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Thorough Examination of Function-Based Community Detection via Social Media for Single and Multiple Purposes

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Abstract –

As the Internet has grown, social networks have drawn interest as research subjects from a wide range of academic fields. The most precise systems are represented in intricate networks. Complex networks are most commonly characterized by their community structure, in which the relationships between node groups are more intimately linked to one another than with the network as a whole.Finding the main clusters and community structures in complex networks, like web charts and biological networks, enables the discovery of organizational rules. The communities appear to overlap in general. One of the defining characteristics of social networks is overlap, which is the state of an individual being a member of multiple social groups. Overlapping community discovery has drawn a lot of interest recently in social network application domains.Numerous approaches utilizing various tools and techniques have been put forth to address the issue of overlapping community discovery.This paper presents a thorough analysis of single and multi-purpose functions for community detection, as well as a comparative analysis of the heuristic overlap community detection algorithm over social media.

Keywords: single function, multi-purpose function, optimization algorithm, heuristic classification, community detection, and seed community

I. OVERVIEW

The 21st century has seen a rapid advancement in communication and technology, making information access necessary.and make the best use of it possible, making it an essential human need and a necessary component of their everyday existence. The Internet is without a doubt the most convenient and quick way to obtain information in the modern world. In addition to serving as a network that links millions of computers worldwide, the Internet also serves as a platform that links millions of individuals and thousands of social groups, and it is always expanding. One of the most widely used internet apps, social media is quickly rising to prominence as one of the most crucial communication tools available today. The rate at which people access social media rises in tandem with the frequency at which people use the Internet. Social media is predicted to play a near-essential role in internet usage in the near future. Social media apps aim to meet almost everyone's needs by employing technology that goes beyond simple communication. many subjects, including games, learning, and searching. People won't need another tool if they can find nearly anything they're looking for on social media. Along with Researchers can now access and analyze data on vast networks, such as social media, thanks to advancements in computer technology and network analysis.The analysis of individual and social group structures and behaviors in the press (separation, clustering, relationship determination), electronic commerce and online advertising (customer profile creation and trend analysis, personalised advertising and offering), physical structure analysis (transportation, installation, infrastructure), and analysis of large data sets (media tracking, academic publication analysis, genetic research) are just a few of the fields that use complex network analysis today [1]. Finding communities and communities in networks is the most pressing problem in

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network analysis today. Identifying their communities in networks is used in a variety of fields, including engineering, physics, chemistry, biology, and social sciences. For instance, functional units of proteins can be identified or their functions can be predicted thanks to the discovery of biological communities [2]. Given the immunization interventions for infectious diseases in related networks and knowledge of the spread of viruses in social networks, community structure is a crucial topological feature in sociology [3].The ability to classify nodes based on the structures of the groups they belong to and to reveal groups is a crucial aspect of community discovery. In a social network structure, a set of nodes is referred to as a community if its link count exceeds the total number of connections outside of it. Communities, sometimes referred to as clusters or modules, are collections of nodes that work together in networks and typically share common functionalities [4]. Figure 1 provides a grid that schematically depicts the communities.The majority of community detection techniques are based on the division of links between groups. The most significant issue that arises in real-world network structures is the overlapping circumstance known as the potential for nodes to belong to multiple groups. Nonetheless, a lot of algorithms typically include nodes in a group because of the intricacy of the processes, disregarding overlap [5]. Accurate information about the structure of complex networks cannot be obtained by this grouping [6].For the purpose of identifying overlapping communities in intricate networks, numerous algorithms exist. The most popular algorithm is CPM. But CPM lacks the flexibility needed for actual networks. When the network is extremely dense, CPM detects meaningful clicks; when the network is sparse, it does not.Therefore, the network's capabilities have a significant impact on CPM.A Genetic Algorithm (GA) is used by GA-Net + [7] to adopt overlapping communities. The process creates a line chart from a node chart. The line chart's nodes display the node chart's edges, and the node chart's edges display the relationships between their neighborhoods[8]. The line chart is then presented as an overview of the genetic algorithm, and in order to achieve fit, it is transformed into a node chart at each stage [9].Other popular research for community discovery includes overlapping ensemble detection in networks [11], network communities [10], and an algorithm for rapidly identifying overlapping ensembles [12].Optimisation algorithms represent an additional technique for community discovery within social networks.The process of finding the best answer to a problem is called optimization. Heuristic optimization algorithms, which are widely used in daily life, are the basis for meta-heuristic optimisation algorithms, a decision-making mechanism [13]. It is intuitive, for instance, to make decisions at crossroads and move from one location to another based only on a feeling of direction, not knowing where the path will lead. Meta-heuristic algorithms are the structure that determines which approaches to use when three heuristic algorithms are beneficial for a problem from different perspectives.An overview of a heuristic community detection algorithm over social media is provided in this paper. The remainder of the document is structured as follows: The social media community and algorithm are described in Section 2. Single and multi-purpose function based metaheuristics community detection methods are presented in Section 3. A comparative analysis of the community detection algorithm over six different data sets is covered in Section 4. The paper is concluded in Section 5 with an outline of the foundational and ongoing work.

II. Social Network Community

Networks are used to represent the majority of complex networks.

The World Wide Web (WWW), for instance, is a network of linked webpages; social networks are networks in which individuals are represented as nodes and the relationships that bind them as edges. In a

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similar vein, biological networks are made up of nodes that express biochemical molecules and boundaries that specify the connections among them [14]. The majority of research in recent years has been devoted to comprehending how network topology affects system dynamics, behavior, and network structure and evolution.Understanding complicated network architectures also requires identifying community structures [15].Groups of nodes are referred to as communities in networks.where ties inside groups are abundant and connections across groupings are rare. The association of people who communicate regularly is another definition of a community. Because of this, communities are essentially collections of nodes that interact similarly and have shared traits [16].Communities inside network architectures provide us specific information about people's study topics, interests, patterns, and other characteristics. In actual networks, theThe structure of networks is not uniform. Systems that focus and group together in a certain region, which we refer to as ensembles, are most likely collections of nodes with related features and functions [4].There are several concrete application areas in communities. For instance, by allocating the same servers to each client cluster, clustering web clients with comparable interests or locations together improves service performance on the WWW. In online buying systems, an efficient advice system between the buyer and the supplier may be built by identifying the community of consumers with similar interests[17].

