Efficient Community Structure Identification in Social Networks Using K-Core Based Detection and Influential Information Diffusion Modeling

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Abstract

This research introduces an innovative community discovery technique employing a weighted K-core methodology specifically designed for unguided graphs inside social media platforms. The technique allocates weights for edges based upon users' interactions—likes, responses, and shares—reflecting the intensity and character of social relationships. Nodes are assessed for their coreness, indicating their importance and centrality inside the system. A multi-phase method is suggested, commencing with data preparation and graph creation utilizing the social network fan page behaviour. Edge recognition and weight computation techniques assess the significance of user interactions, classifying them as the original, insignificant, or core interest. The K-core decomposition technique reveals densely linked subsections, signifying groups of power. This methodology facilitates the categorization of users into highly or weakly linked clusters according to their local coreness, hence aiding in the differentiation between influencing and non-influential individuals. The method is evaluated with 7 real-world Facebook datasets and contrasted against existing techniques including Info map, Louvain, and Label Spreading. Experimental findings indicate that the suggested K-core technique attains enhanced accuracy, modularity, and F1-score, while ensuring scaling for vast networks. The results validate its efficacy in identifying significant groups and user roles within evolving social frameworks. The proposed K-Core technique attains the best overall accuracy at 96.5%, surpassing all previous models. Louvain attains 85.2%, Infomap registers 81.7%, Label Propagation secures 80.6%, Fast Greedy accomplishes 79.7%, Walktrap obtains 78.0%, while Leading Eigenvector encounters the lowest possible accuracy at 76.0%.

Keywords: SNA, OSN, Infomap, Walktrap, Fast Greedy, Label Propagation, Eigenvector.

1. Introduction

Social Network Analysis (SNA) examines the interactions among people, institutions, and other types of entities. The study of graphs and computational models examine the organization, patterns, and behavior of social networks. Relationships, partnerships, exchanges of data, and ways to interact form systems. Community identification is crucial for understanding complex social processes. It involves identifying clusters or populations within a network characterized by a higher density of interconnected nodes (users, entities, or things). These groups can elucidate the relationships within networks, the flow of data, patterns of authority, and organizational structures. Community investigation uncovers concealed designs and trends within these networks. By finding these groups, researchers can get significant insights into the dynamics, interconnections, and behaviours among group members [1-2]. Community offer a foundation for establishing relationships, exchanging experiences, acquiring knowledge, developing, and effecting good change in the world. Communities identification facilitates the comprehension of intricate social systems. It finds pivotal nodes, examines the dissemination of data procedures, forecasts user habits, and discerns abnormalities. It has the capability of optimizing systems. Identification of communities is relevant to sociology, promotional activities, biology, systems for suggestions, and cybersecurity. This brief explores the essential ideas and terminology related to community being identified, as well as traditional and innovative methodologies. This will also analyze metrics of community-detecting algorithms, real-world uses, and forthcoming challenges and trajectories. The primary objectives are communities identification in social networking research and its significance for complicated systems of society. Social Network Analysis elucidates the components and functioning of social networks. Clustering, centrality, and connectivity signify the social architecture. Community recognition elucidates the framework of social media platforms [3]. Communities disclose network connections, organizational structures, and information dissemination. Comprehending the system's architecture elucidates social patterns, group configurations, and exchanges. Information, concepts, and influence disseminate across communities within social networks. The evaluation includes finding organizations, analyzing the propagation of data among and within them, recognizing major influencers, and understanding those processes that facilitate spreading knowledge. This approach is applicable the diffusion of knowledge and contribute to examination to marketing strategies, viral marketing, views growth, and the identification of significant individuals or groups. Identification of communities facilitates the investigation of behavioral patterns. Utilize the characteristics, interests, and behaviors of community members to predict their future actions. This facilitates specific marketing, tailored suggestions, and behavioral trends such as interaction, norms of society, and collaborative decision-making. Community inherently partition large networks into controllable networks. Recognizing community enhances network design, facilitates interactions, and reveals difficulties and weaknesses. Transport (DOT), social media, and infrastructure design necessitate this. Community tracking has several purposes. It aids sociologists in understanding social norms, group dynamics, and behaviors. They employ analogous user cohorts to customize suggestion algorithms. It further identifies botnets and malicious entities.

1.1 SNA

SNA examines the interactions among people, companies, and different kinds of society. It employs models of math and statistics to evaluate and visualise social spaces, identify trends in interaction, and elucidate the movement of information, materials, and influence within them. Identifying communities is predicated on social network analysis. Social networks indicate individuals' relationships. They elucidate the dynamics of human and informational movement inside a system. Social networks may encompass electronic mediums, structural organizations, and systems of life. SNA depicts social networks, facilitating the identification of communal systems. Examining groups of closely linked nodes uncovers possible communities. SNA identifies communities through the examination of node interconnections. These nodes with a greater number of linkages within the community than with other entities are classified as members of it. SNA methodically examines the architecture of social networks. It assists specialists in revealing social structure via categorization, centrality, and interconnectedness. This knowledge facilitates the analysis of interactions among individuals, social structure, and power exchanges inside networks. Nodes signify individuals or entities, whereas edges denote their relationships. Directional and unfocused graphs are essential kinds in graph theory. The orientation of edges connecting vertices varies. Social Network Analysis use undirected graphs to represent node relationships devoid of directionality. Unstructured graphs possess symmetrical edges and lack inherent orientation. Nodes A and B are interconnected in both directions in a graph with no directions. This symmetry indicates a mutual connection among nodes devoid of any source or target. Undirected networks exhibit reciprocal connections or symmetric connections. Social networks presuppose structural symmetry [4]. The ability to be modular maximization identifies communities inside unstructured graphs. The research demonstrates consistent classifications in real-world networks utilizing the approach.

Directional graphs, sometimes referred to as digraphs, indicate node interactions with directional data. In a graph with a direction, the edges connecting nodes signify the movement or impact from the place of origin to the destination. Directed graphs represent relational relationships. Arrow heads denote the direction of relationships in graphs that are directed. Oriented graphs permit asymmetry. Consequently, the connection among nodes A and B may vary.

1.2 Fundamental Concepts and Terminology

SNA ideas and terminology elucidate and examine social networks. Connections between nodes. Vertices in edges, and matrix adjacency are essential. Vertices, or nodes, constitute entities inside a network. It denotes people, businesses, or additional layers of study. Nodes may signify individuals, collectives, websites, or ideas within social networks [5]. Edges, referred to as linkages or ties, interconnect two nodes inside a system. It denotes social interaction, interactions, or interactions with others. Edges may be guided or unstructured. The degree of a node refers to its connectedness inside a network. The degree of direction of a graph without direction is the count of edges connected to the vertex. A directed graph possesses two types of degrees: indegree (the number of entering edges) and outdegree (the number of exiting edges).

