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Original Research

Distribution Patterns of Cyberbullying in Social Media using Social Network Analysis

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Abstract

Social media, widely known by the public, has become one of the tools to facilitate written expressions in daily life. The adoption individuals from various backgrounds use this technology, ranging from children, adolescents, adults, and the elderly. Social media positively influences human life, but various parties can also misuse it with harmful desires. One example of adverse treatment on social media is cyberbullying, which is now no longer a stranger in social life. In this research, the Social Network Analysis method is chosen to identify the distribution patterns of cyberbullying on social media. This method is used to analyze the required metrics such as indegree centrality, outdegree centrality, betweenness centrality, and reciprocity to understand the reasons for the spread of an event. This study has understood the distribution patterns of cyberbullying actions on social media by looking at communication between users and their relationships to find out the reasons for the perpetrators of cyberbullying actions. This result significantly impacts the community by better understanding the procedures in social media to avoid other users' bad behavior.

Keywords: Social Media, Social Network Analysis, Cyberbullying, Patterns.

Introduction

The emergence of the Internet and social media has opened up various possibilities for spreading information. One of this information is the distribution of informative content like news that is currently still being abused by bad behavior towards others that are destructive to bring down the dignity and dignity of someone using hurtful words. According to research conducted by Ybarra and Mitchell, it was found that 19% of children aged 10 to 17 years experienced unpleasant behavior in cyberspace as victims and perpetrators. In 2005 there were 3767 data from children attending secondary education; 11.1% experienced cyberbullying during the last two months, 4.1% were cyberbullying perpetrators, and 6.8% were both (Patchin & Hinduja, 2010).

Regarding cyberbullying in Indonesia, the Indonesian government enacted Act No. 11 in 2008 about Information and Electronic Transactions or *Informasi dan Transaksi Elektronik* (ITE). This action includes committing criminal offenses in polluting reputation, spreading sensitive issues, carrying out threats or extortion, accessing other people's electronic systems, and transferring electronic documents belonging to others will be subject to sanctions (Frensh, Kalo, Mulyadi & Bariah, 2017). But what is unfortunate is that the applicable law cannot be effectively enforced. Social media sites have become a means to freely give opinions and responses from users to other internet users. Until now, there are still not many cyberbullying perpetrators followed up by the government to be examined or prosecuted. This condition is because the existence of wrong actions against fellow social media users has spread very widely. The assumption that activity is only carried out from virtual media and based on words is still considered taboo for prosecution. At the same time, the law will only be enforced on Internet users who act and support the occurrence of illegal actions that tend to lead to cyber bullying and not cyberbullying itself.

In this research, the purpose is to find patterns in the spread of cyberbullying actions, which are the subject of problems on the Twitter social media platform. Identification of the distribution patterns can determine the purpose behind the distribution of these actions. This research can prove that communication and relationship that is formed is a critical element in carrying out an activity on social media.

Literature Review

Previous researches

Cyberbullying is an action aimed at one or many people intending to demean or hurt an individual committed in cyberspace (Natalia, 2016). Cyberbullying has become one of the many ways to deliver verbal attacks that are negative to the community to impact, such as mental damage to each individual. Cyberbullying is an act of bullying that demeans other individuals, such as ridiculing or taunting. It's just different from where it is implemented. The real account owner can no longer access actions such as changing someone's account photo, insulting someone else, hijacking someone else's account, or changing passwords that can point to someone's account is one example of Cyberbullying (Maya, 2015). A study by Yana Choria Utami stated that Indonesian people felt rude behavior from various circles, especially young people, based on 4,500 teenagers and children who volunteered as respondents. It can be stated that a person can have a higher level of depression compared to other groups that are only beaten and ridiculed directly. This condition can occur because cyberbullying in the community could happen without knowing the status and age (Utami, 2014). Social Network Analysis (SNA) is one way to find and identify the spread of Cyberbullying behavior in the community through social media platforms. This calculation method is commonly used to analyze the distribution patterns of information. SNA enables users to identify groups or individuals who are the main point in the network and reveal information hidden in complex networks (Serrat, 2017).