By recognizing communities, hierarchical organizations in complicated real-world networks may be planned. Communities within communities are a common feature in real networks.The best example of a hierarchical arrangement is the human body.The body is comprised of organs, organ-derived tissues, and tissues composed of cells. Business firms are another instance of a hierarchical organization. One way to conceptualize business enterprises made up of midlevel workgroups is as a pyramid that extends from the workers to the top of the organization. Another meaning of "vertex similarity" is the concept that distance between nodes on a spaceplane serves as a similarity criteria. Traditional grouping techniques frequently employ this strategy. In case nodes are unable to be positioned on a spaceplane, an adjacency matrix may be employed. Even if they are not neighbors, it may be said that they are similar if their neighbors are also similar. Measuring the number of distinct pathways between two nodes, the length of the shortest route, or the random walk may also be used to identify commonalities between nodes [18].Although the initial research on identifying community structures implied that a node could be a part of only one community, networks are made up of various connections in which nodes can be found.be a part of multiple communities; this arrangement is known as overlap. Examples of human relations relationships between two people include those involving family, friends, and coworkers. Hence, one of the most important problems in the analysis of actual social networks is finding overlapping communities. In Figure 2, a network of three distinct communities is displayed. Four nodes in the network are part of multiple communities, demonstrating how communities in networks overlap.Since the community and modular structure are used to determine how well the systems function, they are regarded as crucial components of real-world social networks. Still, a lot of Effective and efficient community discovery techniques have been developed in response to uncertainties regarding community identification.

A. Conventional Approaches

a) Partitioning Graphs

It involves splitting the nodes into k groups of fixed sizes so that there are as few edges as possible between the groups. However, it is not a suitable approach for social network analysis when the number of groups present in social network structures is unknown beforehand. Iterative bi-sectioning is one of its most important algorithms [19]. Min-Cut, Max-Flow Theorem. A dividing line where there are the fewest edges between groups is depicted in Figure 3 for k = 2.

b) Organizational Structure

Groups within social networks are typically entwined in a hierarchical structure. It is an approach that combines removing low-affinity nodes, grouping similar nodes, and dividing groups. Depending on the similarity criterion that is chosen, different results will be obtained [4].

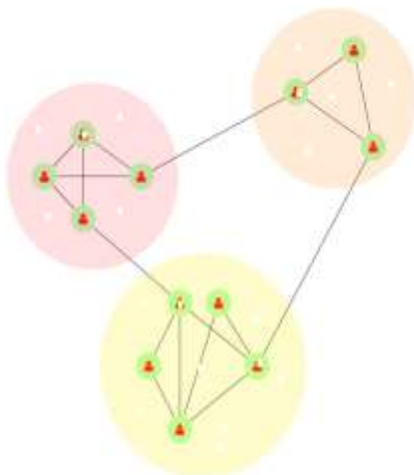

Figure 1 Network configuration with three communities

c) Dividing Grouping

Each node is viewed as a point in space, and the group number k is predetermined in this case. Assuming a given function, the objective is to partition the points into k groups based on how far apart they are from the center. The most often utilized components are k-means, k-central, k-median, and minimum k-clustering [20]. The drawback remains the same in this instance: knowing how many d) Clustering Spectrally Numerous strategies and procedures that divide data into sets using an eigenvector like S or another matrices generated by it [21]. This method involves taking the similarity matrix's eigenvectors and grouping them using a function like k-means [20].The Laplace matrix is the most often utilized matrix. This method allows the number of groups in the line to be determined from the eigenvector components.

B. Algorithms for Segmentation

It is a technique that seeks to identify and eliminate the edges in a graph that link groups in order to discriminate and reveal the teams. How to identify the edges that join these groups is crucial. The Girvan-Newman algorithm is the most widely used algorithm [22]. In this case, edges are chosen according to a factor known as edge centrality. Every edge's centrality value is computed. Deleted are the edges with the highest centrality value. Repetition of the first step and deletion of the edge with the highest value are the

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next steps in the process.Edge betweenness, random walk edge betweenness, and current flow betweenness are also employed in addition to the edge centrality criteria [4].

C. Methods Based on Modularity

The most popular and frequently applied quality function in graph analysis is modularity. Though not entirely validated, a high Good groups are thought to be indicated by a modularity value [4]. A line is deemed to have a group structure if its modularity value is greater than that of a random line of the same size and degree on the graph. A high modularity value, however, does not always imply the existence of a group structure. Certain random graphs can have high modularity values even though they lack group structure.

There is no linear time solution to the NP-Complete problem of improving the modularity function. Nonetheless, successful algorithms with a range of convergences have been created [23, 24]. The alteration that maximizes the function of quality

D. Adaptive Formulas

The random walker model is the most widely used dynamic algorithm for community exploration.This technique results in the random walker remaining in the community for an extended period of time if the graph's connections have a high density; logically, this means that the chart has strong communities [4].

E. Alternative Approaches

In addition to the previously listed and widely used techniques, there are techniques based on statistical inference (Bayes, etc.) [25, 26], techniques that tag nodes and use the tag that their neighbors share the most in each iteration to split groups in this manner [4], click filtering techniques [27], approaches to deal with overlap, and multi-resolution techniques.