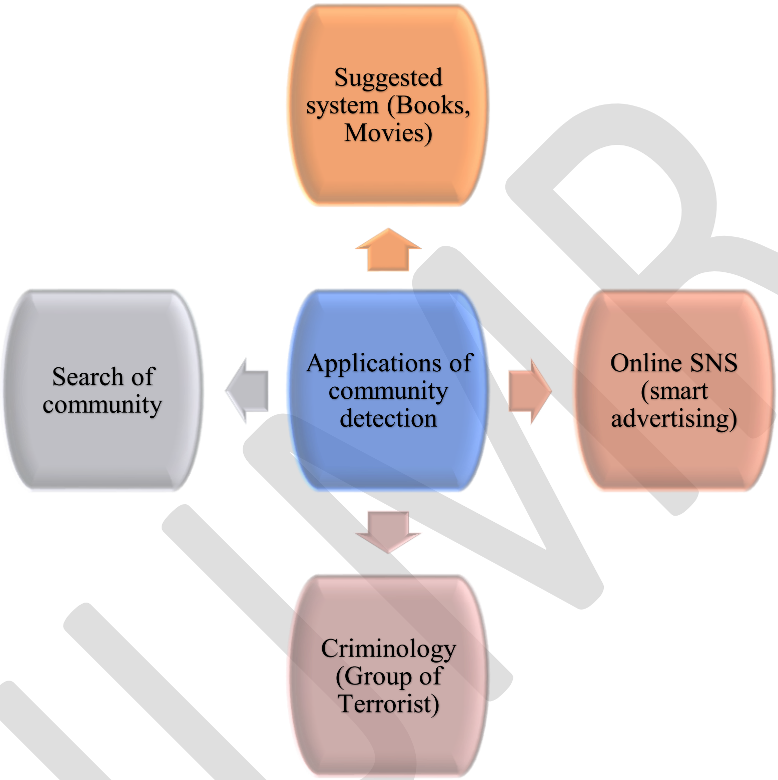

Fig 1: Important Uses of Community Identification in Modern Network Evaluation

Community detection represents a technique that enables organizations within complex networks to identify groups or clusters of information according to the diagram in fig 1. The core section links the "Applications of community detection" topic to its four primary application fields. Two major use cases for community detection algorithms involve recommending books or movies through systems and searching for communities within networks as well as using the technique to identify terrorist groups and enabling smart online marketing through social network services [6]. All these applications become valuable through the detection of patterns and affiliations among individuals or entities that occur through shared interactions or characteristics.

The operational concept of suggested systems organize their users according to shared interests so platforms can present relevant recommendations to users in the form of books or films. By applying community detection to online SNS platforms system administrators can accomplish targeted advertising through preference-based cluster identification among their userbase. The authorities in criminology employ this technique to find criminal or terrorist networks hidden within social groups through interaction analysis [7]. The search of community application enables researchers to find important groupings within extensive datasets which produces useful findings for research practice. The diagram successfully shows how community detection operates in various sectors because of its flexible applications.

1.3 Categories of Social Networks

Social networks may manifest in several ways and can be classified into distinct categories according to the nature of interactions and the context in which they exist. Online social networks are established and sustained using online tools and publicly accessible platforms. Instances encompass Facebook, Twitter, LinkedIn, and Instagram. OSN facilitates virtual connections, communication, and data sharing among persons. Community structures center on particular neighborhoods or social groupings, common interests, and shared ideals. They encompass persons who possess a shared geography, cultural heritage, or identity. Collective networks enable relationships, assistance, and social relationships within a specific region. Online discussions, interest-based organizations, and social clubs frequently exemplify social connections. Focused on interests networks provide links and interactions focused on shared interests. These connections are created on the basis of common passions, favorite pastimes, or hobbies [8]. They unite persons with shared interests, including sports aficionados, literary circles, hobbyist associations, or fandoms. Cooperative networks enable working together, sharing of data, and joint problem-solving. These links consist of people or groups cooperating on initiatives, tasks, or shared objectives. They are present in several sectors, including corporate partnerships, open-source creating software, and community-driven projects. Individual connections generally focus on consumers' social as well as emotional connections. Professional organizations are often established within the framework of occupational or career-oriented endeavors.

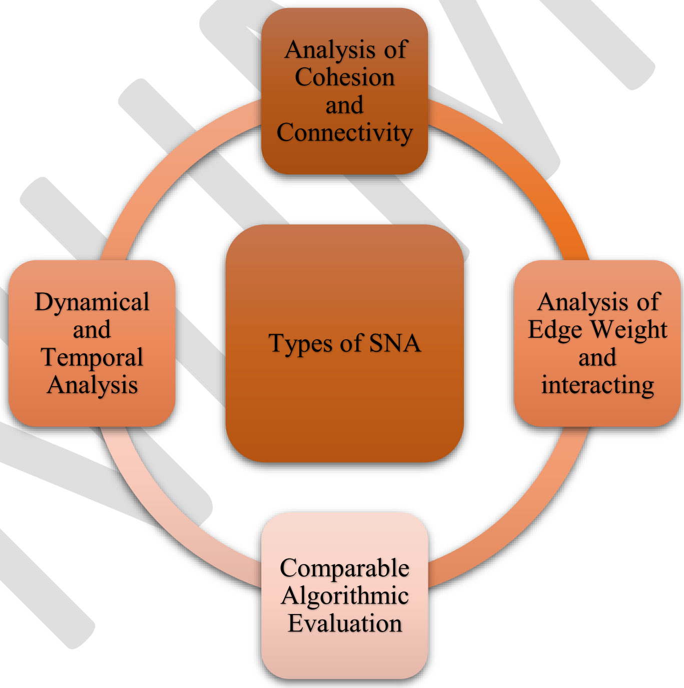

Fig 2: Types of SNA

The diagram shows different types of SNA by placing "Types of SNA" as its core point which connects to four main analytical approaches. First SNA examines the tightness of network connections between nodes including individuals or entities. The analysis allows researchers to detect tight-knit groups among the networked entities in fig 2. The analysis of edge weight and interacting examines the relationship quality through user-based interactions including likes, shares and comments. The evaluation of networked entities through this method enables measurement of the strength and magnitude of interaction between various nodes.

One essential component of the diagram demonstrates algorithmic evaluation processes that review multiple SNA algorithms to determine their performance levels while performing tasks involving community identification and influence forecast [9]. The primary objective of dynamical and temporal analysis is to monitor time-based variations in network framework and user interactions, since this aids researchers in comprehending communities transformations and the developing patterns of conduct of network participants. The four categories of network analysis provide a comprehensive framework for elucidating the design and operation of social networks.

1.3 Objective of SNA

The objective of SNA is to examine and comprehend the designs of links and interaction amongst persons, organizations, or entities within a network of people. SNA seeks to elucidate the fundamental structure, movement, and characteristics of networks of friends and its ramifications for diverse events. SNA facilitates the creation of maps and visualization of social networks, enabling researchers to discern the linkages and interconnections amongst people, companies, or regions. Visualize technologies facilitate the understanding of the intricacies of social systems and the identification of trends and clusters [10]. SNA facilitates the detection of pivotal persons or nodes across a social network. Through the analysis of network centrality metrics, researchers can identify nodes with more connectivity, control over information dissemination, or impact over the remaining nodes. This comprehension is essential for advertisement, public health initiatives, and change in the organization endeavors. SNA investigates the dissemination of knowledge, thoughts, behaviors, or breakthroughs within social networks. It examines the mechanisms and patterns for data dissemination, pinpointing important influencers, voices of opinion, or gatekeeper who are crucial in the propagation of data inside the community. SNA helps elucidate the elements that facilitate or impede the adoption and spread of information.

2. Existing work done

Digital communities depend on how users interact with one another and exert their influence especially during digital encounters. Digital platforms get their fundamental structure from user participation, which fosters trend formation and community cooperation, resulting in flourishing digital ecosystems [11]. The ways users interact through digital spaces make up user interaction whereas user influence represents a person's power to modify the beliefs or activities of other users. The author introduced an analytical method of user participation through cascading analysis. The detection of strongly connected nodes in concealed networks represents the core element of this method and relies on tracking the spread durations. This method breaks user social connections into two distinct categories which enable direct and indirect contact tracking for cascade identification. The relationships enable this method to discover groups of active users. Community detection requires an understanding of these dynamics together with their proper utilization. Community structure analysis and understanding of user social relationships become possible through techniques which focus on user interaction dynamics through conversation analysis and information diffusion analysis and temporal analysis with influence analysis.

