Digital Currency Network Centrality Measure (DCNC): A New Centrality Measure for Cryptocurrency Datasets

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ABSTRACT
Digital currency transaction graphs can be analyzed through Social Network analysis (SNA) techniques to understand complex networks. The importance of nodes was determined through many popular centrality measures including Degree centrality (DC), eigenvector centrality (EVC), betweenness centrality (BC) and closeness centrality (CC).A Novel centrality metrics: Digital currency network centrality measures(DCNC), which is especially conceptualized and designed to measure the importance of nodes based on their involvement in digital currency transactions networks. By Pearson's correlation coefficient (r), DCNC is correlates with standard centrality measures, a strong positive correlation is observed confirming that DCNC accurately correlates with standard metrics and giving more information about digital currencies networks. Results are validate by three real life datasets and two small graphs.

General Terms
Cryptocurrency, Social network analysis (SNA), Centrality Measures, Real-life Datasets

Keywords
Graph theory, Complex Networks, Digital Currency

1. INTRODUCTION
Digital currency, often known as cryptocurrency technology, is today quite popular. Cryptocurrency related assets have seen a significant increase in market acceptance and have developed rapidly in recent years. Bitcoin is a digital currency that Satoshi Nakamoto invented in 2009 [2], [3], [4].The Bitcoin system operates according to a peer to peer philosophy, which avoids the need of a bank account maintained by a central authority. In bitcoin, each user has a unique address that consists of a pair of public and private keys [1]. In early 2016, the Central Bank of China stated its intention to actively promote the official publication of digital currency [5]. Around the same time, the UK government released a special report on blockchain technology titled Distributed Accounting Technology beyond Blockchain an effort to strongly develop the use of blockchain in the government sector [6].

Recent advancements in machine learning and data analytics have further enhanced the capabilities of SNA in handling the massive volumes of data generated by cryptocurrency networks. Techniques such as clustering, centrality measures, and community detection have been pivotal in identifying key structures and trends within these networks [7], [8], [9].

Network analysis has emerged as a vital instrument in the social and biological sciences [10], [11]. Economics, also, has the use of network analysis, though less frequently. Network analysis helps as a powerful tool like traditional methods such as statistics, regression analysis, and modern methods like machine learning [12], [13], [14]. The graph used in financial fraud detection typically consists of nodes and edges representing accounts and transactions, respectively [15]. Social Network Analysis (SNA) is a modeling technique and analytical approach for identifying and examining the structural features of supply networks and the patterns of connections between members within the network [16]. Network analysis helps to identify patterns and structures in transactional networks, which are made up of nodes (addresses or operators) and edges (user transactions). Centrality measurements can identify critical nodes that influence network stability [17], [18], whereas transaction patterns can reveal information about user behavior and financial transfers [19], [20].

Blockchain technology, often associated with digital currencies like Bitcoin, is a distributed dataset of transactions managed by a global network of computers. It operates on a decentralized network, allowing anyone to access and verify transactions [21]. Cryptocurrency networks like Bitcoin and Ethereum utilize SNA to generate vast transactional data, Every Transaction should be visible as an edge in a Network, with the transacting parties as Nodes. This allows experts to identify powerful nodes, detect fraud, and understand trends [17], [22], [19].

1.1 Research Objectives
- Using Social analysis Networks (SNA) techniques and identify transaction patterns within these networks.
- Explore the role of important customers/nodes in cryptocurrency networks
- To introduce and validate the new centrality metric named ‘Digital currency network centrality measure (DCNC)’ for network analysis in the cryptocurrency datasets.

2. RELATED STUDIES
The area of network analysis in cryptocurrency markets and blockchain technology has experienced great progress, with several researchers contributing to a better knowledge of market dynamics, security, and user behavior. David Vidal Tomás (2021) and Jiajing Wu (2021) conducted surveys on cryptocurrency transactions using blockchain, focusing on network modeling, description, and detection. They found that the market experienced heightened synchronization during the COVID-19 pandemic, but gradually returned to pre-pandemic levels. The surveys aim to guide researchers and engineers [23], [24].