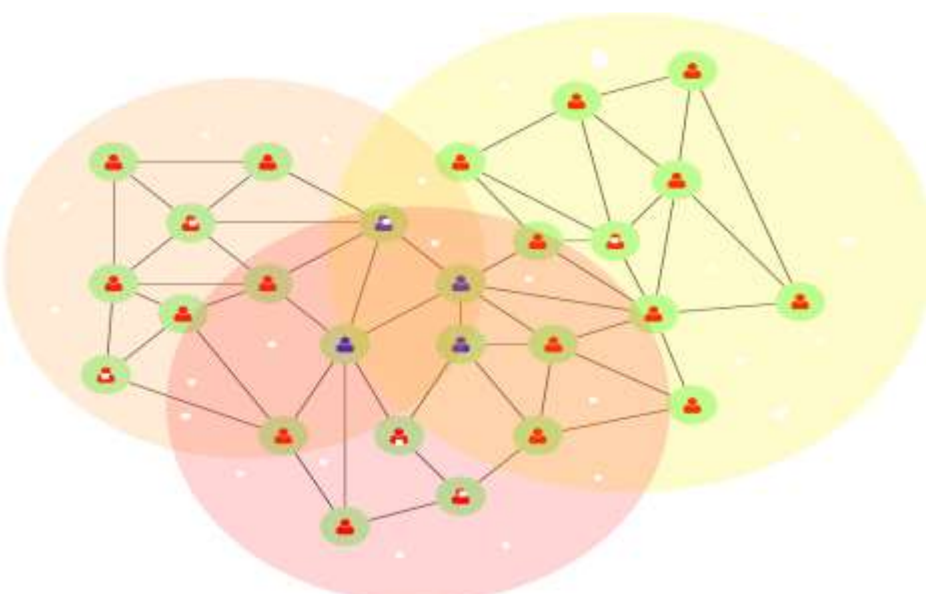

Fig. 2 Overlapping community

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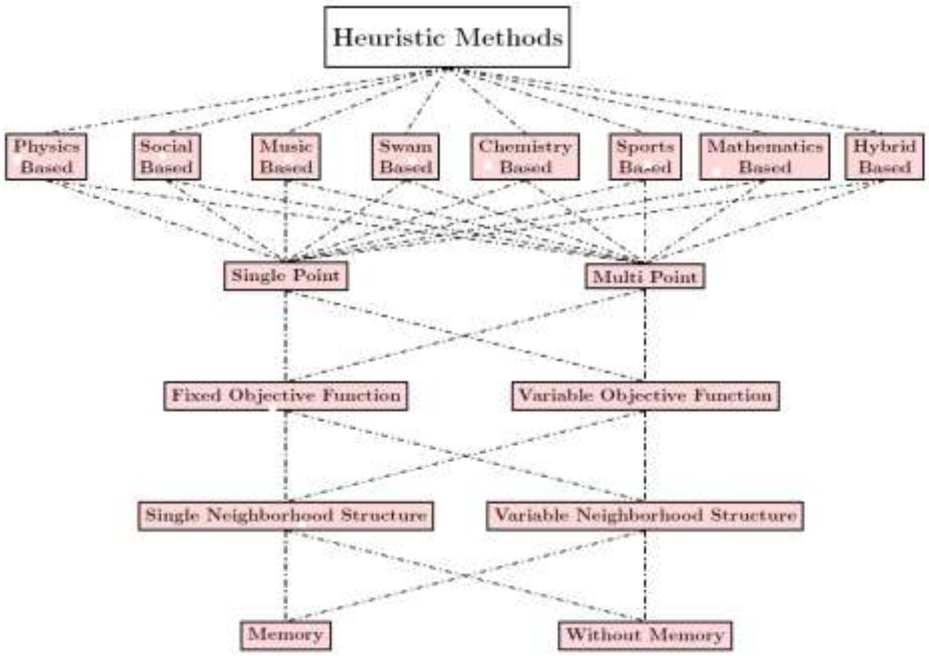

Fig. 4 Meta-Heuristic Methods

III. METHODOLOGICAL OPTIMIZATION METHODS Any issue pertaining to determining values for unknown parameters

An optimization problem is one that must be satisfied under specific constraints. Optimization entails optimization. Finding the best solution out of all the options for a problem under a certain set of circumstances is the task at hand. In other words, heuristic algorithms have the ability to converge but do not ensure a precise result. This circumstance offers a resolution that is nearly perfect [29].

Heuristic algorithms are necessary for the following reasons:

• It's possible that the optimization problem has a structure that makes it impossible to pinpoint the precise solution.

• Heuristic algorithms have the potential to be much more clear easier to make decisions for.

• Heuristic algorithms are useful for learning and for assisting in the precise solution's discovery.

• The most difficult parts of real-world problems (such as which objectives and constraints should be applied, which alternatives should be tested, and how to gather problem data) are frequently overlooked in definitions created using mathematical formulas. More substantial errors could result from inaccurate data used during the model parameter determination stage than from the heuristic approach's potential for producing a suboptimal solution [29].

A decision-making process based on heuristic optimization algorithms—which are widely applied in daily life—is known as a meta-heuristic optimization algorithm [30].

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The meta-heuristic Algorithms, which are becoming more powerful and well-liked in recent years, solve search or optimization problems using a straightforward methodology. The following is a summary of the cause of these:

a. They also provide general approaches to solving the problem that can be used when various kinds of objective functions, constraints, and decision variables are present. The type of objective function, limiters, and variables used in the problem modeling are not relevant factors in determining the strategies for solving the problem.

b. It is independent of delimiters, decision variable count, and type of solution space.

c. There is no need for highly defined mathematical

models that can occasionally not be used due to the high cost of solution time and are challenging to set up for the model and purpose function of the system.

d. They don't require a lot of computing time because they have strong processing power.

e. It is simple to change and adjust to them.

f. It produces good outcomes for large-scale nonlinear and multinational problems.

g. Unlike classical algorithms, a solution algorithm for a given problem does not necessitate some assumptions that may be challenging to verify in adaptation. h. Similar to classical algorithms, it doesn't call for modifications to the target problem. They modify themselves to address various problems.These benefits make meta-heuristic algorithms widely used in a variety of fields, including computers, engineering, and man-made intelligence, and new versions are advised.

Figure 4 illustrates general-purpose meta-heuristic methods. They are bio-based (evolutionary algorithms, ant colony algorithms, bee colony algorithms, artificial immune algorithms, firefly algorithms, enzyme algorithms, sapling development algorithms, invasive weed optimization, monkey search algorithms, bacterial bait search algorithms), physics-based (multi-point heat treatment algorithms, electromagnetism algorithms, particle collision algorithms, big bang big crash algorithms), swarm-based (particle swarm optimization, ant colony optimization, bee colony optimization), and social-based (multipoint taboo Eight distinct approaches: investigation algorithm, parliamentary optimization algorithm, imperialist competitor algorithm), sports-based (league championship algorithm), music-based (harmony search), and chemistry-based

The group evaluates techniques (such as artificial chemical reaction optimization algorithms) and mathematics-based techniques (such as meta-heuristics and base algorithms)[31]. Additionally, hybrid approaches that combine them exist.Even though there are many highly effective algorithms and techniques in the literature, it is crucial to design, develop, and implement new strategies in the scientific field with the continuous improvement philosophy and always strive for better. Additionally, new meta-heuristic algorithms are continuously being proposed because the algorithm that yields the best results for all problems has not yet been designed. It is suggested that the current ones operate more efficiently.