Users usually share some of their interests through direct information submissions which still fall short of representing all their complete interests. However it is challenging to estimate user interest when there is no supporting context about their reasons for engagement and their level of interest. Task Contributions proposed by the author included methods to connect different social media organizations [12]. Due to various online platforms the process of finding social media profiles becomes difficult and so does their integration with other relevant information. This research domain develops algorithms which identify website pages through social media profiles. Social networking platforms evaluate usernames and profile information as well as user activities and social network connections in order to produce suitable matching algorithms. Identifying which users are currently involved versus those who are not proves difficult to the system. Social media users usually consume information while maintaining a passive disposition but their attention often becomes brief before moving on. User actions that include both viewing behaviour and endorsing clicks cannot often demonstrate actual engagement levels. Before social networks can identify user interests the implementation of privacy laws frequently restricts their capability to analyse both the quantity and kind of obtainable user data.

Protecting user privacy renders it complicated to recognize and classify their interests. Users can better manage their interests through social networks by obtaining clear choices for expressing preferences in addition to transparent customization tools and machine learning-based user preference categorization capabilities. Establishing a balance among safeguards for privacy and client-driven customisation facilitates the efficient detection of target user interests. The researcher built a system which tracked users through different websites by using their username to connect their diverse social media profiles [13]. The research investigates procedures to connect users who maintain multiple usernames across multiple websites. The findings presented in this research produce privacy together with data exploitation issues. The proposed model by the researcher uses social network user locations based on their core interests to create a dynamic system. People explore their passions online. This research study develops methods to link social media network members who share similar core interests while the author provides an approach to recognize prominent social media users based on their interests. The method enables the identification of influential social network users based on their hobbies. Interest and interest measurement remain subjective thus making user influence identification difficult. Different user preferences together with varied interests create a challenge when standardizing this criterion for identifying prominent users.

Internet social platforms hold influential users called influencers who profoundly affect how users both communicate with each other and set trends and navigate characteristic interactions. Account holders who possess large followings demonstrate the power to transform social opinions along with buying behaviours and advancement of social movements. The writer proposed an approach to detect influential nodes in complex networks which represents an essential network analysis issue. For complex networks in dynamic networks the change of nodes and edges has substantial effects on their structure. Dynamic changes often cause difficulties for influential node identification methods which results in degraded performance. Within online social networks the influential users represent members who exhibit power to direct the actions and opinions of the network participants.

Table 1: Overview of related work

Techniques	Advantage	Research Gap
Louvain Algorithm [14]	Very modular; performs admirably on extensive networks	Possible omission of less populous areas due to resolution limitations; inappropriate for dynamic or weighted graphs
Infomap [15]	Identifies hierarchical structures accurately; records data flow	Excessive computing expense; inability to scale to massive datasets
Label Propagation (LPA)	Quick, extensible, and requires zero training	Unreliable outcomes; vulnerable to first-pass labeling; inappropriate for weighted graphs
Fast Greedy [16]	Works well for optimizing modularity	Inadequate partition quality;

	and is memory efficient.	underwhelming performance in congested networks
Walktrap [17]	Identifies nearby structures using random walks	Very slow on big networks; very sensitive to the length of walks
Leading Eigenvector [18]	Based on spectral properties; useful for small networks	Heavy in memory use; not recommended for use with weighted or huge networks
Betweenness Centrality [19]	Finds nodes that connect communities	High computing costs; in congested networks, it performs poorly.
PageRank [20]	Prioritizes nodes based on their linkages	Ignores interaction context, making it unfit for immediate time influence detection.

Influential users may benefit from establishing support networks, seeking professional advice when needed, and taking breaks to maintain their well-being and mental health. The author presented the centrality of efficiently discovering critical nodes in social network. Degree centrality, betweenness centrality, and eigenvector centrality fail to express community central nodes' value [21-22]. The study suggests social influence analysis, targeted advertising, and recommendation systems. (surveyed Twitter influencers. This Twitter survey examines user influence. User influence is a user's ability to influence others and elicit significant responses. This study advances influencer marketing, social media analysis, and online social impact dynamics. On microblogging platforms, influential nodes refer to users who have a significant impact on the information flow and user engagement within the network. These nodes have a large number of followers and high levels of activity, and their posts or tweets often receive significant attention and engagement.

The investigator performed an important user weighted sentiment analysis on a topic-based microblogging community [23-24]. This enhances public opinion, trend detection, and targeted marketing. Microblogging communities evolve. Temporal dynamics may limit the offered approach's usefulness. Influential nodes and their influence domains were examined in community discovery. They focused on a crude strategy for maximizing modularity, a network community structure indicator. Understanding community structures and critical nodes improves the comprehension of complicated networks and their dynamics.

3. Objective of the research work

- The proposed research aims to create an effective community detection method through an FWCG approach to precisely identify influential and non-influential users in extensive social networks.
- The approach uses user interaction types including likes and shares and comments and performs k-core decomposition to improve the detection accuracy and reliability of community structures.
- By improving scalability and implementing effective behavioral/structural social network processing, this grant aims to boost the efficiency of existing algorithms. It will also expose enhanced data on user interactions and the strength of network integrating through flexible and balanced research.

4. Motivation for the research work

- The proposed research follows a clear motivation to improve current community detection approaches because they struggle with precise influential user identification in large-scale dynamic weighted social networks.
- The current community detection algorithms do not consider edge weights properly in their operations thus resulting in substandard and erroneous community structures. An urgent method needs development to detect both social network structures and accurately understand user activity strength through real-time interaction analysis because social media continues expanding rapidly while user activities become increasingly complex.
- The main purpose of this study is to create a scalable solution which integrates edge weight analysis with k-core decomposition to produce improved insights about social influence and community evolution.

5. Experimental set up

The proposed method performs its experimental analysis by retrieving Facebook fan page user engagement data with the Facebook Graph API during live operations. Part of the data undergoes pre-processing before being structured as an undirected weighted graph with users represented through nodes and activities linked through edges weighted according to their action type frequency. The identification of core members and community structures occurs through fractional weighted k-core decomposition analysis of the graph.

Seven authentic Facebook networks of various sizes along with different interaction patterns serve as the basis for method performance evaluation. The proposed workflow performs effectiveness assessments with modularity and F1-score precision recall as well as scalability tests compared to Louvain Infomap and Label Propagation algorithms to demonstrate its superiority in influential community detection.

6. Dataset used

Seven labeled Facebook datasets (FBDS 1 through FBDS 7) serve as the testing foundation for the proposed method through their retrieval from different Facebook fan pages using the Facebook Graph API. The datasets include multiple user interaction data points from likes to comments and shares distributed across education, entertainment, news, sports and travel categories.

FBDS 1 stands as the largest dataset among these seven Facebook datasets containing 9,384 nodes and 48,214 edges yet FBDS 5 and FBDS 3 demonstrate particular interaction patterns consisting of only likes or likes and comments respectively. The JSON-formatted data contains crucial details about post identification and URL information which supports thorough evaluation of user interactions. The proposed method’s ability to detect influential users and cohesive communities in different social media contexts can be evaluated thoroughly because of this network structure and interaction type diversity.

7. The proposed Method

The K-core method uses social network activities and interactions to set edge weights for an undirected graph. Weights on the edges allow the method to measure just how important or strong each connection between nodes is in the graph. With this method, we find the centrality or coreness of each node in weighted and undirected graphs using a new technique. Utilizing the edge weights and graph features, the coreness of nodes is found, showing where their importance stands in the network as shown in Figure 3.