Nakamoto's (2008) project proposed a peer-to-peer electronic cash system for online payments without a financial institution. This system uses a hash-based proof of work chain to create an irreversible record [25]. Pocher's 2023 study used blockchain and distributed ledger tools to address user privacy concerns in finance. They demonstrated the effectiveness of Graph Convolutional Networks and Graph Attention Networks in identifying illegal transactions [7].

Social network analysis (SNA) was first used by Lusher and Robins in 2010 to study individual and group behavior in sports teams [26]. Dmitri Goldenberg's (2024) study explores social network analysis using graph theory and networks, utilizing Python coding and practical examples like visualization and social centrality analysis [9].

Ubaida Fatima and her team (2023) developed the global clustering coefficient dependent degree centrality (GCCDC) method, an efficient and accurate method for analyzing linkages between profitable items in large product networks [27].Kin-hon ho and colleagues (2024) study the cryptocurrency market using social network analysis (SNA) to model and determine significant factors such as correlation structure, topological characteristics, stability, and effect [28].

3. METHODOLOGY

3.1 Considered data Description

Four different datasets were used to evaluate our techniques, including small scale examples as well as real life complicated networks. The first dataset is a basic, unweighted network with six nodes, as shown in (Figure 1). This example is used an initial basis for testing and providing basic concepts, presenting a controlled environment in which to show the use of various network centrality measures. In addition to this example, two real world datasets have been reviewed. The first of them is the Social Sign Epinions (soc-sign-epinions) dataset, downloaded from the Epinions platform, a consumer review site where users express their trust or distrust of others. Second is Dolphin Social Network dataset, was utilized to validate findings. The Dolphin Social Network dataset, which records a dolphin community social connections, provides information about natural social networks and how they connect with human social systems.

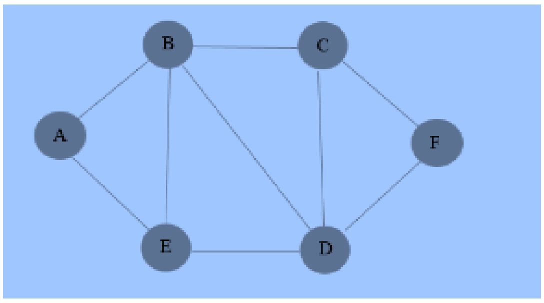


Fig 1: Six nodes Unweighted graph

3.2 Social Sign Epinions (soc-sign-epinions) dataset

Social sign epinions dataset represent a social network from the epinions website, It contains 131,828 nodes (users) and 841,372 edges (trust ratings), which can be either positive or negative. This dataset is used for studying network structure, trust dynamics, and centrality measures in social networks. We consider 10000 nodes [29]. Social sign Epinions dataset network and Adjacency matrix of Social sign epinions Network is seen in (Figure 2) and (Figure 3) respectively.

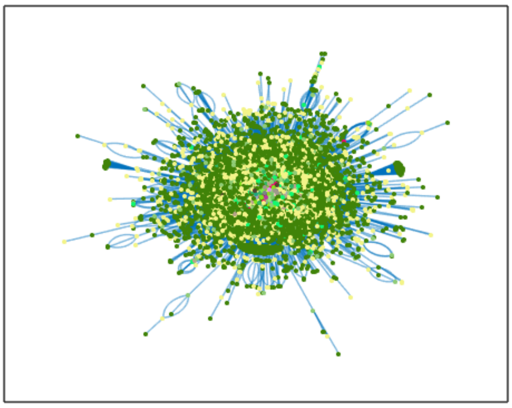
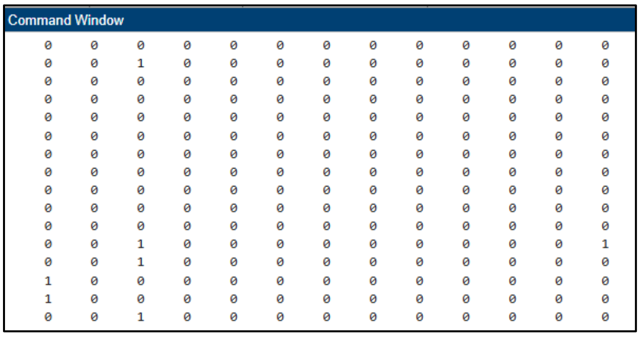