There are some researches conducted by utilizing Social Network Analysis. Research conducted by Anwar, Iriani and Manongga (2018) was analyzed to determine the distribution patterns of pornography on social media using social network analysis methods. The data obtained comes from tweets belonging to Twitter user accounts. In their research, the analysis of pornographic distribution patterns was carried out using 5 data differences when the data was taken. The study results are that the distribution is only a search result based on keywords because of the lack of results from the betweenness centrality and reciprocity analysis. The purpose is to determine the spread of pornography, including the relevance of the relationship between Twitter users (Anwar, Iriani & Manongga, 2018). Other research by Sucipto and Alamsyah (2016) studied text network analysis based on social network analysis and text mining to determine the perception of brand quality in conversation content on Twitter social media. This study produces opinions of word groups based on the number of words typed in tweets and sorted into categories based on their value. A's value indicates the highest level, and F indicates the lowest level. This study aimed to identify the perceived quality of a provider brand in conversation content on Twitter social media (Sucipto & Alamsyah, 2016). Ignatio, Putra and Bratawisnu (2018) researched determining top brands using social network analysis in e-commerce Bukalapak and Tokopedia in 2018. This study shows that the top brands on the Twitter social media platform are superior to Bukalapak. This research concludes that social e-commerce can be an alternative top brand by looking at social networks formed on the social media platform Twitter. This research aims to determine social network analysis methods for e-commerce in Bukalapak and Tokopedia through the social media platform Twitter (Bratawisnu, Putra & Ignatio, 2018). The study by Latupeirissa, Sediyono and Iriani conducted a study in 2019 regarding social network analysis to analyze communication collaboration in Ambon sea aquaculture centers. Based on research conducted, the report results are lameness in communication collaborations caused by the unbalanced presentation of the centralized network value by the percentage indegree is 47%, and outdegree value is 15%. The results of this study can be used to assess and improve communication collaboration. This research aims to find alternative actors who can act as a solution in communication collaboration (Latupeirissa *et al.*, 2019). Lastly, Rafta conducted a 2014 study on social network analysis by looking at news trends on Twitter accounts "@detikcom" and "@Metro_TV." After analyzing the two related Twitter accounts, the results obtained have the same tendency of reporting, in this case, concerning the disaster. Besides the similarities, there are also differences between the two accounts, namely the topic of disaster discussed by each account. The purpose of this research is to look for news trends in the two accounts that are the target of the study, namely "@detikcom" and "@Metro_TV" (Rafta, 2014).

It can be seen from the previous research that cyberbullying is affecting many, especially younger generations. The implementation of Social Network Analysis in analyzing the spread of information between the victim and perpetrators relating to cyber bullying, especially among Twitter users in Indonesia, has never been conducted. This research should provide good insight into this exchange of information that may contribute to preventive actions in the future.

Social Network Analysis

Social Network Analysis is achieved by analyzing the anatomical structure of a network. Identifying the main features of social networks can also be done as a user and the connection, and this relationship will create the formation of a network to be analyzed (Popp, Balogh, Oláh, Kot, Harangi Rákos & Lengyel, 2018). Social Network Analysis can enable the identification of actors or groups who play a central role in a network (Serrat, 2017). This identification does not escape the existence of several important metrics, such as indegree centrality, outdegree centrality, betweenness centrality, reciprocity, and community (Iriani & Priyanto, 2013). Indegree Centrality is the importance of an actor by showing how many relationships lead to a point. Outdegree Centrality is an actor's importance in showing how many connections come out of a point. Betweenness centrality is the degree to measure how far an actor can handle the flow of information between actors in a network. Reciprocity can show the proportion of reciprocal relationships, which describes the probability that the link will have the inverse relationship (Priyopradono, Manongga & Utomo, 2012). In SNA, the community is a group of actors in which intensive interaction occurs. The community can be called a sub-network (between communities remain connected in one network, not separate).

Materials and Methods

Figure 1 is a Flow Chart of the experiments in this research that shows how the methodology is applied to analyze the distribution patterns of cyberbullying on social media platforms, which is Twitter.