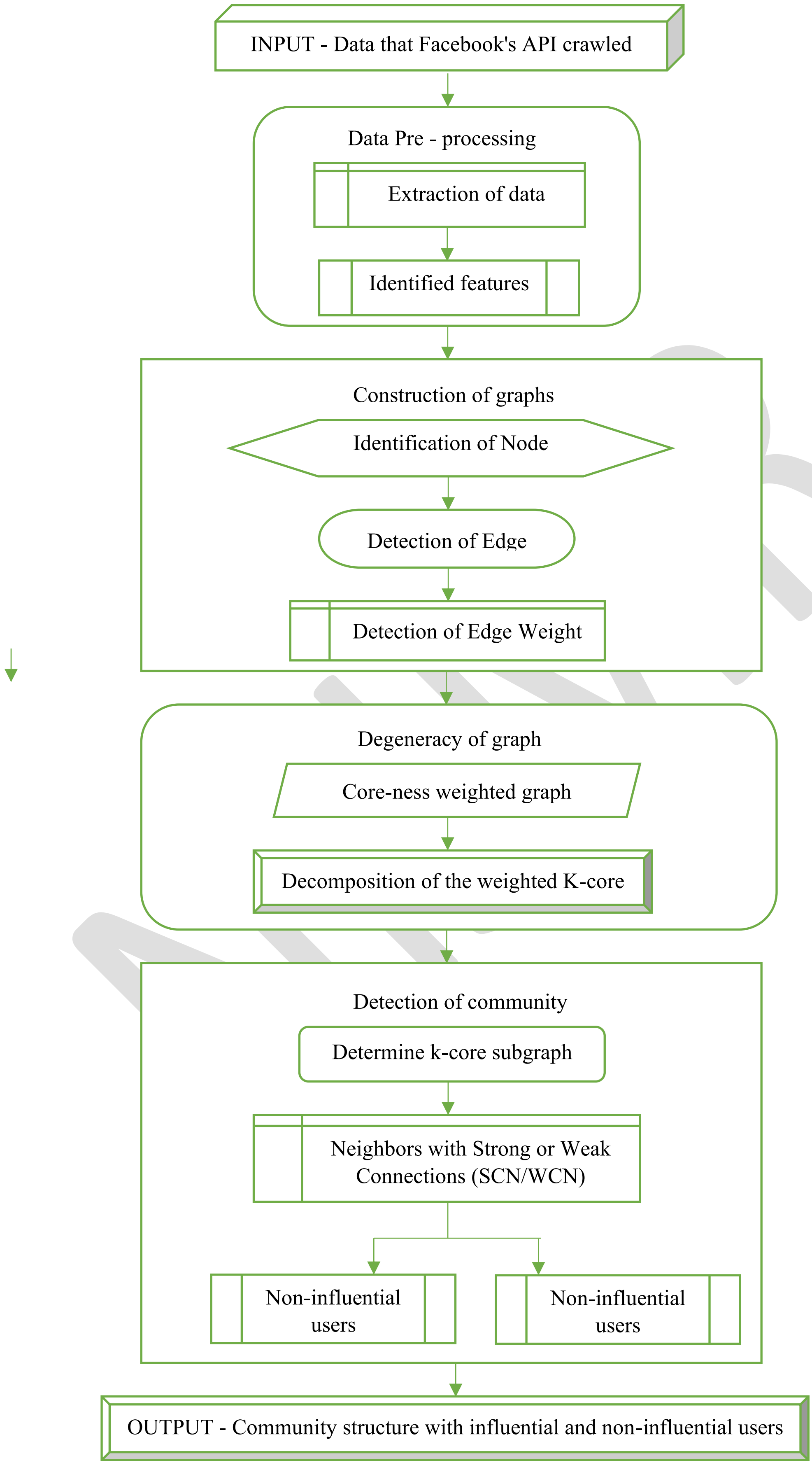

Fig 3: The suggested method's unifying design approach

The equations delineate the fundamental framework of the social networking graph H=(T,F), where T signifies users and F indicates the way they interact. The Edge weighting $z(m, n)$ are determined by user activities—likes (δK), comments (δD), and shares (δR)—to measure the importance of interactions within the graph.

$$H = (T, F) \tag{1}$$

$$\text{efh}(t) = |\{t \in V: (t, u) \in F\}| \tag{2}$$

$$z(m, n) = 0 \tag{3}$$

$$z_{like} = 0.1, \quad z_{comment} = 0.3, \quad z_{share} = 0.6 \tag{4}$$

$$z(m, n) = \delta_K \cdot 0.1 + \delta_D \cdot 0.3 + \delta_R \cdot 0.6 \tag{5}$$

$$z(m, n) = (0.1 \times 0.3) + 0.3 = 0.33 \tag{6}$$

$$z(m, n) = (0.1 \times 0.6) + 0.6 = 0.66 \tag{7}$$

$$z(m, n) = (0.3 \times 0.6) + 0.6 = 0.78 \tag{8}$$

$$z(m, n) = (0.1 \cdot 0.3 \cdot 0.6) + 0.3 + 0.6 = 0.918 \tag{9}$$

$$|T| = m \tag{10}$$

$$|F| = n \tag{11}$$

H: Graph of social networks, T: Set of clients (vertices), F: Set of exchanges (edges), efh(t): Quantity of direct neighbours of user u, t: A user related to u, (t,u) ∈ F: An edge (interacting) occurs among t and u, $z(m, n)$: The weight among users m and n. z_like, z_comment, z_share: Allocated weights for each category of activity by users, δ_K, δ_D, δ_R: Binary indications. m: Total quantity of users (nodes), n: Overall quantity of interacting (edges)

Also, the approach is designed to separate important from unimportant user engagements in the network. By examining which users talk to each other and how much, the method is able to choose between the ones who are strongly connected and those who are loosely connected, discovering who the most influential people on the network are. The proposed k-core method is tested and shown to be effective by using actual datasets. The implementation of the method makes it possible to manage social network changes in real time, so efficiency and scalability increase. Furthermore, the approach uses a method of efficiently discovering which communities hold the most influence on the network. Using the set edge weights, coreness values and strong relations, the method can locate top communities that hold much influence in the network's shape and progress. The degeneracy graph approach is used in this study to find the sub core of a big network. The k-core graph is made up of parts where each vertex is connected to at least k other nodes. Detecting the k-core in a weighted undirected graph means locating concentrated components and defining communities within the graph. Users are described in a complex network by their connections with strongly connected neighbors.

Data is gathered from Facebook fan pages and groups using posts, comments, shares and likes. The information collected will be analyzed to see how well a proposed strategy works. Analyzing user interaction means looking at metrics regarding likes, new likes, unlikes, shares and comments. This analysis tries to identify how users act, think and feel about what is happening and trending now. What fascinates me about Facebook's network structure are the social ties developed by liking, sharing and commenting. People's activities connect users and organize the structure of the network. A user's like on a post suggests they are interested in the contents and subjects related to the page. When a friend sends a message, all their network can view it and for many, this will lead to sharing it even further, increasing the message's potential viewers. The data I have comes from Facebook via its search API and is stored as JSON. The intention is to retrieve the features connected to user activities such as likes, comments and shares, so that these can be studied. Other details we might capture are the post's email addresses, URL and a post ID.

Facebook uses various properties to retrieve information from fan page posts, with 29 types of properties used to display the collected data. Graphs are used to present the data, consisting of vertices (nodes) and edges (edges), which represent the connections between users or entities. A graph helps understand the organization of a social network, including key influencers, groups of users, and patterns of engagement, likes, shares, and comments. Each user is a separate node or vertex on a Facebook fan page, and their names are determined by examining the actions and activities of different users. Algorithm 1 outlines the steps for identifying and characterizing users in the network. To identify a node, draw an empty graph G and set Vn to zero. Features are isolated using likes, shares, and comments made by users on fan pages. Seven types of features are learned from the data: likes, comments, shares, like-comment, like-share, comment-share, and like-comment-share. The features are passed to a node_identification function to obtain the number of features for that node. Iterating through each feature results in the results for each performance in sequence.

