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Anti-Rumor in Social Network Using Influencers Detection Algorithm

A Thesis

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بسم الله الرحمن الرحيم

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Dedication

"It always seems impossible until it's done."

—Nelson Mandela

I dedicate this thesis

To my mother and father, whose words of support and perseverance illuminated my path.

To the assistant on this journey, my husband and children

To my dear sister, companion of the road.

To all my friend, my happiness centers on our friendship.

Ansam

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In the name of Allah most gracious and merciful. I am thankful to my creator who blessed me with the ability to complete this thesis and for everything.

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Abstract

Although online social networks can provide a potential opportunity for interchanging information among individuals. Information pollution on the internet is one of the most crucial global concerns. Since the popularity of social media has grown, it has become a lot more difficult. The information pollution make people think and act in ways that are not true. On the Internet, there are many kinds of information pollution, rumor is still an enormous challenge. It is a harmful social phenomenon that needs to be paid attention to. This work is going to combat rumors on online social networks by involving trusted influencers. They are members of online social networks (OSNs) who have a high influence than the others. Identify the influential users through interaction information flow and interaction relationships among users. They can play an important role in minimizing the effect of rumors. The proposed model detecting influencers by uses some criteria to achieve this task. The next step after the detection process is classify the new rumor according to topic using Naïve Bayes classifier. Finally employ those influencers to combat rumors. To evaluate the proposed model, a two dataset was used (PHEME and Ukraine dataset); this demonstrates that the model can identify influencers with a high influence score who disseminate anti-rumor in social networks. The results emphasize that the model has a good performance in discovering influencers as well as spreading anti-rumor compared with passion point methods.

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List of Abbreviations

Abbreviations	Meaning
BC	Betweenness Centrality
CC	Closeness Centrality
CID	Categorical Influencer Detection
CSV	Comma-Separated Values
DC	Degree Centrality
FDA	Functional Data Analysis Theory
IDF	Invers Document Frequency
JSON	Java Script Object Notation
KNN	K-NN Regression
LDA	Latent Dirichlet Allocation
MAE	Mean Absolute Error
MSE	Mean Squared Error
MTICM	Multi-Try Independent Cascade Model
MUOD	Massive Unsupervised Outlier Detection Model
NB	Naïve Bayes
NPMI	Normalized Point–wise Mutual Information
OLS	Ordinary Least Squares
OSN_S	Online Social Networks
RMSE	Root Mean Squared Error
SNA	Social Network Analysis
SI	Susceptible Infected
SIR	Susceptible Infected Removed
SIS	Suspected Infected Susceptible
S_{NET}	Social Network
SVR	Support Vector Regression
TF	Term Frequency
UIRank	User Impact Rating Algorithm
VAE	Support Vector Regression

1.1 Introduction

Currently, Social Networks serve as a real-time communication medium for user interaction. They are frequently utilized to express their personal experiences and valid opinions on various issues such as news, politics, celebrities, sports, events, and products. As a result, online social networks have a valuable resource for sharing and learning information [1].

Social media is a type of communication that is widely utilized to link individuals all over the world. Social media has also become one of the best places to get the most up-to-date and breaking news worldwide. Some people use social media sites like Facebook and Twitter to share their experiences, everyday activities, and opinions. However, social media can promote false information, such as hoaxes, slander, and hate. [2]

Since its inception in 2006, Twitter has developed from a specialty service to a popular craze. By the end of 2019, the platform claims to have over 330 million active users who "write over 500 million tweets every day" in 33 different languages. The service's essential principle has kept the same: users can send brief messages (tweets) of up to 140 characters and get notifications from other users [3].

During events, Twitter has become one of the essential communication mediums. Officials could disseminate pertinent information to humans, such as disaster victims, via Twitter, and citizens could interact with catastrophe-related information. Social media known for spreading rumors, misinformation, and erroneous theories. False rumors can cause confusion among individuals and officials and interfere with disaster management. Rumors labeled as “unverified and instrumentally relevant information statements in circulation that arise in contexts of ambiguity, danger or potential threat, and that function to help people make sense and manage risk” [4].

Spreading harmful information is a severe threat to members of online social networks. Modeling rumor propagation contributes to interpreting rumor propagation patterns in social networks, limiting the spread of rumors to a significant range. For handling rumors on social media, three basic measures should be taken are known as “Rumor Diffusion,” “Rumor Detection,” and “Rumor Intervention.”. Every day, a great deal of information comes via social media, and rumors grow in tandem, in a never-finished process [5].

Among the various definitions of influencers may come that they include proposed criteria of influence in the definition of an influential user, such as leaders, authoritative actors, and others. Influential users can start trends to occupy different roles on social media, such as a leader of a country, musician, artist, actor, actress, director, or journalist. Besides, many interactions and information between users are attracted, sent and received via multiple mechanisms.