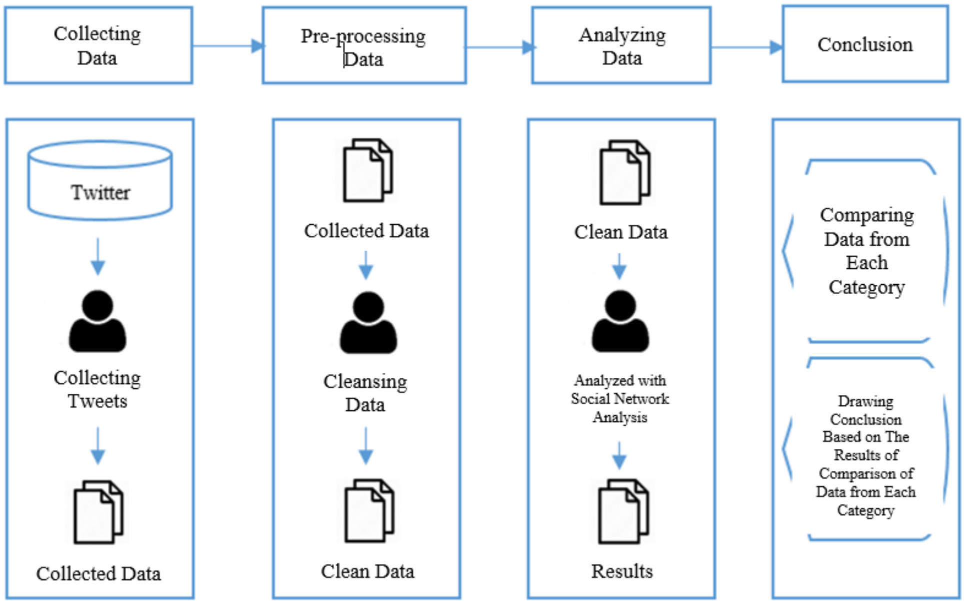

Figure 1. Experiments flow chart

Based on Figure 1, it can be seen that there are four essential stages in this methodology for analyzing the five categorical datasets, namely:

Stage 1: Collecting Data

In this stage, the research begins with installing Python 3.7.0 and continues using the Command Prompt on the computer to run data retrieval commands on Twitter's API that has a specific period between January 1st, 2010, and June 1st of, 2020. The process will also be limited to only taking 700 tweets, in which the content is only using Bahasa Indonesia. The data needed will be categorized into five categories based on its keyword in the query search of the command to get the appropriate data. These keywords state various synonyms of the word "stupid" in Bahasa Indonesia: *bodoh*, *bego*, *goblok*, *idiot*, and *tolol*. These words are commonly used in everyday language in Indonesia and are often used in texts in the context of bullying on social media. Then the data retrieved will be entered into a file with the format of .csv following the keywords of the data collected, which will be used to conduct analysis using the R Studio tools application.

Stage 2: Pre-processing Data

The collected data will be pre-processed to eliminate all the unnecessary data in this stage. Each category of the datasets will be cleansed or filtered by removing the useless data manually, in this case, the useless data can be seen by not having any interaction with one or another. The datasets that have been pre-processed will be saved into another file with the same format.

Stage 3: Analyzing Data

In this stage, each category of datasets will be visualized into networks and analyzed using the 'igraph' package in R. The analysis carried out includes an overview of the network and the metrics that exist in the SNA, such as degree centrality (indegree and outdegree), which is the degree of determining the importance of an actor based on the interaction the actor is having with another, betweenness centrality which is a measure of how far an actor / a node can handle the flow of information between actors in a network which if it has high values can be interpreted that the actor has a large capacity as a communication liaison for other actors in the network (Priyopradono *et al.*, 2012) using the following equation (1), reciprocity to determining that there is a communication that occurs between nodes on the network and forms a particular relationship using the following equation (2), and community to states the results in the form of communication made by nodes that exist on the network so that they have a joint relationship and form a group or community. The network is based on user-to-user interaction on Twitter's social media platforms, such as mentions, retweets, comments, and replies. The formed network is a directed graph that shows cyberbullying to participants. The network formed can then be exported into graphic format.

$$B(v) = \sum_{i \neq j, i \neq v, j \neq v} \frac{g_{ivj}}{g_{ij}} \tag{1}$$

$$R = \sum_{ij} (A \cdot A')_{ij} \tag{2}$$

Stage 4: Drawing conclusions and documentation

In this stage, the research will be evaluated to obtain conclusions based on the results by comparing data between five different categories to improve the quality of the results obtained during the study and increase the effectiveness in concluding.