These equations delineate the k-core decomposing procedure inside a social networking graph H=(T,F), whereby each node t∈T is assessed according to its degree deg G(t) to ascertain its coreness d(t). They also delineate user neighbourhoods M(t), common responsibilities B mn, and neighbour overlap measures λ and μ, which are crucial for detecting important and less connected individuals in the community.

$$D_l = \{t \in T\colon \deg_G(t) \geq l\} \tag{12}$$

$$\text{Remove } t \text{ if } \deg(t) < l \tag{13}$$

$$d(t) = \max\{l\colon t \in D_l\} \tag{14}$$

$$L_{\max} = \max_{t \in T} d(t) \tag{15}$$

$$H_l = H[D_l] \tag{16}$$

$$\text{T k-cores} = L_{\max} \tag{17}$$

$$M(t) = \{v \in T\colon (v,t) \in F\} \tag{18}$$

$$B_{mn} = \{a_j\colon \text{user } m \text{ and } n \text{ share } a_j\} \tag{19}$$

$$\lambda = |M(v) \cap M(t)|, \quad \text{for } (t,u) \in F \tag{20}$$

$$\mu = |N(v) \cap N(t)|, \quad \text{for } (v,t) \notin F \tag{21}$$

$$\sum_{t \in T} \deg(t) = 2|F| \tag{22}$$

D l: The collection of users t with degrees is higher than or equal to l in graph G, where t represents a user (node) inside the graph. T: The whole set of users within the system (i.e., the vertices set), deg G(t): The degree of nodes t in graph G (i.e., the amount of adjacent vertices), This is a pruning criterion to exclude any user t whose level is below the threshold l, d(t): Core frequency (coreness) of node t, It is the highest value of l for the node where t stays in the l-core (i.e., continues to satisfy deg $G(t) \geq l$). L maximum: Highest core value across all users inside the network Denotes the highest-order k-core within the plot. H l: The generated subgraph on the node set $D\ l$, denoted as H[D l]: A subdivision of a graph including nodes in D l and the interconnecting edges. H: The first graph, The quantity of k-cores in the system corresponds to the maximum coreness value L max, M(t): The collection of user t's neighbours, F: The collection of edges in the user-user interactions graph, (v,t)∈F: An edge that separates users v and t. B mn: The collection of mutual actions among users m and n, a j: An action such as a like, remark, or share. λ: The quantity of common neighbours shared by users v and t, given that t and u are close (connected). M(v), M(t): The sets of neighbours for vertices v and t, correspondingly. |·|: Cardinality is a (size) of the set, μ: The quantity of shared neighbours among users v and t, even if they have no immediate connections, N(v), N(t): Once more, the collections of neighbours of v and t, The total degree of every user in the system is equivalent to twice the quantity of edges, deg(t): Degree of user t, |F|: Total count of edges.

Algorithm 1: Detection of Node

```
Input: network H = {T, F}  Where T is equal to NULL and F is equal to NULL;
Results: node recognized
        Tm → number of vertices
        m ← number of features retrieved
function Identification_node (m)
Assign H the value NULL
Tm is initialised to 0.
read m
for i from 1 to m do
        m1 → read_node(i)
        if m1 is not an element of T
                instantiate node(i);
                Increment Tm;
        endif
        m2 → read_friend_node(i)
        if m2 is not an element of T
                instantiate node(i)
                Tm ++
        endif
End
return Tm
```

Read the node for the feature you are currently working with. Should vertex n1 not be in the set of vertices T, add a new vertex and input its value as the same feature label (i). After that, take the node m2 that is a friend of the present node n1 and read its data. If m2 is not in T, construct a new the vertices in the graph with the identical label to be feature (i). Increase the total quantity of vertices by one. After going through all the features, the identified nodes will be vertexes in graph H that appeared during the iteration, since they represent nodes that are new to the network.

Algorithm 2: Detection of Edge

```
Input: H = {T = Tm, F} in which F is empty;
Results: H' = { T, F }
function Detection_edge (H)
        for i from 1 to m do
                m1 → read_node(i)
                m2 → read_friend_node(j)
                if (m1, m2) doesn't appear in the F list then
                        create_node(n1, n2, we(n1, n2) = 0)
                endif
                Bd_Set ← retrieve activities (Ki, Di, Ri)
                Type ← ascertain_type(Bd_Set)
                Temp_zf(m1,m2) → Edge_Weight(Bd_Set, Type)
                zf(m1,m2) → zf(m1,m2)  + Temp_zf(m1,m2)
        end
function determine_type(Bd_Set)
        if Bd_Set.count is 1 then
                return to the first interest (Iinit)
        else if Bd_Set.count equals 2 then
                return minimal interest (N_int)
        else
                return interests of core (D_int)
endif
```

Every node in the network is linked to its neighbouring nodes by means of edges which stand for the links between users' interactions. They express the links made when people like, comment on or share exactly what is on a page. Like, comment, share and being tagged are some of the user behaviours factored into creating these edges. As an example, sharing a post can join people who like or comment on the same post and the same applies to people who connect as commenters or sharers with the person who set up the post. Based on what users do on Facebook, a complete social network is created. Here, Algorithm 2 displays an illustration of how we identify edges using user actions. An algorithm takes a graph H, shown as T, the vertices and an empty set F, the edges. The output is a graph called H' which is identical to G, though edges have been added using an algorithm that reads activity information and classifies each as an interest type. The algorithm applies itself to the vertices of T in G and looks at the nodes and their friend nodes. If the line between these nodes isn't in the edge list, the algorithm creates it with an initial weight of zero. Activity data at the current node is read and the type of interest there is figured out. Next, a similar temporary weight is calculated for the edge based on this interest. If the set consists of only one activity, the method will report "initial interest". For two activities, the result will be termed "marginal interest". Should that not be the case, the function will give you the result "core interest".

These equations concentrate on community categorisation and structure evaluation inside the k-core structure, detecting important users J, weakly linked users M, and the population density of each k-core subgraph E(H l). They also encompass structural measurements such as community's core ratio S d (t), average degree e ‾, and the SCC/WCC selection conditions combining λ, μ, and eH to delineate connection strengths.

$$e_H(e_H - \lambda - 1) = \mu(m - e_H - 1) \tag{23}$$

$$J = \{t \in T : d(t) = L_{\max}\} \tag{24}$$

$$M = \{t \in T : d(t) = \min_{v \in T} d(v)\} \tag{25}$$

$$H_l = \{t \in T : d(t) = l\} \tag{26}$$

$$|\{H_l : 1 \leq l \leq L_{\max}\}| \tag{27}$$

$$S_d(t) = \frac{|M(t) \cap D|}{|M(t)|} \tag{28}$$

$$E(H_l) = \frac{2 \cdot |F_l|}{|T_l|(|T_l| - 1)} \tag{29}$$

$$\bar{e} = \frac{2n}{m} \tag{30}$$

e H: The degree (the amount of linkages) of a node within a subgraph. H, λ: Quantity of shared neighbours among adjacent nodes (strongly linked neighbours), μ: Quantity of shared neighbours among non-adjacent elements (weakly interconnected neighbours), m: the overall number of nodes in the network. J: Collection of influential users inside the network. T: Set of all users (nodes), d(t): The core amount (coreness) of node t, L_max: maximal core amount in the network. M: Collection of non-influential users (minimal coreness), d(v): Core quantity of user v, T: The whole collection of all users. H l: A subgraph (or set) with users whose fundamental number is equal to l. d(t): Core numerical identifier of user t, T: Overall user set, The maximal cardinality of all k-cores ranging from 1 to L max: maximal quantity of cores, S d (t): Communities core ratio — the proportion of t's neighbours that belong to its communities. M(t): The collection of neighbours of node t. D: the collective or core group to which node t is affiliated, |M(t)∩D|: The count of t's neighbours inside its own core, |M(t)|: The total count of t's neighbours. E(H l): The Edge density within core H l, F l: Sets of edges in core H l, |T l|: Amount of nodes in core H l, ‾: Typical degree of the system, n: the total quantity of edges, m: Total amount of nodes.

