Implementation of Girvan-Newmann Algorithm in Community Detection on Youtube Social Media

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Abstract*—Youtube is one of the largest information dissemination platforms. Youtube has over a billion monthly users and over six billion hours of video views every month. Seeing the immense popularity of Youtube, it creates opportunities for influencers to interact with audiences and influence the behavior of the global community. This research focuses on the analysis of community structure in the YouTube social network using the Girvan-Newman algorithm which aims to understand the pattern of interaction and social structure within the YouTube network. The study was conducted on two experiments with different tissue sizes: small tissue with low density (0.0169) and large tissue with higher density (0.1436). The results showed that small networks were more fragmented, while large networks had a more complex structure with more relationships between nodes. The value of betweenness centrality in small networks is uniform, reflecting a simple structure without dominant nodes. In contrast, in large networks, there are variations that reflect the existence of crucial pathways to connect communities. Modularity in both networks shows a pattern of fluctuations that reflect changes in the structure of the community during the process of algorithm iteration. The number of communities formed varies, from 12 communities on a small network to 999 communities on a large network, with many small communities consisting of only one node.

***Keywords*—community detection, Girvan-Newman, betweenness centrality, modularity.**

I. Introduction

A. Background

Social media, especially YouTube, has now become an important part of everyday life, serving as a means of communication, education, entertainment, and even shaping social opinions. According to the Indonesian Internet Service Providers Association (APJII), 61% of internet users in Indonesia regularly watch YouTube, making it the most popular social media platform with a usage percentage of 93.8% among internet users [1].This popularity makes YouTube not only a place to share content, but also an arena for many influencers to build close interactions with their audience. Today, YouTube is the third most visited site in the world, with more than one billion monthly visitors watching more than six billion hours of video each month. Every minute, more than 100 hours of new videos are uploaded on the platform. This condition shows how massive the growth of content on YouTube is and how much influence this platform has in shaping trends and behaviors of the global community [2]. This popularity makes YouTube not only a place to share content, but also an arena for many influencers to build close interactions with their audience. Today, YouTube is the third most visited site in the world, with more than one billion monthly visitors watching more than six billion hours of video each month. Every minute, more than 100 hours of new videos are uploaded on the platform. This condition shows how massive the growth of content on YouTube is and how much influence this platform has in shaping trends and behaviors of the global community [2].

In the context of social network analysis, one of the main challenges is understanding how communities are formed within large networks like YouTube. Communities within social networks reflect groups of individuals who have a more intensive pattern of interaction among themselves compared to other individuals outside the group. This community detection is important because it can help uncover the underlying social structure of a network, understand group dynamics, and analyze the spread of information within that network. Various studies have been conducted to explore community detection using the Girvan-Newman algorithm. Based on this phenomenon, this study focuses on the application of community detection methods using the Girvan-Newman algorithm to identify community structures in social networks. The main goal of this research is to understand the patterns of interaction and social structure in the network, as well as provide in-depth insights into the dynamics of communities on platforms such as YouTube. The results of this research are expected to make a significant contribution in the field of social network analysis and support data-based strategic decision-making in the digital era.

B. Problem Statement

Based on the above background, the formulation of the problem in this study is as follows:

1. How can communities formed in social networks be identified using the Girvan-Newman algorithm?
2. How can the structure of social networks be analyzed to understand patterns of interaction and relationships between individuals in the detected community?
3. How can community dynamics in social networks be utilized for marketing strategies, online community management, or social research?

C. *Research Objectives*

Based on the formulation of the problem, this study aims to:

1. Identify the communities formed in the social network using the Girvan-Newman algorithm.
2. Analyze the structure of social networks to understand patterns of interaction and relationships between individuals in the detected community.
3. Provides insight into community dynamics in social networks that can be leveraged for marketing strategies, online community management, or social research.

II. METHODOLOGY

A. *Girvan Newmann Algorithm*

Various studies have been conducted to explore community detection using the Girvan-Newman algorithm. The Community Detection by Node Betweenness Using Optimized Girvan-Newman Cuckoo Search Algorithm [3] research for example, optimizes this algorithm with the Cuckoo Search Algorithm (CSA) to detect communities and identify the most influential individuals based on their betweenness values. This research shows the importance of algorithm optimization to ensure speed and accuracy in community analysis.

In addition, the Evaluating Methods for Efficient Community Detection in Social Networks study [4] compared the Girvan-Newman algorithm with other algorithms such as Louvain and Propinquity Dynamics, using metrics such as modularity and NMI. This study highlights the advantages and disadvantages of each method in detecting communities in social media datasets. On the other hand, the Girvan-Newman algorithm has also been applied in other contexts, such as the Community Detection research using the Girvan-Newman Algorithm in Recommendation System [5]. which uses this approach to improve social network-based recommendation systems and e-commerce through user community analysis.