After drawing all the conclusions available based on the results of this experiment, the research will end with making documentation in the form of a research report containing research data, the analysis process of the study, and the results of the research that has been conducted.

Results

The following section will discuss the analysis results using RStudio tools to various statistical measures and the centrality of the individuals in the network to determine the distribution pattern of Cyberbullying on Social Media Twitter.

Indegree Centrality

Table 1 shows data analysis with the top 10 accounts with each keyword category's highest indegree centrality levels. Based on these results, it can be seen that each Twitter account affected by cyberbullying behavior has a different level. Still, it cannot be ignored that several accounts have the same indegree centrality value.

Table 1
Indegree Centrality Analysis Results

No.	Category	Node	Indegree Centrality
1	*Bodoh*	show*******	8
2		darw********	5
3		math******	4
4		kart****	4
5		subt*****	4
6		wtfs*****	4
7		pend*******	4
8		idto*****	4
9		andi*****	3
10		alif*******	3
11	*Bego*	subt*****	18
12		Askn****	9
13		AREA*****	7
14		coll**********	6
15		PLAY***	4
16		andi*****	3
17		ebon***	3
18		ahma*****	3
19		Joko****	2
20		snug*******	2
21	*Goblok*	subt*****	18
22		Askn****	13
23		AREA*****	11
24		Sant*****	7
25		usta**********	7
26		peny*********	6
27		bela***********	5
28		Devi*****	4
29		juye*****	4
30		doMb****	4
31	*Idiot*	cctv*******	45
32		IDIO**********	13
33		subt*****	12
34		Topa********	7
35		Sabe****	6
36		asli**	6
37		lura******	5
38		Jkch********	5

No.	Category	Node	Indegree Centrality
39		Netf*****	5
40		SonO********	5
41	*Tolol*	AREA*****	18
42		subt*****	18
43		Askn****	7
44		PLAY***	6
45		BadC*******	6
46		jawa****	5
47		rece**********	5
48		gata*********	3
49		pend********	3
50		coll**********	3

It can be seen that some of the ten accounts with the highest in-degree centrality level values are the same account even though they are in a category with different keywords. This finding proves that the account concerned gets wider cyberbullying behavior than the results obtained from the data analysis.

Outdegree Centrality

Table 2 shows the result of data analysis with the top 10 accounts with the highest outdegree centrality levels of each keyword category. Based on these results, it can be seen that every Twitter account that carries out cyberbullying behavior has a different level. Still, it cannot also be ignored that several accounts have the same outdegree centrality value.

Table 2
Outdegree Centrality Analysis Results

No.	Category	Node	Outdegree Centrality
1	*Bodoh*	miek********	7
2		Sabe****	5
3		ksat*********	3
4		Fira********	3
5		Harr********	3
6		Ontn**	3
7		Suli****	3
8		ybri**	2
9		your***********	2
10		Nauf******	2
11	*Bego*	boyp*****	10
12		nahl***	7
13		miek********	5
14		midn****	5
15		Arie*********	3
16		angg********	3

No.	Category	Node	Outdegree Centrality
17		keyb***	3
18		hiip****	3
19		Jang*******	3
20		trac*******	3
21	*Goblok*	buka*******	13
22		hype***	10
23		peny*********	10
24		scen********	6
25		Devi*****	5
26		xixa*****	5
27		Anto*********	4
28		kele*********	4
29		sunr*****	4
30		woun***	4
31	*Idiot*	fiec***	16
32		idio******	15
33		Baby*********	14
34		Juli*******	13
35		purp***********	10
36		Uncl********	8
37		darw*********	8
38		itsa*********	8
39		rizq*********	8
40		GoSt********	5
41	*Tolol*	samu***********	7
42		beye***	3
43		Araa********	3
44		khal******	3
45		tida********	3
46		glori*********	3
47		dips******	3
48		thif******	3
49		pucc*********	2
50		Ihsa*******	2

It can be seen that some of the ten accounts with the highest central level outdegree value are the same account even though they are in a category with different keywords. This observation proves that the account concerned carried out broader cyberbullying actions than the results obtained from the data analysis.