1.2 Problem Statement

The transmission of information pollution has always been a subject of concern. The Internet has compounded the situation by making it easier to disseminate this information to a wide number of individuals.

A large number of rumors on social media causes confusion in the way individuals deal, so there is a need for mechanisms to reduce the effects of negative rumors.

1.3 Thesis Aims

Enhancing the credibility of online social networks, limiting the debilitating effects of information pollution, and prompting detection and containment of fraudulent content flowing on the Internet crucially achieved through:

1. Detecting the influencers' object on any topic.
2. Classifying the new rumor according to the predefined topic.
3. Employ influencers to eliminate the spread of a rumor.

1.4 Related Works

This section summarizes works that are closely related to the present study. Various studies about detecting influencers in social media and employing influencers in various applications are reviewed.

Huynh et al in [6] present a model for representing influencers in social networks based on the relationships between users and brands. the model of this work is known as SNet. It is based on a graph that shows the relationships between users' influence, speed of dissemination of information, their preferred brand, and the sharing of similar brand characteristics. It is called the passion point. Positive results are gained due to the employment of the results in influencer marketing**.**

Erlandsson et al in [7], suggest using learning to discover influencers through relationships between users. They present the implementation of several experiments to verify the results on social networks and compare the influential users who appeared in the results in terms of degree and page centrality. Their results showed that using this method produces faster results than other methods.

Tridetti, Stéphane in [8], presented during his master's thesis the extraction of influencers and their use in the marketing campaigns of companies or brands for a specific target audience through their permanent activity in continuing to support this brand. Collecting data from Twitter requires him to use a step-by-step algorithm to create a graph of who the influencers are and how they exploited.

An organization creates a new product and wants to advertise it through a micro-blog network**.** Jianqiang et al [9], suggest an algorithm called the "User Impact Rating Algorithm (UIRank)" proposed to identify influencers among users based on interaction information flow and interaction relationships. This algorithm is achieved by using a graph through which it tracks influential users by the content of the Tweet, the way information is disseminated to the user, and their frequency of influence. Accordingly, this algorithm shows excellent results in finding influencers regarding the criteria that are employed.

Azcorra et al [10], different influencers categorized into several categories based on some values. By applying their 'Massive Unsupervised Outlier Detection Model (MUOD)" based on functional data analysis theory (FDA) [11] and testing it on social networks, they found different influencers identified and distinguished automatically. Besides, they find that there are features associated with each group of influencers, such as the ability to attract the largest number of likes, attract participation, or attract the largest number of followers.

In [12], A proposed work to identify social media influencers carried out by employing a fictitious dataset. Social Network Analysis (SNA) and weighting of SNA measurements used. The present study finds a list of SNA measuring data that are then weighted. While the results identify the top influencers on social media and their relationships with other accounts, the relationship visualized in a model to determine the spread's route, the SNA Measurement Results, and Spreading Influencer Models that are weighted differently. Hence, each SNA calculation generates a unique set of influencers.

Arora et al in [13], A mechanism for calculating influencers on social networks such as Twitter, Instagram, and Facebook suggested. They use nested learning algorithms (ordinary least squares (OLS), K-NN regression (KNN), support vector regression (SVR), and Lasso Regression models), and then get and calculate the cumulative results to show the regression index of the influence. The research has implications across various domains of ecommerce, viral marketing [14], social media marketing [15] and brand management, wherein identification of key information propagators is essential. The results proved that communication, admiration, feelings, attraction, and participation play an important and key role in determining influencers.

Thanh et al in [16] propose a method for finding topics in microtext by employing a deep learning approach that includes VAE and word vectors to approximate the LDA (Latent Dirichlet Allocation) processes. This investigation employs microtext-based topic modeling to identify categorical influencers. This research was carried out using two datasets [17] [18]. They have been established that the vocabulary of found themes closely reflects human judgment.

Askarizadeh et al in [19] the authors have used influencers to spread anti rumors on social media using PHEME dataset [20], presenting a concept of social network-based soft rumor control. The premise of the suggested model is that as people's knowledge increases, they more exact judgments concerning rumors. Anti-rumor communications distributed to increase public awareness through the use of respected authority and trustworthiness.

Ebuka et al, in [21] explain the effect of social media influencers on the purchasing intentions of social media users and focus on expanding the horizon of source credibility by applying the model experimentally to a diverse group of social media influencers for the first time. With a similar effect, they should use this finding in a formal industrial context to ensure that they meet the stated objectives. The findings of this research show that trustworthiness, attractiveness, and influenced product pairing all have a favorable and significant effect on buy intention.

Table 1.1 summarizes the review of relevant works to familiarize ourselves with research techniques, researchers' names, used data in implementations, and performance evaluation criteria.