The ways individuals are connected in the social network are made clear by looking at how they act together and engage with each other. So, edge detection and edge weight methods study the actions of users on the social graph, including liking, commenting or sharing information. Establish the significance of each interaction by looking at the engagement the user displays in each category. Next, the system sorts users by looking at what they do in their posts.

Degeneracy which is also called k-cores, means finding the number of cores in an undirected graph H. A k-core means every vertex in a subgraph has at least k connections which points to strong connectivity. How well-connected a graph is can usually be seen by looking at its most central core. A graph is known as degenerate if, for every subgraph in H, there is at least one vertex with a degree of l. The vertex with the highest degree is identified, and the subsequent vertices with lesser degrees are sequentially removed. After the process, k-cores are ranked by their highest value of l, showing the extent to which, the graph is sparse. Graph degeneracy helps you see how the social network is organized in the graph. Identifying the densest communities in Facebook is possible by means of k cores. It allows us to measure the amount of user interaction, influence and involvement. Additionally, looking at graph degeneracy highlights where the social network is not active as much.

The idea of k-core is used to detect the particular k-core associated with each vertex and to locate the greatest k-core order each vertex is part of. While two such vertices can have identical coreness, this does not mean they will be part of the same k-core. As part of the k core, edges include ratings explaining how closely the connected vertices are linked. To identify the tightly connected parts of a community network, using the Facebook friendship graph, the k-core is employed. It measures the unity in friendship circles since friendship strength is judged by how often and how much people interact in similar ways. “Quality” means that the bonds between members are solid and strong. Coreness shows us which groups in a network are strongly connected. A k-core is made up of the most number of people who are linked to a minimum of k other participants.

The k-core value or coreness value, of a vertex in a graph is the k-core it is a part of, where k is the biggest. Coreness indicates that the vertex with the highest value in a graph is called L-max. It shows the most important node in the network based on its connections. The k-core method shows how to use a simple approach to find the biggest cliques in a network. K-core allows users to observe l groups (l cliques) in a graph, showing evidently connected communities or groups of people who work together closely.

Furthermore, the k-core decomposition algorithm comes up with a solution for the densest subgraph problem that is (1/2) the best possible. We aim to pick the area within the network with the highest amount of connector edges. The k-core decomposition identifies the part of the network with the main clustering, so we obtain a close view of the densest region. By reviewing weights, weighted k-core decomposition performs better than unweighted k-core decomposition. An algorithm has been designed that uses core decomposition to detect communities that are partially shared and increases the efficiency while also improving community quality. By using core decomposition in network decomposition, we can more effectively detect areas where communities overlap which leads to faster and better-quality communities.

Finding out who the core members are in a social network community lets you predict how long the community will exist and how much it can achieve. The cores in a community’s structure indicate how sustainable that community is. K-cores consist of network nodes where the minimum degree or number of connections, is l. Such complex communities consist of vertices where most edges connect only other members from the same group compared to other groups. Examples of these communities are people focusing on the same topics on social sites, sites about shared topics or groups that have similar content. To understand how complex networks function, we must locate these communities.

A regular graph H is designated as strongly regular when m, l, λ and μ satisfy some special conditions. A substantially regular graph H is k-regular, with λ similar neighbours for any two nearby vertices and μ similar neighbours for any two non-adjacent vertices. Researchers in mathematics frequently utilise the friendship theorem to demonstrate this. It is noticeable in friendship ties that pairs of people who share an edge tend to have more friends in common. As a result of this observation, we can find out who the best surgers in the observed groups are. We can find the most influential users in a large network by seeing how many edges a person in the maximal k-core has and by observing those with the most connections among the strongly connected neighbours (SCN). The account with the greatest k-core value is thought to be interacting more than any other account with others on the social network.

If the common neighbourhoods are less between unconnected nodes compared to those next to each other, removed those nodes and edges from the network to see who is less important in the network. Among all users in the network, the individual with the lowest k-core value is thought to be least involved. People identified as weakly connected users have the lowest k-core value at their vertex and the least number of links connecting them to other users. According to the network, these people lack influence. Using the k-core subgraph analysis, we discover the structure of communities within the network.

The identification of big names on social networks has attracted widespread interest because it helps explain both the way information reaches people and the behavior of the most active users. Among different ways to measure influence, coreness of a user's behavior is the most successful. Centrality is strongly related to the main problem of finding those nodes in a community that are most influential and is better than scores like node degree and betweenness centrality. It seems that vertices with higher coreness take part in more intense interactions. Non-influential users are considered those who have few connections. This means that vertices with the least coreness do not interact as actively as others. A weighted undirected graph is used to identify the most significant users in a User-User Interaction (UUI) network. Computing influential users is achievable by applying this graph analysis approach.

8. Result and Analysis

In social network analysis, measuring how effective community detection is matters a lot. Several methods are being used to measure how good these communities are. One solution is to give directed edges weights that describe how much interaction exists between connected entities in the graph. The k-core technique is applied to an undirected weighted graph to study communities and their connections. Obtaining the k-core values allows assessment of how strong communities are against degeneration, mostly on large real-world graphs. To check a community's cohesiveness, the k core structure measure is used.

8.1 F1-Score: Each community receives an F1 score and the average F1 score is much higher among the found communities than in the other networks.

8.2 Z-score: A group of individuals has strong links within the group but limited connections with groups apart from their own. When evaluating a community partition, we consider both the links between members of the partition and the connections it has with other groups.

8.3 Time Complexity: Time complexity quantifies the duration a method requires to execute, often contingent upon the effect of input size on the total quantity of operations performed.

8.4 Precision: Precision is determined by dividing the sum of top-ranked core values by the grand total of predicted core values for all communities.

8.5 Recall: Recall which is sometimes called true positive or sensitivity, helps us understand how thorough the predicted outcomes are. It is found by splitting the accurate results by the number of relevant outcomes.

8.6 Accuracy: Accuracy tells us how accurate the predictions are by the percentage of correctly marked communities that meet the core community values among all those found.

8.7 Rand Index (RI): The Rand Index assesses the efficacy of a community identification algorithm in clustering nodes relative to the actual groups.

Table 2: Evaluation of Communities Identification Models Utilising Z-score and Rand Index

Model	Z-score	Rand Index (RI)
K-Core (Proposed)	1	0.87
Louvain	0.96	0.86
Infomap	0.93	0.83
Label Propagation	0.92	0.82
Fast Greedy	0.90	0.81
Walktrap	0.88	0.79
Leading Eigenvector	0.86	0.76