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Because of this awareness, scholars have successfully added new meta-heuristic techniques to the body of literature in recent years. A. Algorithms for Socially Based Meta-heuristic Optimization

The literature contains a large number of recently suggested social-based heuristic optimization techniques. The most renowned The most commonly utilized among them is the Tabu search algorithm. Others have been filed more recently [32].

a) Algorithm of Imperialist Competitor

The Imperialist Competitor process (ICA) starts the process by generating an initial population, just as analogous evolutionary algorithms. The top few nations in terms of initial population are selected as imperialist nations, and the remainder people become imperialist colonies. The states that make up the empire divide up all of the specified regions. The colonies start to gravitate in the direction of the right imperialists after being distributed among the imperialist powers. Empires' strength is determined by the imperialist's capacity and their their areas ceded to the imperialists. The algorithmic process is ongoing, with the race between the imperialists having begun. Not able to

The imperialism will be removed from the race if it manages to get stronger or achieve success. Robust empires gain power during the race, whereas weak kingdoms deteriorate and head toward collapse. The race goes on until there is only one empire left, at which point other nations become colonies of the empire that survives thanks to an algorithm. Territories and imperialists will hold equal status and authority in the utopian society that is created at the conclusion of the race [33].The algorithm's flow chart is displayed in Figure 5.

b) Educating Algorithms for Learning-Based Optimization

The Teaching Learning Based Optimization is another newly created meta-heuristic optimization technique. optimization issue, with the fitness function's best value being the optimal solution. There are two scenarios in which the TLBO algorithm operates: The Method of Instruction and The Process of Learning[36].It is well acknowledged that the instructor plays a crucial role in the teaching process as the one who imparts information to the students. Students are a clear indicator of a teacher's quality. It has been shown that when pupils have excellent professors, both their circumstances and grades improve.

As a result, the interaction between the teacher and the student affects the teaching process. Students are the primary component in the learning process [37].To help in understanding the phases of the TLBO algorithm, a flow chart has been produced, as shown in Figure 6.

Algorithm (TLBO) [34]. The TLBO algorithm operates based on how a teacher affects their pupils in a classroom. The teaching and learning capacities of instructors and pupils at a school are described by the algorithm. Two fundamental elements of this algorithm are the teacher and the pupil [35].The population in the algorithm is the group of students, and other design variables for the optimization issue are the many disciplines that are taught to the pupils. The outcome of a student is comparable to the optimization problem's fit value. For the entire population, the teacher is thought to be the best option.The vocabulary employed in design

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c) Algorithm for Social-Emotional Optimization

A novel social-based optimization method called the Social-Emotional Optimization Algorithm (SEOA) mimics human conduct [38]. The human community is linked to the term "social." The community's residents work to elevate their social standing.

The SEOA's operational processes are listed in the algorithm.1. A step-by-step breakdown of the algorithm for social-emotional optimization

1. Get going

2. Every person is created one after the other, and the problem space is randomly assigned to each one of their starting places.

3. The goal function is used to compute each person's fitness value.

4. j. Based on the person's emotional index, their behavioral actions are dictated.

5. The whole population's location is updated.

6. The emotional quotient is calculated.

The optimal option, if the termination condition is satisfied,

7. The best option is approved if the termination requirement is satisfied. Step 2 is returned if the condition is not satisfied.

8. Come to an end.

Every individual in SEOA is a virtual person. People base their decisions on how to behave at each phase on the corresponding emotional index [39]. There are three categories for the emotional index: low, medium, and high. An action is chosen based on the emotional index. Depending on whether the intended behavior is accurate, the status value is recycled from society in accordance with the chosen behavior. The person's emotional index rises if this decision raises the social status value. If not, the social status value drops as the emotional index decreases [40].

c) Organizing Brainstorms

In generally acknowledged organizations, brainstorming is a popular technique to foster creativity, such as fostering creative contemplating. Osborn created brainstorming for the first time at the advertising agency in 1939. He organized this approach to problem-solving in Applied Imagination before the end of 1957 [41, 42]. Following then, brainstorming sparked a global interest in academics and business. People from various ethnic backgrounds get together during the brainstorming process to collaborate and interact in order to provide brilliant ideas for solving problems. The phases in the BFOA process that were created using brainstorming inspiration are listed in Algorithm Two steps to the Brain Storming Optimization Algorithm explanation:

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1. Get going

2. Individuals who might be possible solutions are produced.

3. There are n individuals and m groups.

4. N people are assessed.

5. Each cluster's members are ranked, and the cluster's center is assigned to the best member.

6. A value in the range of 0 to 1 is created at random.

(a). In the event that a generated value is smaller than P5a's predefined value

(i). At random, select a cluster center.

(ii). Create a random person to take the place of the selected cluster center.

7. Generate new persons.

(a). It generates a random number between 0 and 1.

(b). Should the generated value fall short of P6b,

6 (i). Select a random set a with probability P

(ii). Create a random number in the range between 0 and 1.

(iii). If the amount is below the predetermined

value of P6b

iii, 1) To create new people, choose the cluster center and add a random value.

If not, select a random person from the cluster and combine them with the value that was created at random to create new people.

(c). If not, choose two clusters at random to produce new people.

(i). Create a value at random.

(ii). Choose and combine two cluster centers, then add the randomly produced value to create additional people if the generated value is smaller than the predefined probability of P6c.

(iii). If not, two individuals are chosen at random from each cluster to merge, and the created value is added to create new individuals.

8. If n additional people are created, proceed to step 9 and then step 7.

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9. The point at which the predefined maximum number of iterations has been achieved; if not, proceed to step 3.