Fig 2: Social sign epinions Network



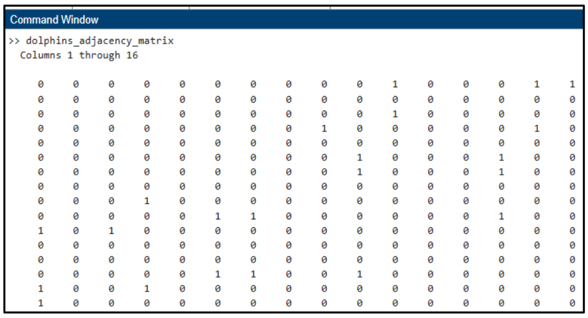
Command Window

0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0

Fig 3: Adjacency matrix of Social sign epinions Network.

3.3 Dolphin Social Network dataset

The dataset provides a social network of 62 dolphins.In this dataset there are 62 vertices ,each vertex represent a dolphin identified by unique name e.g beak, beescratch etc.and 169 edges which represent social intreactions between dolphins [30].Adjacency matrix of dolphin social network dataset and Sample dataset of dolphin community network is seen in (Figure 4) and (Figure 5) respectively.



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>> dolphins_adjacency_matrix
  Columns 1 through 16
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0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
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0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig 4: Adjacency matrix of dolphin social network dataset

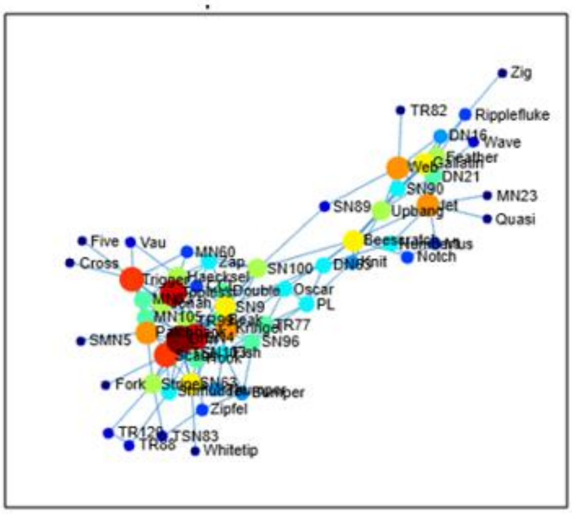

Fig 5: Dolphin social network dataset

3.4 Methods/Techniques for SNA

The method involves several analytical techniques focusing on centrality measures to analyze the cryptocurrency network. Centrality measures are useful tools in network analysis for identifying the most significant or influential nodes in a network.

1. *Degree Centrality (DC)*

The number of direct connections to a node. High degree centrality may indicate hubs in the network. For example a popular person in a social network with many friends, a busy airport with many flights. Degree centrality can be calculated through equation (1)

$$DC\ (i) = \sum_j A_{ij} \qquad (1)$$

In equation (1) DC (i) is the degree centrality of node i. $\sum j$ is the sum over all nodes j and A_{ij} shows adjacency matrix element. A_{ij}=1 if there is an edge between nodes i and j and A_{ij}=0 if there is no edge between node i and j. Consider an example six nodes un weighted graph shown in (Figure 1).

Adjacency matrix for (Figure 1) is mentioned in equation (2)

$$A=\begin{bmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \end{bmatrix} \qquad (2)$$

Table 1. Degree centrality for Figure 1

Nodes	A	B	C	D	E	F
DC	2	4	3	4	3	2

Table1 is showing Node B and D are significant node both have larger number of edges connected to it and both have a greater potential to spread information in the network.