Betweenness Centrality

Table 3 shows the result of data analysis with the top 10 accounts with the highest levels of betweenness centrality of each keyword category. Based on these results, it can be seen that each Twitter account that communicates with other accounts has a different level. Still, it cannot also be ignored that several accounts have the same value betweenness centrality.

Table 3
Betweenness Centrality Analysis Results

No.	Category	Node	Betweenness Centrality
1	*Bodoh*	Nauf******	1
2		zaqi*	1
3		cwan***	1
4		mrH4***	1
5		Djan*****	1
6		sedm***	1
7		baha*****	1
8		Izza********	0
9		ybri**	0
10		cape****	0
11	*Bego*	seon*****	2
12		yong****	2
13		rscb****	2
14		orey**	1
15		jung********	1
16		min9*****	1
17		ONLY***	1
18		hren****	1
19		97JH**	1
20		Kupr********	1
21	*Goblok*	peny*********	11
22		auto******	5
23		scen********	4
24		Pray****	3
25		sbyf***	2
26		woun***	1.4
27		Kent******	1
28		inju********	1
29		swee********	1
30		xixa*****	1
31	*Idiot*	IDIO*********	13
32		Juli*******	5
33		darw*********	4
34		Jeir**********	2
35		riri******	1
36		syar*****	1
37		pena**********	1
38		Riio******	1

No.	Category	Node	Betweenness Centrality
39		rick****	1
40		befo********	1
41	*Tolol*	PLAY***	6
42		tida********	2
43		glor**********	2
44		beye***	1
45		egyr******	1
46		sepe*********	1
47		parg******	1
48		cenl***	1
49		IHas******	1
50		tass***	1

The initial value of betweenness centrality owned by each node is generally zero, so it can be assumed that each account does not have some form of communication with other accounts. The value of the element betweenness centrality on an account will affect the distribution pattern of cyberbullying actions due to a formed connection. This finding can indicate that the accounts that carry out these actions have a relationship, but this relationship cannot be ascertained the truth.

Reciprocity

Table 4 shows the result of the analysis conducted for each data category to determine the reciprocity value. This section states the results of a level of relationship that nodes in a network in a particular type have. The table shows that the level of data in one category with another category has a different value, so it can be stated that the relationship based on differences in keywords used by Twitter users can affect a relationship and communication.

Table 4
Reciprocity Analysis Results

No	Category	Reciprocity
1	*Bodoh*	0.02023121
2	*Bego*	0.01443001
3	*Goblok*	0.02906977
4	*Idiot*	0.02911208
5	*Tolol*	0.04366812

The initial value of reciprocity owned by all nodes on the network in each keyword category is generally zero. Still, it can be seen that the value of each data category has a slightly higher value than the initial value. This finding can prove that there is communication between nodes on the network and forms a relationship in carrying out an act of cyberbullying.

Discussion

Community

The network formed in Figure 2, Figure 3, Figure 4, Figure 5, and Figure 6 results from executing the code to create a network visualization with communities based on data categorized according to the keywords. This section states the communication results made by nodes on the network to have a mutual relationship and form a group or community. Groups whose members communicate can be seen based on their color, and these colors are given to distinguish one group from another.

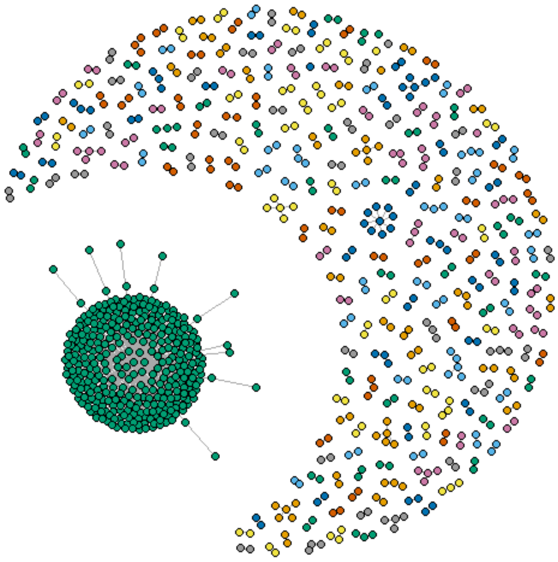

Figure 2. Visualization Results for the "Bodoh" Category Network with Community

Figure 2 shows the results of the code execution previously done by forming a network model of the data set with the keyword category "*Bodoh*." In this network, various colors represent several nodes, and different colors indicate the relationship between members of the node's community formed because of their communication.