Research on community detection with the Girvan-Newman algorithm is very relevant in understanding the structure of social networks, including on the YouTube platform. By mapping communities on these networks, we can gain insights into how users connect with each other, identify groups that share similar interests or interaction patterns, and uncover patterns of information distribution and influence within those communities.

B. *Community Detection*

The development of social network analysis includes the development of methods and algorithms used to analyze various types of networks, including dynamic networks, heterogeneous networks, and directed social networks. In addition, in some cases, community detection on social networks has become a solution to detect group dynamics through various methods such as parallel community detection. [1]. Community has many definitions in computer science. One is a network that is described as a graph consisting of a group of nodes with more sides connecting them to each other than the sides connecting other nodes in the network [2]. One of the definitions of community that researchers agree on is a network that describes a group of groups with nodes that are connected more often than other group nodes. [3]. One of the publications on community detection that has been carried out by researchers with affiliates in Indonesia is literature research on community detection techniques [2], namely 1) centered on nodes, such as k-click and k-club; 2) group-centered, which must meet the requirements of density group; 3) network-centric, such as node similarity, latent space model, spectral clustering, and modularity maximation; and 4) hierarchical-centered, such as divisional and agglomerative clusters.One of the definitions of community that researchers agree on is a network that describes a group of groups with nodes that are connected more often than other group nodes. [3].

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To identify and detect communities on social networks, various community detection algorithms, also known as clustering algorithms, have been developed. These algorithms can generally be differentiated into 2 i.e., Non-overlapping algorithms have one node in the network that has more than one community and also Overlapping algorithms have one node in the network that is not part of another community [1]. The algorithm is used for grouping or splitting nodes, as well as looking for a tendency to strengthen or split [4]. Research on community detection is inseparable from the analysis of actors that have high influence (centrality) and network analysis (such as social networks). As in a study that has detected communities with #FIFAWorldCup hashtags on Twitter, it found 8 different main communities. The results of the analysis can be used to understand how behavior socializes and interacts on a social network [5].

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The results of the analysis can be used to understand how behavior socializes and interacts on a social network [5]. Another study used community detection to look at spider species, which saw that out of the 159 communities formed, China has the largest spider community with 279 species of spiders, followed by Japan, the USA, and New Zealand as the 3 countries with the largest spider communities [4]. Another study used community detection to look at spider species, which saw that out of the 159 communities formed, China has the largest spider community with 279 species of spiders, followed by Japan, the USA, and New Zealand as the 3 countries with the largest spider communities [4].

C. *Youtube social media*

Social media is one of the important sources of information for young people [19] and YouTube seems to be very relevant. Where, young people watch videos on YouTube to gain new knowledge and make their own opinions [20]. In April 2020, YouTube ranked second among the online video platforms with the highest number of active users worldwide after Facebook. This makes it the most famous and well-known online video platform of all time [21]. In 2019, nearly two-thirds of German teenagers aged 12 to 19 said that YouTube was their favorite online website. With ninety percent of them watching YouTube videos regularly. Comparable results were also found in the United Kingdom and Israel [22].

Research on Youtube data has been conducted before by Cynthia Pasquel-López, Lucía Rodríguez-Aceves, and Gabriel Valerio-Ureña. The study focuses on social networks among EduTubers (content creators who focus on education) to understand the influence of collaboration and recommendations between channels that have similarities in terms of language, audience, and topic. The study found that there is a relationship between out-degree (the number of recommendations given by the channel) and digital engagement. This means that EduTubers with higher levels of digital engagement tend to provide more recommendations [23]. The research describes how these factors can increase exposure and discoverability on Youtube.

III. RESEARCH STAGES

The flow of the research stages carried out in identifying communities on the YouTube social network is shown in Figure 1. Flow of Research Stages.