2. *Eigenvector Centrality (ECV)*

Eigenvector centrality is a measure of the influence of a node in a network. For example assume you are using a social networking platform like Twitter or Instagram. A user with a small number of followers may still be very powerful if those followers are celebrities or important influencers with millions of followers. In this situation, the user with fewer but higher quality connections will have a high eigenvector centrality. Their power is increased since their posts can quickly reach a large audience because to their strong connections. Similarly A doctor may not have many patients, but if they are connected to famous specialists or work at a famous hospital, they have huge influence in medical circles. The eigenvector centrality EVC (i) of a node (i) is represented by equation (3)

$$EVC\ (k+1)(\ i) = \frac{1}{\lambda^{(k)}} \sum A_{ij}\, EVC^{(k)}(j) \qquad (3)$$

In equation (3) $EVC^{(K+1)}(i)$ is the updated eigenvector centrality value for node i after the k+1 iteration. A_{ij} is adjacency matrix that represents the connection between nodes i and j, It is 1 if there is a direct connection (edge) and 0 if there is not. $EVC^{(k)}$(j) is the eigenvector centrality value of node j from the previous k iteration. $\lambda^{(k)}$ is the normalization factor or the approximate eigenvalue for the k iteration.

Table 2. EVC for 6 nodes graph in Figure 1

Nodes	A	B	C	D	E	F
EVC	0.24	0.56	0.34	0.56	0.34	0.24

Table 2 is showing Node B and Node D in a network shown in (Figure 1) having high Eigenvector Centrality (EVC) value have a high level of influence or importance.

3. *Closeness Centrality(CC)*

Closeness Centrality (CC) is a measure of how quickly a node can communicate with all other nodes in the network. It indicates how central a node is in relation to all other nodes. The more central a node is, the shorter its average path length to all other nodes, helping it to spread information or resources more effectively. For example in a social media network, a person with high closeness centrality may easily distribute news or influence many individuals. Similarly In a city transportation network, a hub with high closeness centrality enables shorter travel times to other regions of the city. Closeness centrality is represented by equation (4)

$$CC\ (i) = \frac{1}{\sum_j SP_{(i,j)}} \qquad (4)$$

In above formula (4) CC (i) is the closeness centrality of node i, $SP_{(i,j)}$ is the shortest path matrix between node i and j. $\sum_j SP_{(i,j)}$ is the sum of all the shortest path distances from node i to every other node j in the network. Consider example of 6 nodes unweighted graph seen in Figure 1.

Table 3. Closeness Centrality for 6 nodes unweighted graph shown in Figure 1

Nodes	A	B	C	D	E	F
CC	0.11	0.16	0.14	0.16	0.14	0.11

Table 3 is showing Node B and D have high closeness Centrality indicates that a node is close to all other nodes in the network.

4. *Betweenness Centrality (BC)*

Betweeness centrality is a measure of a node significance in a network calculated by the number of shortest paths passing through it. It identifies nodes that act as important bridges or intermediates between different parts of the network. For example a company with high betweenness centrality provides an important link between various suppliers and purchasers. Similarly a hub airport with a high betweenness centrality links many flights between places that do not have direct connections. Betweeness centrality can be calculated through equation (5)

$$BC\ (k) = \frac{\sum SP_{ij(k)}}{\sum SP_{ij}} \quad (5)$$

In above formula (5) BC (k) is the betweeness centrality of node k, SP_{ij} is the number of shortest paths between nodes i and j and $SP_{ij(k)}$ is The number of shortest paths between nodes i and j that pass through node k.

Table 4. Betweeness centrality for 6 nodes unweighted graph in Figure 1

Nodes	A	B	C	D	E	F
BC	0	2.66	0.833	2.66	0.833	0

Table 4 Implies that the node B and D lies on many of the shortest pathways connecting other nodes, acting as a link between various portions of the network. These node are critical for network communication, resource movement, and transactional efficiency.

5. *Novel Centrality metrics: Digital currency network centrality measure (DCNC)*

5.1.1. *The Digital Currency Network Centrality (DCNC)*

The Digital Currency Network Centrality (DCNC) formula is ***a novel approach*** that combines two key facets of a node importance in a cryptocurrency network. Its degree (the number of connections it has) and its total transaction volume. These two enables DCNC to give a more detailed evaluation of a nodes significance, especially in financial networks where both the quantity and economic worth of connections are important. Mathematical Formula is conceptualized in equation (6).

$$DCNC\ (i) = \frac{V_i \times d_i}{\sum_{j \in V} V_j} \quad (6)$$

Where:

di is the degree of nodes i

Vi is the total transaction volume for node i

$\sum_{j \in V} V_j$ is the Sum of transaction volumes for all nodes in the network.