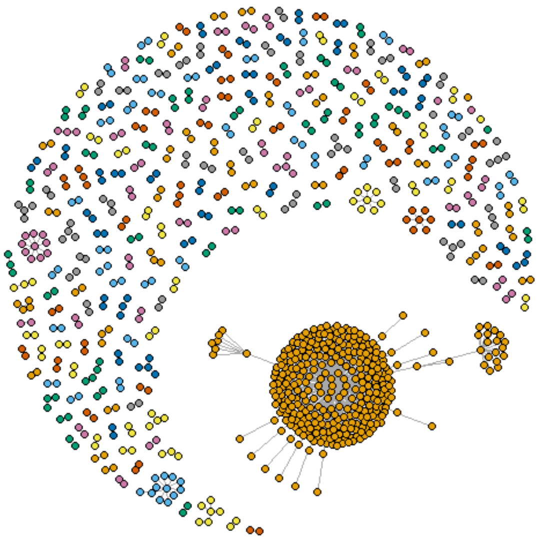

Figure 3. Visualization Results for the "Bego" Category Network with Community

Figure 3 shows the results of code execution previously done by forming a network model of the data set with the keyword category "*Bego*." In this network, various colors represent several nodes, and different colors indicate the relationship between members of the node's community formed because of their communication.

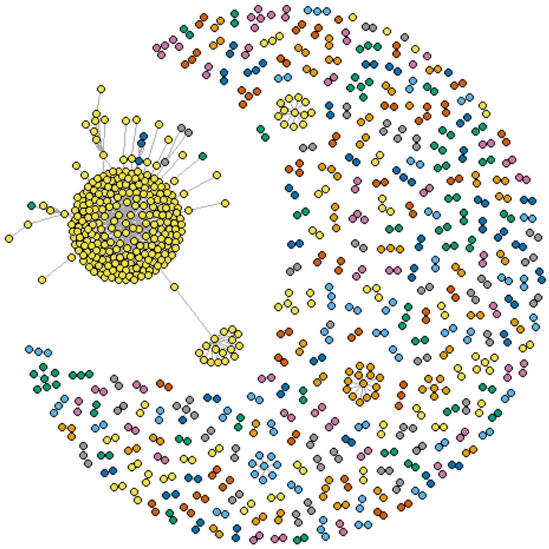

Figure 4. Visualization Results for the "*Goblok*" Category Network with Community

Figure 4 shows the code execution results that have been previously done by forming a network model of the data set with the keyword category "*Goblok*." In this network, various colors represent several nodes, and different colors indicate the relationship between members of the node's community formed because of their communication.

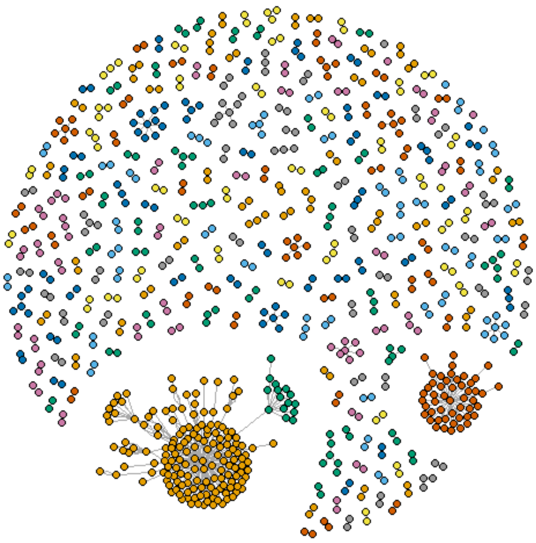

Figure 5. Visualization Results for the "*Idiot*" Category Network with Community

Figure 5 shows the results of the code execution previously done by forming a network model of the data set with the keyword category "*Idiot*." In this network, various colors represent several nodes, and different colors indicate the relationship between members of the node's community formed because of their communication.