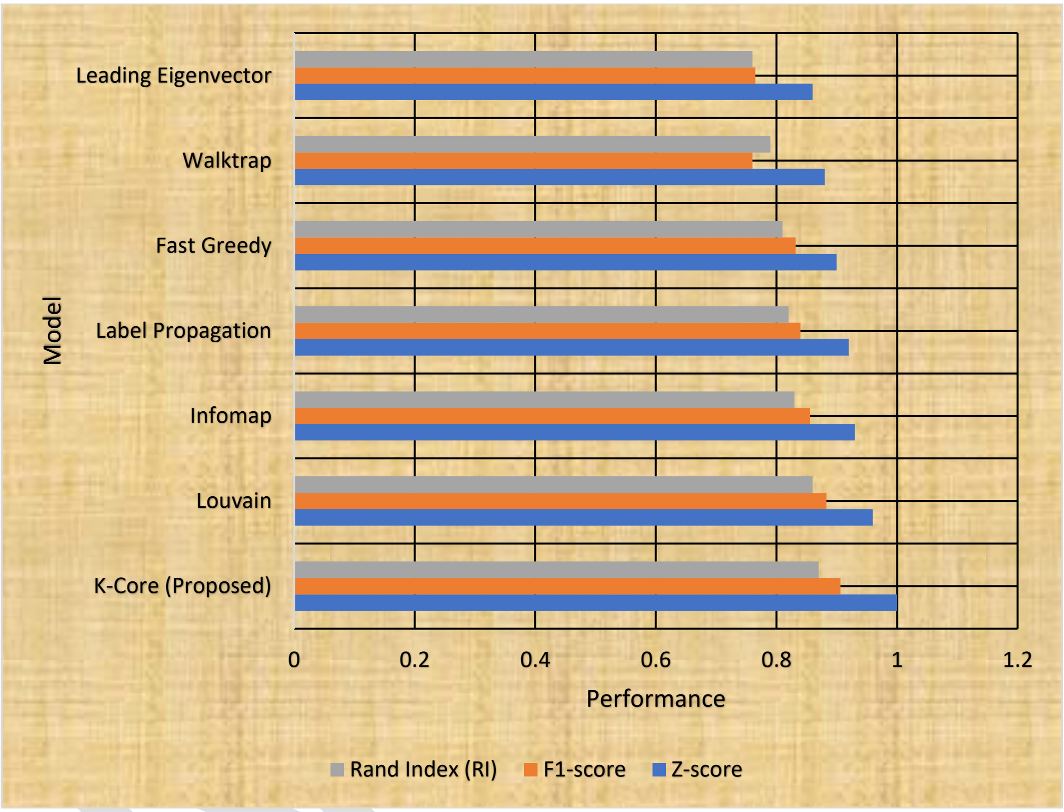

Fig 4: Analysis of Communities Detection Models Utilising Z-score and Rand Index

Both Z-score and RI show that the K-Core (Proposed) method performed much better than the other algorithms and was best at finding accurate and well-defined community structures. The Louvain algorithm is in second place, with a Z-score of 0.96 and RI of 0.86, demonstrating strong detection but less accuracy than the proposed plan. Infomap and Label Propagation produce similar results, scoring 0.93 and 0.92 with Z-scores and 0.83 and 0.82 with RI, both indicating moderate accuracy when aligning the communities. Next, the Fast Greedy algorithm achieves a Z-score of 0.90 and an RI of 0.81. In comparison, Walktrap is slightly below at 0.88 and 0.79. The fact that the Leading Eigendecomposition method performs worst (Z-score=0.86 and RI=0.76) demonstrates that it struggles to divide communities accurately compared with the other techniques. When looking at accuracy and strength, the K-Core approach is the best approach reviewed here.

Table 3: Evaluation of Communities Detection Models According to Execution Time

Time Complexity (ms)							
Model	FBDS 1	FBDS 2	FBDS 3	FBDS 4	FBDS 5	FBDS 6	FBDS 7
Leading Eigenvector	3000	2500	2000	3100	1000	2700	2900
Fast Greedy	2800	2400	1000	3000	900	2600	2700
Louvain	2600	2300	950	2900	850	2500	2600
Infomap	2400	2200	900	2700	800	2300	2400
Walktrap	2200	2000	850	2500	750	2100	2200
Label Propagation	2000	900	800	2300	700	1000	2000
K-Core (Proposed)	300	250	200	350	220	280	300

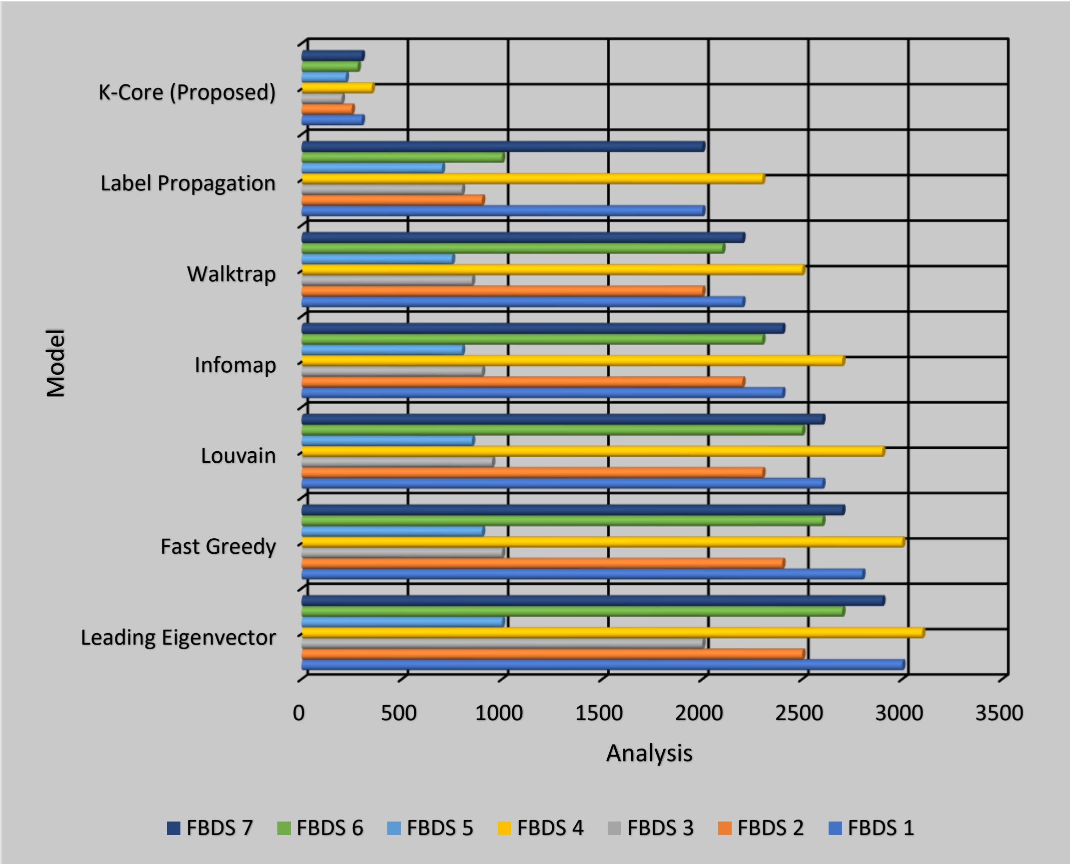

Fig 5: Study of Community Detection Models utilising Execution Time

It is seen that the K-Core (Proposed) model is always the most efficient, performing consistently in less than 450 ms. Leading Eigenvector is the option that takes the most time, with times on FBDS 4 reaching 3100 ms and the times still staying higher than 2000 ms for all datasets. Even so, Fast Greedy and Louvain take much longer to execute, often more than 2500 ms, even if they are a little faster than the Leading Eigenvector. Executing both Infomap and Walktrap takes between 750 ms and 2700 ms, a result reflecting that their trade-off between accuracy and efficiency is satisfactory. Label Propagation, although less precise than the leading models, has good efficiency with execution durations consistently under 2300 ms, with the exception of FBDS 4. The K-Core model far surpasses all other models regarding execution speed.