10. Stop.

e) Algorithm for Group Leaders Optimization

The Group Leaders Optimization Algorithm (GLOA) is an algorithm that was created through evolution, drawing inspiration from the impact of social group leaders. The issue space is split up into various groups, and a leader is chosen for each group [43].Each group's members don't have to be similar characters; they can be chosen at random. Each group selects its best member to be the leader. Every iteration, members of each group want to look like their leaders. The method establishes a solution space between the group members and the leader in this manner. Following a few actions, it was noted that group members had a leaderlike appearance. One person is picked at random to promote variety within the group. A few of The variables of the other group members take their position. Furthermore, a crossover operator facilitates the group's arrival to the local minimum, and another search of the solution space can be conducted to boost variety [44]. Figure 7 f) outlines the algorithmic procedures by which n groups of P members are created and group leaders are chosen based on their appropriateness values. An Algorithm for Social Hierarchies

The social behaviors seen in a range of biological systems and human organizations served as the model for the Hierarchical Social Algorithm (HSA). Several problems with infinite resources have been successfully solved using this meta-heuristic technique. The concurrent optimization of the set of appropriate solutions is the fundamental principle of HSA. Every social group has a workable answer, and these groupings are first dispersed at random to create distinct locations for the solutions. Each group uses development tactics to compete with their neighbors or improve their target function. In this instance, relevant social rivalry and collaboration yield a superior outcome 20. The objective solution is therefore optimized. The optimal solution is identified in a single group at the end of the procedure [1].

g) Algorithm for Human Group Formation

The Human Group Formation Algorithm (HGFA) is a modern social-based meta-heuristic optimization algorithm that draws inspiration from the behaviors of both outgroup and ingroup members that make an effort to stay as close to their groups as feasible. Sociologists have established what constitutes an in-group and out-group in order to categorize people into social groups. Those who are accepted by the group as members of the in-group include which they are a part of. When someone is classified as a member of a group, they identify with that group and believe that they are unique from other groups. They believe that their group is superior to all others. Because of this, even while they are apart from the group, members of the group make every effort to keep the group together [47]. It demonstrates the conversion of the ideas presented in Figure 8 into applications.

h) Algorithm With Social Basis

A novel algorithm known as a Social Based Algorithm (SBA) blends an evolutionary algorithm with a socio-political an Imperialist Competitor Algorithm-based procedure.

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People reside in a variety of communities, including multinational, republican, autocratic, and monarchical ones. Additionally, each community has a unique style of leadership. This strategy aims to include a small number of individuals in the community development trait [48]. Algorithm 3 displays the SBA's process phases.

Algorithm 3: The Social Based Algorithm explained step-by-step:

1. Launching

2. Filling up the parameters

3. adhere to

(a). Clearly stating the optimization issue,

(b). Creating a random population

(c). Choosing a few powerful individuals at random to serve as leaders,

(d). Placing the remaining people at random throughout various areas,

(e). Using the imperialist cost function to launch empires T.Pci, f. the selection of charismatic leaders to be emperors,

4. Ten circles Nd is equal to Nd+1.

5. where i = 1, 2,..., N

(a). Choice (b). Cross (c). Change (d). Substitution

6. Let i be 1, 2,..., N

(a). The leaders of each group are relocated to their kingdom as part of the assimilation program of humans

(i). $x ~ U$ (0, absorption inside x)

d) (ii). $d:$ The separator and imperialist's distance

(b) The revolution of the people

(c). Countries adopt an assimilation program in which the leaders of each group establish their empire and the populace of each nation follows suit

(i). $x ~ U$ (0, external assimilation coefficient x d)

(ii). $d:$ The separation between the imperialist and the leader

(d). The nation-state revolution

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(e). Modifying the address

(f). imperialist race: selecting the weak nation from the weak empire and awarding it to the empire with the highest probability of possessing it