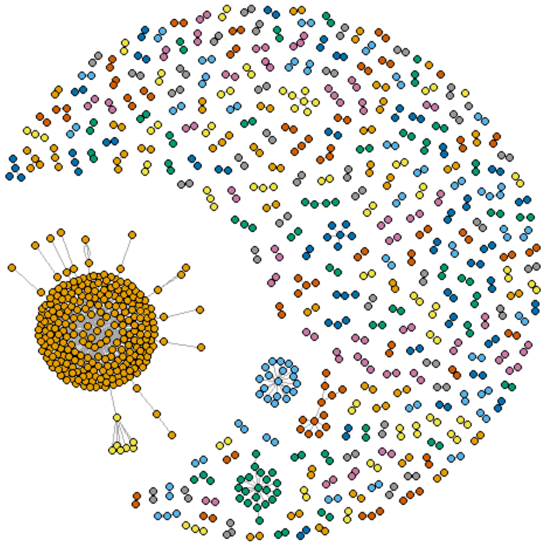

Figure 6. Visualization Results for the "*Tolol*" Category Network with Community

Figure 6 shows the results of code execution that had previously been done by forming a network model of the data set with the keyword category "*Tolol*." In this network, various colors represent several nodes, and different colors indicate the relationship between members of the node's community formed because of their communication.

Based on the above visualizations, it can be seen that there is no sign like an arrow on the edges indicating the activities of a node. This condition happened because, in communication that occurs, a reply is not necessarily obtained. Only one-way communication with other nodes can trigger a connection with the other and end with forming a relationship between nodes. This incident can be why someone gets cyberbullying treatment by many people. This situation is due to communication between actors to take action against the same person. In this case, the perpetrators agree that the victim who has become a target forms a relationship with other actors.

In this case, relationships formed in the community or made by members of groups occur because of an agreement. This agreement triggers cyberbullying done simultaneously or gradually by the perpetrators. This observation can be evidence that the communication carried out by the perpetrators can make the perpetrators and their victims have one relationship, namely the relation between cyberbullying done by the perpetrator and received by the victim.

Conclusion

In this study, the results show that not all nodes or user accounts in the network data set the category to have a relationship with each other. Still, it cannot be ignored that several accounts communicate to form a connection between the perpetrators of cyberbullying actions and create a distribution pattern on social media. Based on observations made, several conclusions can be drawn as follows:

1. An offender can decide to take cyberbullying action against the victim because of the communication between the perpetrator and the victim, which is mostly conducted in one way. This observation can be seen from the reciprocity value shown in table 4 and all the visualizations shown in Figures 2, 3, 4, 5, and 6.

2. The pattern shown from all the visualizations is that this distribution occurs in cases owned by victims who receive mistreatment from several perpetrators. This behavior tends to be possessed by tweets belonging to victims who have received cyberbullying treatment at least once, so it can be concluded that the interaction between the perpetrator and the victim can trigger other accounts to take the same actions to the victim.

3. The relevance of cyberbullying perpetrators arises after several actors have communicated together. This communication is based on mutual and forming relationships between perpetrators, so it can be concluded that creating groups or communities that contain perpetrators in one case of cyberbullying acts against the same victim occurs because of the same opinion from each member of the perpetrators to the victims.

With this research, victim accounts and other accounts can be more careful when making social media decisions. Perpetrators can use the communication made by the victim to carry out their actions by inviting other accounts and bringing up new actors who commit cyberbullying. This finding can help social media users think deeper about the causes and consequences of action so that undesirable things can be avoided and get favorable treatment from fellow social media users.

After conducting research, the author has several suggestions for subsequent study, which also analyzes the pattern of distribution of an event on social media using social network analysis methods, which are as follows:

1. Analysis of the distribution patterns of an event on social media can be performed on social media other than Twitter.

2. The distribution patterns can be analyzed on topics other than cyberbullying, resulting in similar or different findings.

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