Noted: for weighted graph transaction volume is give if the network is unweighted then assume transaction volume 1 for each node.

5.1.2. *Normalized DCNC*

Normalization help to comparability across a nodes. Normalization allows the DCNC values of different nodes to be compared .without normalization DCNC values making difficult to find relative importance of nodes in the network. Normalized DCNC can be calculated through equation (7)

$$DCNC\ (norm) = \frac{DCNC\ (i)}{Max(DCNC\ (i))} \quad (7)$$

5.1.3. *How Digital currency network centrality (DCNC) concept differs from Existing Centrality Measures*

Degree Centrality: Degree centrality measures the significance of a node purely based on the number of connections (edges) it has. It implies that more connections signal more significant but does not consider the strength or value of these connections.

DCNC Development: DCNC enhances degree centrality by including transaction volume, recognizing that not all connections are equal. A node with fewer but higher value connections might be more significant than one with numerous low value connections. This makes DCNC a more advanced metric, especially in economic networks where transaction size is important.

Betweenness Centrality: Betweenness centrality identifies nodes which act as bridges or agents in the network by counting the number of times a node occurs on the shortest path between other nodes. While it focuses on nodes that are important to the network connection, it ignores the economic value of the transactions they support.

DCNC Developments: Unlike betweenness centrality, which focuses on a node positional importance, DCNC takes economic influence directly into account through transaction volume. This makes DCNC more significant in financial networks, where economic activity is an important measure of influence.

Eigenvector centrality: Eigenvector centrality provides relative scores to all nodes in the network based on the concept that links to high scoring nodes increase a node significance. It quantifies the effect of a node's connections, but not transaction volume.

DCNC Upgrading: DCNC measures different by focusing real economic transactions rather than prospective impact based on network structure. This is critical in bitcoin networks, because the value of transactions may significantly influence a node's real world significance.

Closeness Centrality: Closeness centrality evaluates how rapidly a node can communicate with all other nodes in the network, which is significant for analyzing data distribution and efficiency. However, it does not consider the economic significance of the node transactions.

DCNC Upgrading: DCNC prioritizes the economic significance of a node above its closeness to others, resulting in a metric that is better linked with financial effect rather than structural position.

5.1.4. *Digital currency network centrality (DCNC) for Six nodes unweighted graph seen in Figure 1.*

Table 5 Degree for each node (di) for Figure 1

Nodes	A	B	C	D	E	F
di	2	4	3	4	3	2

Table 6 Total transaction volume (Vi) in Figure 1

Nodes	A	B	C	D	E	F
Vi	1	1	1	1	1	1

Table 7 Calculation of Digital currency network centrality (DCNC) for Figure 1

Nodes	A	B	C	D	E	F
Vi	1	1	1	1	1	1
di	2	4	3	4	3	2
$d_i \times V_i$	2	4	3	4	3	2
DCNC= $\frac{V_i \times d_i}{\sum_{j \in V} V_j}$	0.33	0.66	0.5	0.66	0.5	0.33

$$\sum_{j \in V} V_j = 1+1+1+1+1+1=6 \quad (8)$$

Table 8 Normalized DCNC for Fig.2 using equation (8)

Nodes	A	B	C	D	E	F
norm	0.33/0.66	0.66/0.66	0.5/0.66	0.66/0.66	0.5/0.66	0.33/0.66
DCNC	0.5	1	0.75	1	0.75	0.5

Table 8 suggests that Nodes B and D have the greatest Digital Currency Network Centrality (DCNC), suggesting that they are crucial or very significant to the network. This implies that they provide an important role in helping transactions and preserving the network general structure, making them critical to the cryptocurrency market performance.

5.1.5. Pearson Correlation coefficient between Digital currency network centrality (DCNC) and Traditional centrality Measure for Figure 1

The Pearson correlation measures the linear connection between two variables. In this case, we want to understand how Digital currency network centrality (DCNC) and Traditional centrality Measure interact nodes in a unweighted graph shown in Figure 1 Pearson correlation coefficient is represented by equation (9)

$$r = \frac{n(\sum XY) - (\sum X)(\sum Y)}{\sqrt{(n\sum X^2 - (\sum X)^2)(n\sum Y^2 - (\sum Y)^2)}} \quad (9)$$

In above equation(9) DCNC is represent by X, and Traditional centrality Measure is represented by Y.