(g). Elimination; the abolition of empire and the powerless principle

7. Verifying the termination requirement and continuing from steps 4 through 7 until it is satisfied.

8. Stop.

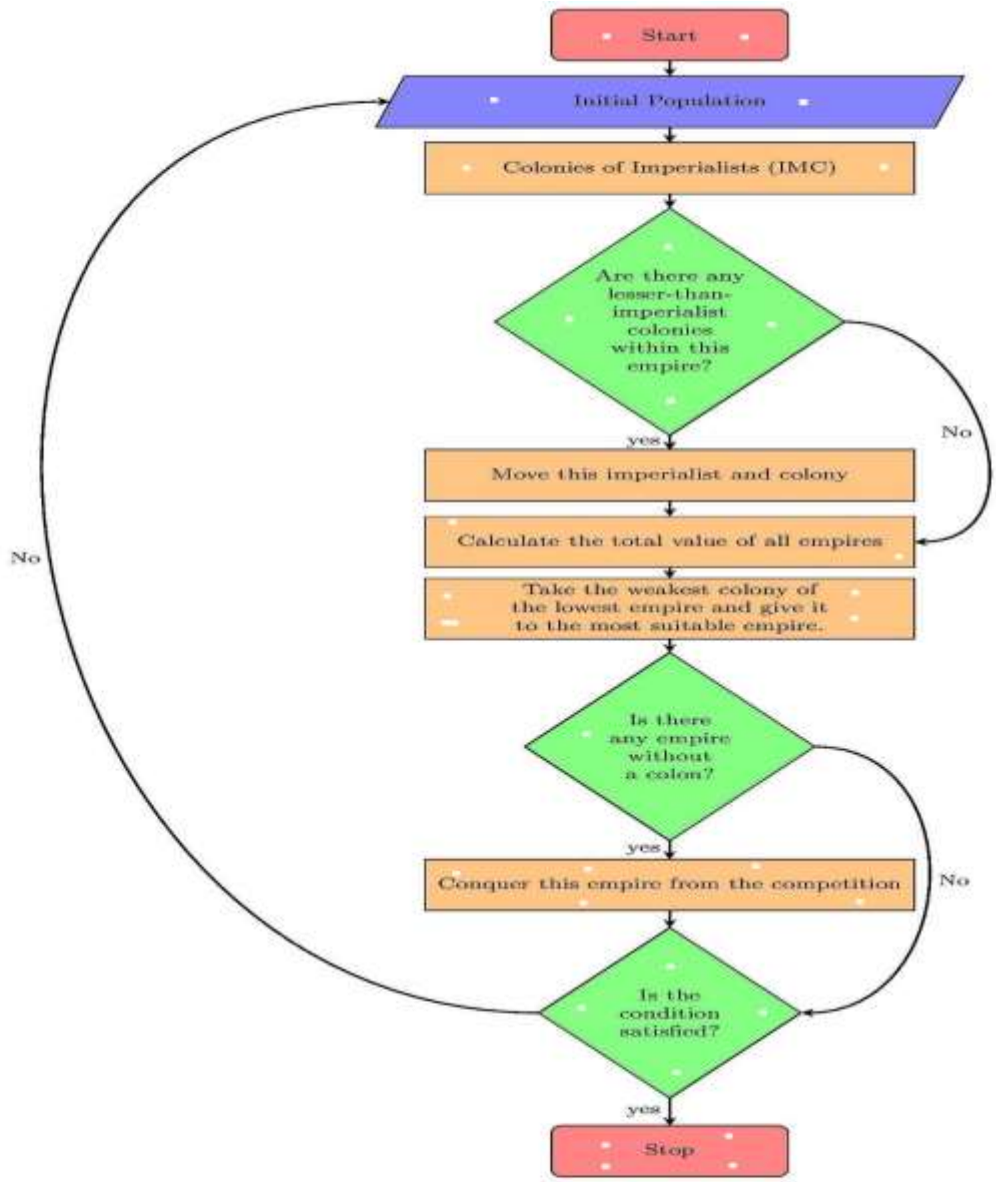

Fig. 5 Flow Chart Of Imperialist Competitive Algorithm

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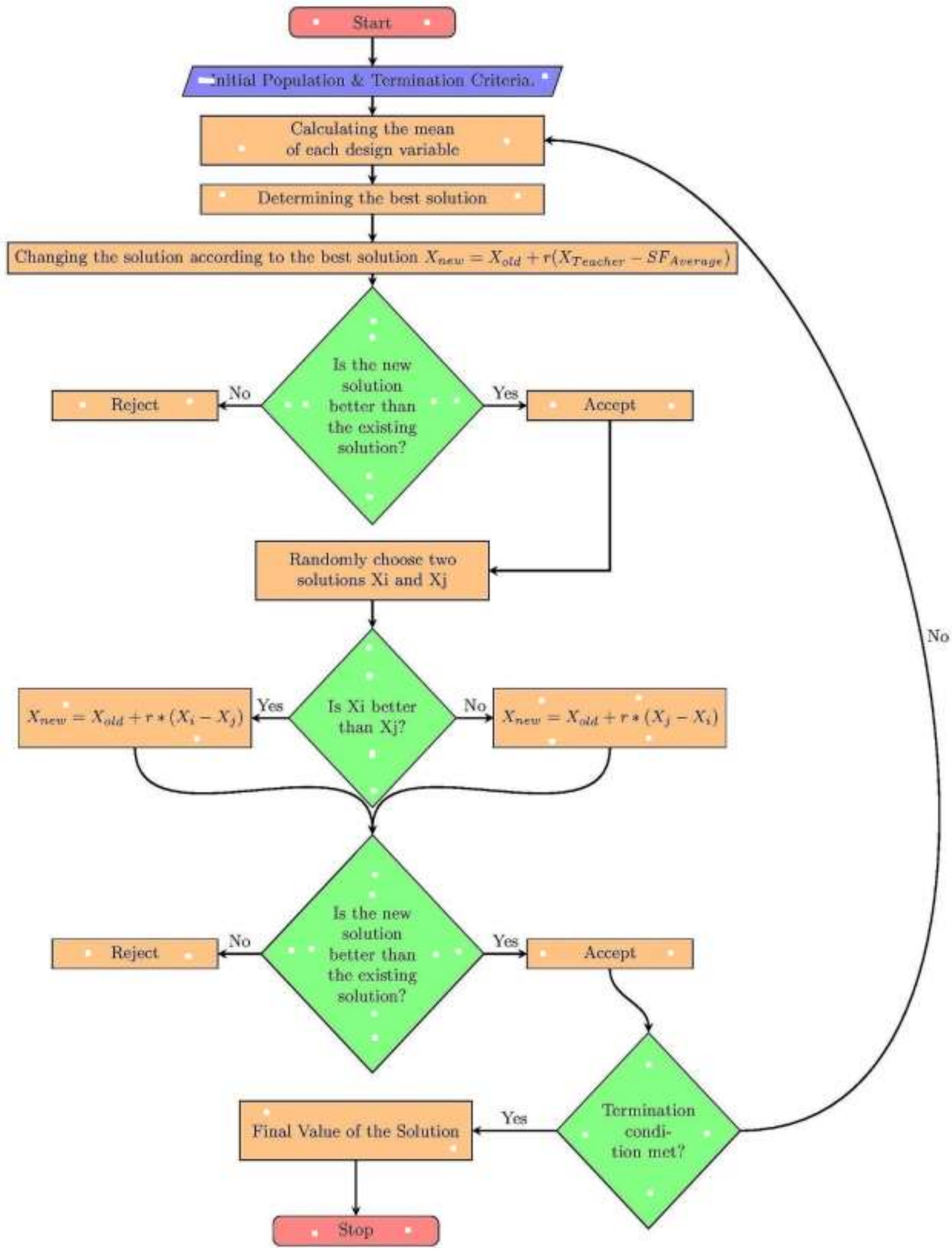

Fig. 6 Flow Chart Of TLBO Algorithm

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IV. BENCHMARK COMMUNITY DETECTION ALGORITHM SOCIAL THEORY RESULT ANALYSIS

Six distinct graphical social media data sets—Word adjacencies, Zachary Karate Club [49], Dolphin social network [50], Les Misérables, books about US politics, and American college football [51]—were used in the performance evaluation to determine the effects of single and multi-purpose based heuristic community detection algorithms. The evaluation parameters included modularity and normalized mutual information.

A structural evaluation of networks called modularity assesses how well a subgraph—a group, cluster, or community—in the network can be used to extract community structure [52]. Communities in a particular network develop as a result of groupings of nodes with higher modularity being relatively dense with one another in the network:

HA = 1 2|HA

$$\mathrm{M} = \frac{1}{2|E|}\sum_{\mathrm{xy}}\left[e_{xy} - \frac{w_x w_y}{2|E|}\right]\delta(C_x, C_y)$$

$$= \sum_{i=1}^{n} fii - f'^2_i$$

A probabilistic function (cx,cy) equals 1 if both nodes x and y belong to the same community structure, and 0 otherwise. fii represents the edge in the community i, and F′ is the belonging probability of a random edge to the community i that is attached to vertices in the community i. Where exy represents the edge from node x to node y, Wx represents the summation of the weights of the edges linked to node x, and cx is the belonging community structure of node x. On the other hand, normalized mutual information is a way to scale the similarity between intra community nodes by normalizing the intra-community mutual information score:

The 0 node and nmi(x, c) are completely different.