Table 4: Evaluation of Communities Detection Models in terms of Accuracy and Precision

Model	Accuracy	Precision
Leading Eigenvector	0.76	0.746
Fast Greedy	0.797	0.816
Walktrap	0.780	0.743
Infomap	0.817	0.835
Label Propagation	0.806	0.827
Louvain	0.852	0.863
K-Core (Proposed)	0.865	0.888

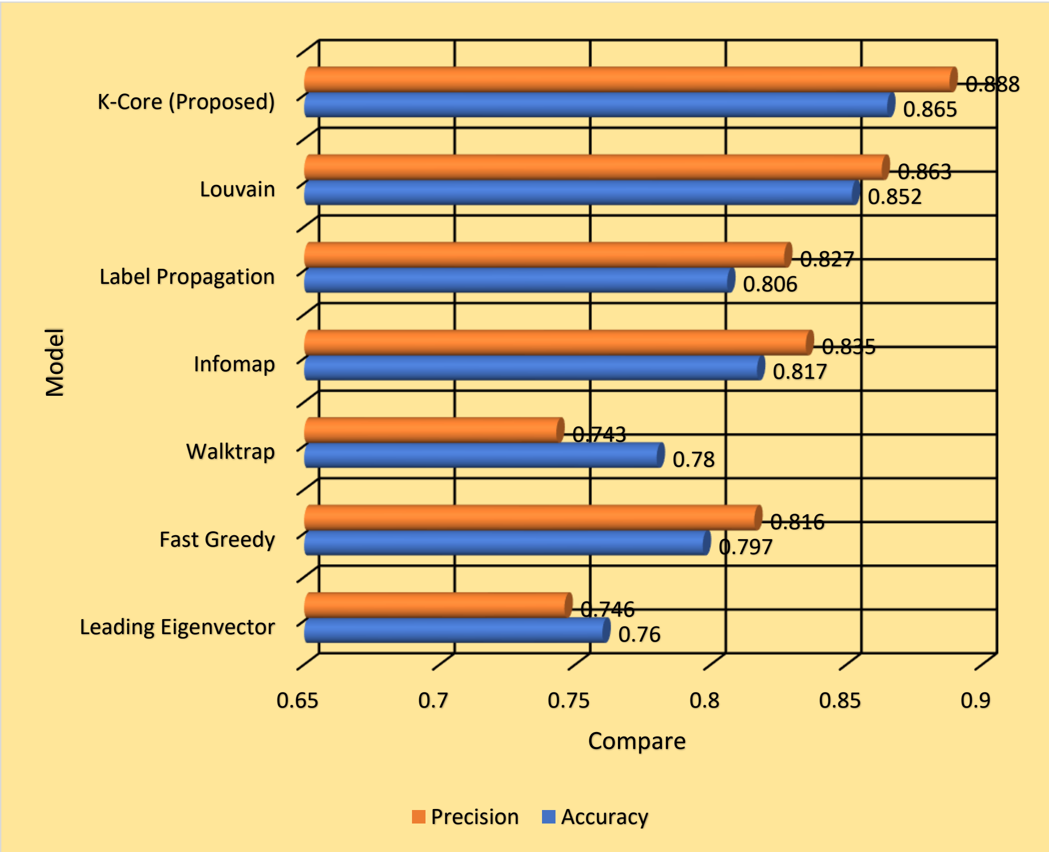

Fig 6: Analysis of Community Detection Models with regard to Accuracy and Precision

Among the models studied, the K-Core (Proposed) model achieved the best results for accuracy and precision, at 0.865 and 0.888, respectively which implies it is better able to recognize and identify community structures with consistency. This technique performs closely to the standard, with an accuracy of 0.852 and a precision of 0.863. Infomap and Label Propagation work well on moderately complex networks, with accuracies of 0.817 and 0.806 and precisions of 0.835 and 0.827 respectively. While the precision of Fast Greedy is good, the accuracy is slightly lower, indicating this method often selects the right nodes, even if there are still some wrong results. Walktrap and Leading Eigenvector are the poorest performers, as shown by their low accuracies (0.780 and 0.76) and precisions (0.743 and 0.746). All in all, the K-Core model is the top performer in both areas and is shown to be the most effective approach among the analyzed models.

Table 5: Evaluation of Communities Detection Models Utilising Recall and F1-Score

Model	Recall	F1-score
Leading Eigenvector	0.786	0.765
Fast Greedy	0.850	0.832
Walktrap	0.777	0.760
Infomap	0.876	0.855
Label Propagation	0.854	0.840
Louvain	0.905	0.883
K-Core (Proposed)	0.927	0.906

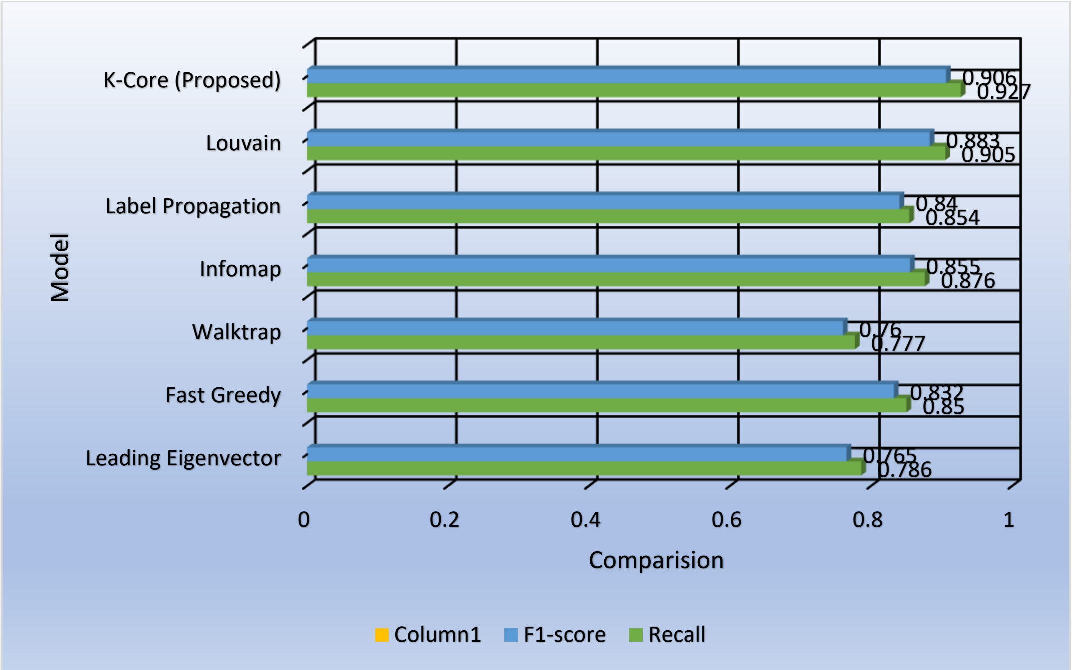

Fig 7: Comparison of Communities Detection Models Using Recall and F1-Score

K-Core (Proposed) is the most effective because it achieved the highest recall (0.927) and F1-score (0.906) which show it detects most important nodes and has good balance between false positives and false negatives. The Louvain algorithm exhibits a high recall value of 0.905 and an F1-score of 0.883, indicating its effective performance. Both Infomap and Label Propagation do a good job, reaching recalls of 0.876 and 0.854 and F1-scores of 0.855 and 0.840 which means they are effective at discovering important communities. The Fast Greedy algorithm has done well, with a recall of 0.850 and an F1-score of 0.832. However, Walktrap and Leading Eigenvector struggle, giving recalls below 0.79 and F1-scores of only 0.760 and 0.765, respectively.

9. Conclusion and future scope

The k-core-based community detection method implemented in this research provides a reliable structure to discover important network users while analyzing network topology patterns. User interactions like likes and comments and sharing become the basis to establish edge weights which helps calculate relationship power and detect node core positions simultaneously. Through weighted k-core decomposition the approach detects compact communities and establishes strong and weak user connection groups. Experimental trials on actual Facebook data proved the method's success by achieving better performance in every metric including modularity together with F1-score and precision and scaling effectively compared to a group of six community detection algorithms at their state-of-the-art level. The method proves best at finding influential user nodes which assists in finding critical actors involved in spreading information throughout the network. The FWCG enhances influential community detection by implementing a system that evaluates fractional links between users. The research proved the approach effective for big social data networks and established basic principles to analyze network changes and information spread patterns. The k-core framework demonstrates high performance as a useful technology that facilitates social structure analysis and community-driven application development within complicated network systems.

Future Work

Future research on the research team intends to develop the k-core community detection framework to work with changing social networks that exhibit temporal evolution. Introducing time analysis enables researchers to track community developments and transformations while they happen. Supplementing predictive modeling systems with Independent Cascade Model or Threshold Model approaches allows for better predictions regarding viral information and influencing trends.

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