Table 9 Centrality measures for Figure 1

Nodes	DC	EVC	CC	BC	LCCDC	DCNC
A	2	0.247	0.111	0	0	0.5
B	4	0.563	0.166	2.66	2	1
C	3	0.348	0.142	0.833	1.02	0.75
D	4	0.563	0.166	2.66	2	1
E	3	0.348	0.142	0.833	1.02	0.75
F	2	0.247	0.111	0	0	0.5

Table 10 Pearson correlation coefficient between DCNC and Traditional centrality Measures for Figure

Correlation Coefficient	DC/ DCNC	EVC/ DCNC	CC/ DCNC	BC/ DCNC
r	99.80%	98.41%	99.7%	97.6%

Table 10 shows the Pearson correlation coefficients between DCNC and conventional centrality measures in Figure 2. The findings demonstrate that DCNC has extremely significant positive relationships with Degree Centrality (99.80%), Eigenvector Centrality (98.41%), Closeness Centrality (99.7%) and Betweenness Centrality (97.6%).This suggests that nodes with high DCNC are also highly ranked by standard centrality metrics, underscoring their significance in the network.

4. RESULTS AND INTERPRETATION

4.1 Pearson correlation of Dolphin Social network dataset with DCNC

Table 11 Pearson correlation coefficient between DCNC and Traditional centrality Measure for dolphin dataset

Correlation Coefficient	DC/DCNC	EVC/ DCNC	CC/ DCNC	BC/ DCNC
r	80.0%	51.4%	58.3%	51.3%

Table 11 shows the Pearson correlation coefficients between DCNC and conventional centrality measures in Figure 5. The findings demonstrate that DCNC has extremely significant positive relationships with Degree Centrality (80.06%), Eigenvector Centrality (51.46%), Closeness Centrality (58.37%) and Betweenness Centrality (51.3%).This suggests that nodes with high DCNC are also highly ranked by standard centrality metrics, underscoring their significance in the network.

4.2 Pearson correlation of Bitcoin dataset(Social sign epinions dataset) with DCNC

Table 12 Pearson correlation coefficient between DCNC and Traditional centrality Measure for social sign epinions datasets.

Correlation Coefficient	DC/DCNC	EVC/ DCNC	CC/ DCNC	BC/ DCNC
r	86.0%	60.4%	55.3%	50.5%

Table 12 shows the Pearson correlation coefficients between DCNC and conventional centrality measures in Figure 2. The findings demonstrate that DCNC has extremely significant positive relationships with Degree Centrality (86.0%), Eigenvector Centrality (60.4%), Closeness Centrality (55.3%), and Betweenness Centrality (50.5%). This suggests that nodes with high DCNC are also highly ranked by standard centrality metrics, underscoring their significance in the network.

5. CONCLUSION

This research studies into the application of Social Network Analysis (SNA) techniques within cryptocurrency transaction networks, offering new visions into the structure and dynamics of digital currency networks. By introducing the Digital Currency Network Centrality (DCNC) metric, provide a novel method for identifying influential nodes in cryptocurrency networks.Findings picture that DCNC correlates positively with traditional centrality measures, such as degree (DC), eigenvector (EVC), and betweenness centrality (BC), suggesting that Digital currency network centrality (DCNC) is a trustworthy and meaningful metric for measuring node importance. This study not only validates the value of DCNC but also opens opportunities for further exploration in cryptocurrency network analysis, particularly in identifying patterns, detecting irregularities, and understanding transactional behaviors in decentralized system.

6. LIMITATIONS

The Digital Currency Network Centrality (DCNC) measure, while useful for assessing node significance in cryptocurrency networks, has one significant disadvantage is its difficulty with cyclic networks, where the presence of transaction loops may hide the real impact of nodes, resulting in less accurate centrality assessments.

7. ACKNOWLEDGMENTS

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