One node is identical to another

Mutual information may be computed using the formula

$$\mathrm{nmi}(\mathrm{x}, \mathrm{c}) == \frac{2 * \mathrm{i}(x, ci)}{e(x) + e(c)}$$

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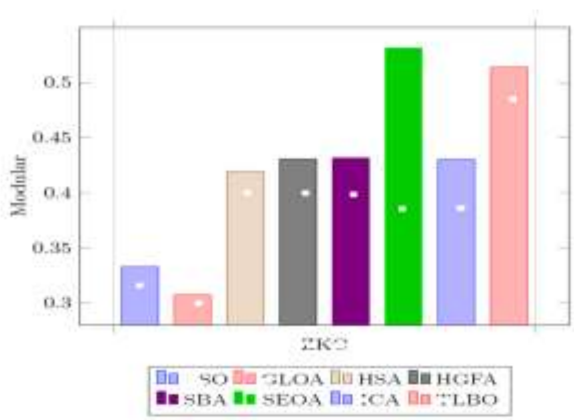
Table 1: A Comparative Examination of Social Theory's Effect on Modularity

Method of Classification	Modularity					
	DCN	BUP	LM	WA	ZKC	ACF
ICA	0.6179	0.6714	0.6122	0.4192	0.4302	0.7211
SEOA	0.661	0.61	0.6121	0.4118	0.5313	0.6107
BSO	0.4844	0.5674	0.5105	0.3611	0.3326	0.6213
GLOA	0.6179	0.6714	0.6122	0.4192	0.4302	0.7211
HSA	0.661	0.61	0.6121	0.4118	0.5313	0.6107
SBA	0.4844	0.5674	0.5105	0.3611	0.3326	0.6213
HGFA	0.4844	0.5674	0.5105	0.3611	0.3326	0.6213
TLBO	0.6196	0.7119	0.6217	0.5103	0.5137	0.6204

Table 2: Comparison of Social Theory's Effects on Normalized Mutual Information

Method of Classification	Mutual Information Normalized					
	DCN	BUP	LM	WA	ZKC	ACF
ICA	0.4844	0.5674	0.5105	0.3611	0.3326	0.6213
SEOA	0.6179	0.6714	0.6122	0.4192	0.4302	0.7211
BSO	0.661	0.61	0.6121	0.4118	0.5313	0.6107
GLOA	0.4844	0.5674	0.5105	0.3611	0.3326	0.6213
HSA	0.4844	0.5674	0.5105	0.3611	0.3326	0.6213
SBA	0.6179	0.6714	0.6122	0.4192	0.4302	0.7211
HGFA	0.661	0.61	0.6121	0.4118	0.5313	0.6107
TLBO	0.4844	0.5674	0.5105	0.3611	0.3326	0.6213

The class label performance evaluation of the benchmark community detection algorithm with and without social theories is displayed in tables 1 and 2 as modularity and normalized mutual information, respectively, where c is the community structure, e is the entropy, and i(x;c) is the information gain for element ci. The integration of social theories with the community detection algorithm leads to a considerable improvement in both assessment parameters. The approximate results of the community detection algorithms



BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO 62.11%, 86.18%, 71.53%, 82.43%, 81.02%, 86.51%, and 86.24% NMI over 33.26%, 30.76%, 41.95%, 43.05%, 43.14%, 53.13%, 43.02%, and 51.37% modularity

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ZKC datasets, as seen in Figures 9 and 10.

The highest NMI information is achieved by the ICA and TLBO algorithms, but the SEOA method leads in modularity.

Fig. 10 Normalized Mutual Information for ZKC Data Set Community Detection

Fig. 11: Community Detection's Modularity Across AFC Data Set

On the other hand, as illustrated in figures 11 and 12, the community detection algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO gain approximately 62.13%, 59.47%, 59.29%, 72.03%, 60.14%, 61.07%, 72.11%, and 62.04% modularity over the AFC dataset. While SEOA and HAS algorithms accomplish modularity, ICA algorithm leads the way.

the highest NMI data. In contrast, the community detection algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO gain around 56.74%, 51.75%, 56.01%, 67.68%, and 61.57% over the BUP dataset.

As seen in figures 15 and 16, there is 61.51%, 67.14%, 71.19% modularity and 42.25%, 52.09%, 52.61%, 52.53%, 51.43%, 69.55%, 57.12%, and 52.51% NMI, respectively. The maximum NMI information is achieved by the SEOA algorithm, whereas the TLBO method leads in modularity. On the other hand, as illustrated in figures 17 and 18, the community detection algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO on the LM dataset gain approximately 51.05%, 50.98%, 58.61%, 60.79%, 60.71%, 61.21%, 62.17% modularity and 42.25%, 52.09%, 52.61%, 52.53%, 51.43%, 69.55%, 57.12%, and 52.51% NMI, respectively. The maximum NMI information is achieved by the SEOA algorithm, whereas the TLBO method leads in modularity. In contrast, the WA dataset, BSO, GLOA, and HSA community discovery algorithms About 56.74%, 51.75%, 56.01%, 67.68%, 61.57%, 61.51%, 67.14%, and 71.19% modularity are gai