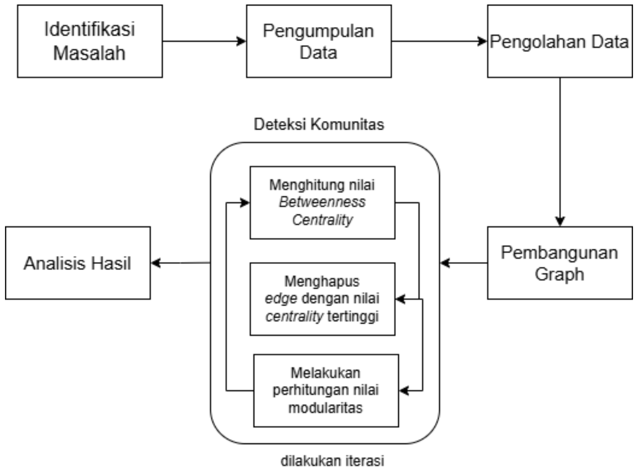


Figure 1 Flow of Research

The stage starts from Problem Identification, which is to understand the number and characteristics of the community that will be formed. Followed by Data Collection from YouTube and Data Preparation, such as cleaning and calculating centrality values. The next stage is Graph Development using NetworkX, followed by Community Detection using the Girvan-Newman method to separate the graph into smaller communities. After that, a Modularity Calculation is carried out to evaluate the quality of the community, and ends with a Result Analysis to assess the community based on modularity and its components.

A. *Data Collection and Preparation*

The dataset that will be used in this project is the Most Subscribed Youtube Channel from Kaggle, https://www.kaggle.com/datasets/surajjha101/top-youtube-channels-data. The dataset has 999 nodes, which shows the total number of users in it, and 7,185 edges, which shows all the friendship relationships that exist in it. In the dataset, there are 6 columns which include 'rank', 'Youtuber', 'subscribers', 'video views', 'video count', 'category', and 'started'. The description of these attributes will be listed in Table 1.

Tabel 1. Attributes of Dataset

Name of Attributes	Description
Rank	The order of youtubers from the most followers to the lowest.
Youtuber	The youtuber's youtube account.
Subscribers	The number of followers of the youtube account.
Video views	The number of video views from the youtube account.
Video count	The number of videos uploaded by the youtube account.
Category	Uploaded video category.
Started	The year the youtuber started to be active.

B. *Exploratory Data Analysis/EDA*

Exploratory Data Analysis (EDA) was conducted to understand the characteristics of the Most Subscribed YouTube Channels dataset. The initial analysis includes the number of nodes, edges, and network density. The characteristics of the dataset will be displayed in Table 2.

Tabel 2. Data Characteristics

Number of Nodes	999
Number of Edges	71585
Network Density	0,1436

The dataset consists of 999 nodes representing YouTube accounts, and 71,585 edges showing relationships between accounts. The network density, which indicates the proportion of existing relationships compared to the maximum number of possible relationships, was recorded at 0.1436. This indicates that the network has a fairly high level of connectivity.

C. Pre-Processing

The pre-processing stage aims to prepare the raw data for use in the Girvan-Newman community detection algorithm. The first step is data cleaning, where empty, redundant, or irrelevant data is deleted to improve the quality and reliability of the analysis. Next, the data was transformed from tabular format to graph form using the NetworkX library in Python. In this graph, each YouTube user is represented as a node, while the relationships between nodes are represented as edges.

This normalization helps ensure that attributes that have different value ranges do not dominate the graph analysis. After normalization, the dataset was converted into a graph with a number of vertices of 999 and a number of sides of 71,585, according to the dataset used. Each node represents a single YouTuber, and the sides between the nodes describe the friendship or interaction between them.

D. Modelling and Calculation

Once the pre-processing is complete, the next step is to apply the Girvan-Newman algorithm to detect the community. This method works in a top-down hierarchical way, i.e. by breaking down the graph into smaller components based on the elimination of the sides that are considered the most important.

a. Initialization

In the initial stage, a complete graph is formed based on the dataset that has been processed. This graph includes all the available vertices and sides in the data.

b. Calculation of Between Centrality

To detect the community, the algorithm calculates the betweenness centrality value for each side in the graph. This value measures how often the side is traversed by the shortest path between the pair of vertices. The formula used is [6]:

$$B(e) = \sum_{u,v \in V(G)} \frac{\sigma_{u,v}(e)}{\sigma_{u,v}} \quad (1)$$

in formula 1, it's giving information about *σu, v* is the number of shortest paths between two different vertices and *σu, v (e)* i is the number of corresponding shortest paths containing a given edge

c. Side Removal with Highest Betweenness

The side with the highest value of betweenness centrality is considered the main link between different communities This side is removed from the graph, and this step is done iteratively. After each deletion, the algorithm updates the betweenness centrality value for all remaining sides.

d. Modularity Calculation

To evaluate the quality of community detection, modularity calculations are performed on each iteration. Modularity measures how well the graph is divided into communities compared to random divisions. The modularity formula [6] :

$$Q = \sum_{s=1}^{m} \left[\frac{l_s}{L} - \left(\frac{d_s}{2L} \right)^2 \right] \quad (2)$$

Which also contains an information in formula 2, *m for number of modules, ls* for *number of edges inside module s, L = number of edges in the network*, *ds is a total degrees of nodes in module s.* The modularity value is calculated for each iteration, and the iteration process continues until the maximum modularity value is found, which indicates the best division of the community.

e. Result Analysis

The end result of this algorithm is the division of the graph into several smaller communities. Each community is analyzed based on its internal structure, such as the number of nodes, the number of sides, and the pattern of interaction between nodes. This analysis provides deeper insights into the dynamics of YouTube's social network, including the potential to identify the most influential influencers or users within a given community.

