	2	2
X4	2	2
X5	1	1
X6	1	1
X7	2	2
X8	2	2
X9	2	2
X10	2	2
X11	3	2
X12	2	2
X13	3	2
X14	3	2
X15	1	1
X16	1	1
X17	1	1
X18	3	2

Source: Compiled by the researchers, using SPSS outputs, Version 28

Table 6 is shown the result of analysis data to distributed the Osteoporosis by using person correlation distance in the clusters2 or3 membership, if

divided into 3 clusters Sun exp, Smoking, Caffeine in and Physical Activity in cluster three, Weight, Height, Diabetic, Ca Supplement, Vitamin D, Family History and Previous fracture in the secand cluster, the others in first cluster. When divided into 2 clusters Weight, Height, Diabetic, Ca Supplement Vitamin D, Family History, Sun Exp, Smoking, Caffeine in and physical Activity in cluster two, and the others in cluster One. When divided into2 clusters Weight, Height, Diabetic, Ca Supplement Vitamin D, Family History, Sun Exp, Smoking, Caffeine in and physical Activity in secand cluster and the others in first cluster, the reason of Osteoporosis in proximity matrix use equation (2)

Table7: Proximity Matrix of the result data by using weightd Correlation Distance

Case	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18
X1		53.45	383.1	385.8	292.4	254.3	305.6	298.5	296.9	335.5	341.7	291.7	299.6	304.7	232.5	271.2	249.3	281.2
X2	53.45		389.5	375.1	292.3	252.5	293.5	290.3	296.7	316.4	318.5	299.2	326.6	323.5	254.6	300.9	261.6	286.9
X3	383.1	389.47		161	335.5	317.7	303.7	289.2	300.1	252.1	299.4	276.7	289.6	296.5	298.1	275.3	288.1	282
X4	385.76	375.05	161		312.8	279.7	296.6	281.7	291	278.7	291.1	262.6	331.3	305.4	303.9	322.2	334.1	283.9
X5	292.4	292.3	335.5	312.8		313.4	315.8	343.6	324.8	291	284.5	313.6	275.3	313.5	302	244	298.2	303.8
X6	254.28	252.53	317.7	279.7	313.4		292	293.6	296.5	268.6	296.5	283.8	283.3	313.9	285.8	294.4	297.8	280
X7	305.59	293.45	303.7	296.6	315.8	292		290.3	299.5	283.5	276.8	287	312.3	308.1	317	300.5	310	320.1
X8	298.51	290.26	289.2	281.7	343.6	293.6	290.3		81.59	285.8	262.5	256.9	302.2	257.1	258.5	283.4	311.2	257
X9	296.93	296.72	300.1	291	324.8	296.5	299.5	81.59		256.6	290.6	264.1	287.8	288.8	282.1	284	311.5	313.7
X10	335.53	316.39	252.1	278.7	291	268.6	283.5	285.8	256.6		364.2	301.7	279.5	302.3	319.8	300.1	289.8	325
X11	341.68	318.45	299.4	291.1	284.5	296.5	276.8	262.5	290.6	364.2		310.5	290.4	266.8	302.4	292	292.7	257.4

X12	291.71	299.19	276.7	262.6	313.6	283.8	287	256.9	264.1	301.7	310.5		282.2	303.4	290.3	351.3	296.2	275.8
X13	299.6	326.56	289.6	331.3	275.3	283.3	312.3	302.2	287.8	279.5	290.4	282.2		232.8	301.1	289.2	300.7	314.2
X14	304.73	323.49	296.5	305.4	313.5	313.9	308.1	257.1	288.8	302.3	266.8	303.4	232.8		330.7	304	304.4	278.6
X15	232.54	254.61	298.1	303.9	302	285.8	317	258.5	282.1	319.8	302.4	290.3	301.1	330.7		257.9	242.4	268.9
X16	271.18	300.86	275.3	322.2	244	294.4	300.5	283.4	284	300.1	292	351.3	289.2	304	257.9		255.3	295.9
X17	249.32	261.59	288.1	334.1	298.2	297.8	310	311.2	311.5	289.8	292.7	296.2	300.7	304.4	242.4	255.3		274.6
X18	281.19	286.88	282	283.9	303.8	280	320.1	257	313.7	325	257.4	275.8	314.2	278.6	268.9	295.9	274.6	

Source: Compiled by the researchers, usingMatlab (R2013a)

the result of method Weighted correlation distance of proximity matrix is same that between elements depend by equation (3). The minimum distance between Menopause years and Age equal to 53.45, the maximum distance between Weight, Menopause years is equivalent to 389. 472. as shown in Table 7.

Conclusions:

1. First and third distance it to methods of clustering using inthis rescarch diveded in 2 clusters or3 clusters membership, it is noted to Both methods the new proposed (Weighted Distance Correlation) and Euclidian distance methods it is the same result by the minimum distance between Age and Menopause years, the maximum distance is between Menopause years and Weight.
2. by using the distance correlation and Euclidian proximity matrix to classify this data the lowest value between two methods is Age and Menopause years and the maximum distance correlation depending on the Euclidian distance and weighted distance correlation is between weight
3. Menopause years It can be shown that the correlated between osteoporosis and menopause because there are many factors effect of Estrogen, a hormone that helps maintain bone density, drops significantly after menopause. This hormonal change causes accelerated bone loss, especially in the 5–10 years after menopause. As a result, postmenopausal women are at a much higher risk of developing osteoporosis.

Recommendations:

1. The following could be considered as recommendations made by the researcher:
2. Pearson correlation distance is a powerful statistical tool for measuring intra-group similarity. It can be to identify the strength and direction of the linear relationship between continuous random variables.
3. The proposed method (Weighted Distance Correlation is a highly effective clustering that can be used with other data.
4. The suggested approach, including its characteristics, uses, and contrast with current approaches.
5. Women should t Because osteoporosis is affected by vitamin D and calcium supplements, women should take them before menopause.

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