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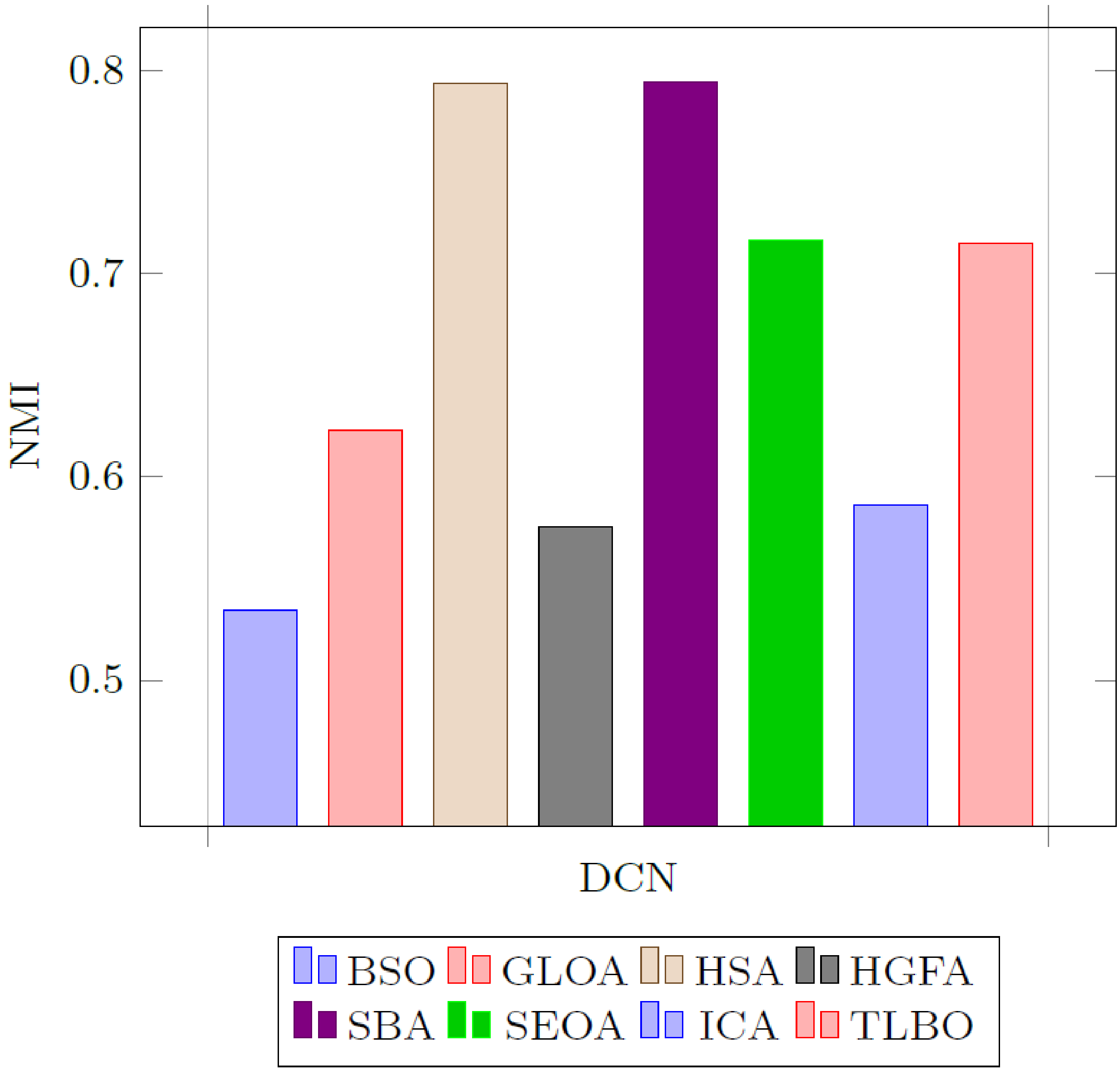

ned by BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO, whereas 42.25%, 52.09%,

Figures 15 and 16 illustrate 52.61%, 52.53%, 51.43%, 69.55%, 57.12%, and 52.51% NMI, respectively. The maximum NMI information is achieved by the SEOA algorithm, whereas the TLBO method leads in modularity. On the other hand, as illustrated in figures 17 and 18, the community detection algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO on the LM dataset gain approximately 51.05%, 50.98%, 58.61%, 60.79%, 60.71%, 61.21%, 62.17% modularity and 42.25%, 52.09%, 52.61%, 52.53%, 51.43%, 69.55%, 57.12%, and 52.51% NMI, respectively. The maximum NMI information is achieved by the SEOA algorithm, whereas the TLBO method leads in modularity. Conversely, the community detection algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO gain almost the same across the WA dataset.

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about 39.15%, 39.27%, 32.84%, 45.82%, 43.01%, 58.22%, 42.68%, and 51.22% NMI and 36.11%, 34.92%, 30.30%, 35.32%, 41.87%, 41.18%, 41.92%, and 51.03% modularity

as indicated by figures 19 and 20. While the SEOA algorithm produces the maximum NMI information, the TLBO algorithm wins in modularity.greater ACF network density, higher performance rate, and comparatively lower over the less dense WA dataset. Heuristic overlap across six distinct social media-based datasets for community recognition algorithms. According to this study, the performance rate of the community detection algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO varies with network density over social media datasets. It obtains a greater performance rate in dense ACF networks and a significantly lower one in weakly packed WA datasets. Additionally, across the greater dense network, TLBO and ICA are able to extract a higher informative community.

Concurrently, SEOA and the less dense networks. Network density affects how well community discovery algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO perform on social media datasets. It accomplishes a

greater ACF network density, higher performance rate, and comparatively lower over the less dense WA dataset. Heuristic overlap across six distinct social media-based datasets for community recognition algorithms. According to this study, the performance rate of the community detection algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO varies with network density over social media datasets. It obtains a greater performance rate in dense ACF networks and a significantly lower one in weakly packed WA datasets. Additionally, across the greater dense network, TLBO and ICA are able to extract a higher informative community.In addition, SEOA and HAS need to achieve greater outcomes with the less dense

V. CONCLUSION AND FUTURE WORK

In order to provide a thorough analysis of overlapping community structure on social networks, this research is regularly faced in daily life, and resolves community discovery that aligns with an approach that has never been used previously. The investigation and analysis have shown that the methods created for identifying overlapping communities in social networks offer answers to this issue by focusing on a single goal. This research also provides a comparative examination of six distinct social media-based data sets using meta-heuristic overlapping community recognition techniques.This study found that the performance rates of the community detection algorithms BSO, GLOA, HSA, HGFA, SBA, SEOA, ICA, and TLBO varied with the density of the social media data set. It achieved greater performance rates in the dense ACF network and significantly lower ones in the minimally packed WA data set. Additionally, across the greater dense network, TLBO and ICA are able to extract a higher informative community. Simultaneously, the less dense networks produce superior outcomes for SEOA and HSA.

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