IV. Result and Discussion

In this study, two experiments were carried out on the dataset that had been owned. The first experiment uses 30 rows of data taken from the dataset based on the *youtuber* who has the most *subscribers* while the second experiment uses the entire dataset. These two experiments used different data centralities. Table 3 shows a comparison of centrality between the two experiments.

Table 3. Centrality Results of Experiments

	First trial	Second Trial
Number of nodes	60	999
Number of edges	30	71585
Network density	0,01694915254237288	0,1436

The first experiment showed a low density of only 0.0169. This indicates that the relationship between big Youtubers is less and separate. While the second experiment had a higher network density, which was 0.1436 which indicates the existence of a tighter cluster or community in the overall network. In this study, the iterations used in the first experiment were 18 times, while in the second experiment the number of *nodes* was 999.

In the calculation *of betweenness centrality* in the first experiment, all *edges* have the same value, which is 0.0023. This indicates that the network tends to be simple. Each node in the same category is connected to each other directly or through a short path, without any bottlenecks or critical paths connecting different categories, such as T-Series which is connected to Zee Music Company because it has the same category. This uniformity of *the value of betweenness centrality* also shows that no *edge* has a more important role than the others in the network. In other words, these networks have not yet shown a complex structure or hierarchy of connectivity.

Meanwhile, in the second experiment, there were two variations in *the value of betweenness centrality that reflected the existence of several* more dominant edges. The value *of the centrality bet* on the second trial can be seen in Table 4.

Table 4. Second trial Betweenness Centrality score

Edge	Betweenness Centrality
(125, 'Bollywood Classics')	0.0000010015
('Bollywood Classics', 579)	0.0000010015
(1, 'T-Series')	0.0000005007
......	......
(1000, 'Dobre Brothers')	0.0000005007

Bollywood Classics has *a higher* value of betweenness centrality *because the edge* that connects them plays an important role in connecting two communities or parts of a larger network. However, in addition to the two *edges*, the other *edge has the same* betweenness centrality *value*, which is 0.0000005007. This suggests that most of the relationships in the network do not act as the main link or the most important path between the other nodes.

Modularity is a measure used to assess the extent to which a network can be divided into communities or groups that are closer within it. Modularity values range between -1 and 1, with higher values indicating that the network has a clearer and more separate community structure. Conversely, a low or close to 0 value indicates that the communities in the network are more mixed or less structured. In the formation of a community using the help of modularity values, the first experiment has an initial modularity value of 0.67875, then there is an increase in the modularity value until it reaches the highest value of 0.6666, until finally the modularity value drops continuously and results in a final modularity of 0. In the second experiment, the initial modularity value produced was 0.99899, then the value decreased and increased again. The maximum increase after the decline was 0.99880. After reaching the maximum increase value, the modularity value continues to decrease until it reaches 0.

The first and second experiments have a similar pattern in the formation of their communities where at first, both experiments experience an increase in modularity values. This signifies that, in the early stages, community formation algorithms tend to separate networks into more separate groups. After several iterations, the communities began to connect with each other. This is reflected in the decrease in modularity value to 0. Although both experiments showed a similar pattern in modularity changes, the second experiment started with higher modularity and showed sharper fluctuations. This may be due to the larger and more complex size of the network, which allows for more interaction between communities. Based on the research that has been conducted, the following is shown the number of communities that can be formed in Table 5

Table 5. Modularity

	First Trial	Second Trial
Nodes	60	999
Edges	30	71585
Network Density	0,01694915254237288	0,1436
Number of Iterations	18 times	999 times
Number of Communities Formed	10 community	999 community

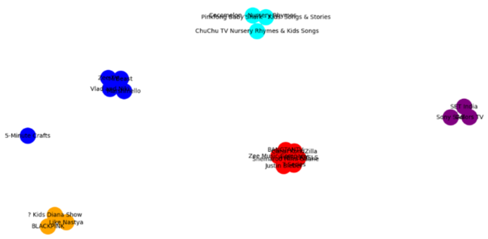
The first experiment resulted in 10 communities that will be shown in Table 6.

Table 6. Community First Experiment

Community	Youtubers who are connected
Community 1	'Canal KondZilla', 'Zee Music Company', 'Shemaroo Filmi Gaane', 'T-Series', 'Justin Bieber', 'BANGTANTV', 'HYBE LABELS'
Community 2	'Zee TV', 'MrBeast', 'Marshmello', 'Vlad and Niki'
Community 3	'Movieclips', 'YouTube Movies', 'Goldmines'

Community 4	'BLACKPINK', '? Kids Diana Show', 'Like Nastya'
Community 5	'Colors TV', 'Sony SAB', 'SET India'
Community 6	'Cocomelon - Nursery Rhymes', 'ChuChu TV Nursery Rhymes & Kids Songs', "Pinkfong Baby Shark - Kids' Songs & Stories"
Community 7	'Dude Perfect', 'WWE'
Coomunity 8	'Music'
Community 9	'PewDiePie'
Community 10	'Gaming'

The visualization of community formation in the first experiment will be shown in Figure 7.



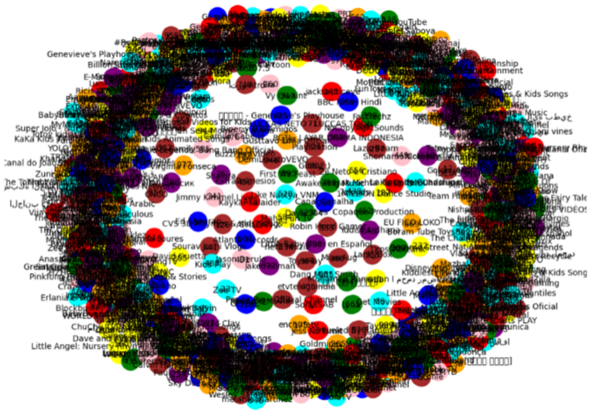
Gambar 7 Pembentukan Komunitas

The image shows some of the communities that have formed. In Figure 7, the clustering of each *node* where *the nodes* in one community are located close to each other and are marked with the same color. The distance between one community and another is quite far so that the grouping can be seen very clearly. Meanwhile, the second experiment resulted in 999 communities. As for Table 6, examples of 10 communities formed in the second experiment will be displayed.

Table 7. Second Community Trial

Community	**Youtubers who are connected**
Community 1	'Bollywood Classics'
Community 2	'T-Series'
Community 3	'YouTube Movies'
Community 4	'Cocomelon - Nursery'
Community 5	'SET India'
Community 6	'Music'
Community 7	'PewDiePie'
Community 8	'MrBeast’
Community 9	‘✿ Kids Diana Show'
Community 10	'Like Nastya'

While in the second experiment it produces a visualization of the cluster shown in Figure 8



Gambar 8 Klasterisasi

V. CONCLUSIONS

Based on the research that has been carried out, several important points have been obtained, namely:

a. Network Density

The first experiment had a low network density (0.0169), which suggests that the relationship between YouTubers is less and more separate. This suggests that the network is made up of several groups that are rarely connected to each other. While the second experiment, with a much larger network (999 nodes and 71585 edges), showed a higher density (0.1436). This indicates that there are more relationships between nodes, and the community structure in the network is closer and connected, which indicates that there are more complex interactions between communities.

b. Betweenness Centrality

In the first experiment, the betweenness centrality value tends to be uniform, with all edges having the same value (0.0023). This indicates that the network is simpler, with no dominant paths or nodes. Each node can be in direct contact with other nodes in its group. Meanwhile, in the second experiment, there was a variation in the value of betweenness centrality where there were edges that had a higher centrality value. This shows that there are several crucial pathways to connect communities within the larger network.

c. Modularity

In both experiments, there was an increasing and decreasing pattern of modularity values. This suggests that at first, community formation algorithms tend to separate existing communities, and after a few iterations, these communities begin to connect with each other.
However, the second experiment showed a sharper fluctuation in modularity values compared to the first experiment. This could be due to the larger and more complex size of the network, which allows for more possibilities for interaction between communities.

d. Number of Communities Formed

In the first experiment, there were 12 communities formed. These communities are made up of groups of YouTubers who have similar or related categories, such as groups that focus on music, children, or sports. In the Second Experiment, the number of communities formed was much higher, reaching 999 communities. However, many communities are made up of just one YouTuber, reflecting more specific segmentation or groupings within this larger network.

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