Table 1.1 A summary of the most important studies in influencer detection

Reference	Application	Technique	Data set	Factor	Evaluation metric
Erlandsson, et al 2016 [7]	______	Association Rule Learning	Data collection from Facebook	Relationships between users	Degree and Page centrality
Tridetti et al 2016[8]	Fashion topics marketing	Centrality Measures	Data collection	Closeness, Betweenness, and	Conceptual and Empirical studies

			from Twitter	Eigenvector Centrality measures	
Jianqiang et al2017 [9]	Micro-blog marketing	UIRank	Data collection from Sina Weibo API	Interaction information flow and Interaction relationships	Precision, Recall, F1 measure
Azcorra et al 2017 [10]	_____	MUOD model	Facebook, Twitter, or Google+ dataset collecting	Connectivity, Activity parameters, and Profiling data	SI(susceptible-infected)
Andre et al 2018[12]	Eradicating hoax accounts	Social Network Analysis (SNA) and weighting of SNA measurements	Facebook hoax	Degree, Closeness, and Betweenness Centrality	Spread pattern
Arora et al2019 [13]	Ecommerce, viral marketing [14], Social media marketing[15]	Underlying machine learning	Facebook, Twitter and Instagram dataset collecting	Regression index of the influence	Mean Absolute Error(MAE), Mean Squared Error (MSE), and Root Mean

	and brand management				Squared Error (RMSE).
Thanh et al 2019[16]	Marketing campaigns	CID	Benchmark dataset[17] [18], showcase dataset	Reach, resonance, Relevance, Sentiment score	NPMI
Huynh et al 2020[6]	Marketing the brand/product/news	passion point	Data collection from Facebook and Twitter	Popularity, Impress	Positive Feedback from the Customers
Mojgan et al 2021 [19]	Anti-rumor spreader	Soft rumor control	PHEME dataset[20]	Interest, Social intimacy, and popularity	Precision, Recall, F1 measure
Ebuka et al 2021[21]	purchase intentions	Reliability and validity	Active social media users	Attractiveness, Trustworthiness, Expertise, Product-Influencer Matchup	Discriminant analysis, Validity

1.5 Thesis Organization

The present study is divided into four chapters. After chapter one which reflects an introduction to the whole research, the contents of the remaining chapters are arranged and described briefly below:

Chapter Two: Theoretical Background

All basic principles are well covered by social networks and rumors in chapter two.

Chapter Three: Proposed Work

This chapter describes the practical stages of the proposed algorithm-based system for influencer detection.

Chapter Four: Experimental Results and Evaluation

This chapter explains the implementation and performance as well as the results and evaluations of the proposed system.

Chapter Five: Conclusions and Future Works

The results and recommendations for future research of the present study are presented in this chapter.

2.1 Introduction

People have grown more communicatively because of the explosive expansion of social networking websites by distributing information about brands, services, and products. These social media platforms have developed into new informational resources for consumers and corporations as well. Social media platforms are regularly used to communicate information and promote products via viral marketing or product placement. The success rate of this sort of marketing enhanced by targeting certain persons dubbed "influential users." [22]

Several previous types of research have been done about these influencers, such as calculating their numbers, their influence, and how they exploit to solve some of the common problems in society and confront them on social media platforms. One of the most important of these problems is confronting rumors and finding solutions to repel them. [23]

The theoretical part of techniques that are used in the current work, such as online social networks, especially Twitter, graph theory, influencer detection, and rumor explained in this chapter.

2.2 Online Social Networks (OSNs)

A social network (SN) is a collection of relationships or interactions in which the nodes are actors and the edges represent those actor's interactions or relationships. Information networks extend the notion of SNs, in which the nodes can be things or actors, and the edges show their interactions. The notion of social networking (SNs) is not limited to the specific situation of an internet-based social media site like Facebook; social network explored in terms of generic interactions between any groups of actors in the social sciences. These contacts can take any traditional or unconventional form, including telephony, face-to-face encounters, email interactions, and postal connections [24].

People use social media to post to platforms, and the substance of these posts varies from country to region. Not only has social media developed into a place where people socialize, but it has also strengthened into a place where people communicate. Social media has become an inextricable aspect of our lives. Typically, the term "social media" refers to interactive media that requires participation [25].

Social network nodes represent individuals or organizations. They can, however, refer to Web pages, journal papers, departments, localities, or even entire countries. The enormous interest in studying social networks today stems from the projected benefits of looking into the research problems surrounding social networks and the obstacles of data gathering and network analysis [26].

Among the most typical examples of strong global social media and instant messaging systems may come Twitter, Facebook, LinkedIn, Messenger, and WhatsApp allowing individuals to communicate and share information, knowledge, and experiences. Although connecting with others and establishing connections has apparent benefits, new hazards emerge in modern society if this technology not adequately exploit [27].

EMarketer found that social media usage rose globally because of people staying at home for weeks or months owing to the coronavirus outbreak. There will be a disparity in the number of people who benefit from Facebook, Instagram, Snapchat, and Twitter's new users in 2020.3.23 billion individuals, or 80.7 percent of all internet users, will visit a social network at least once a month in 2020. By 2021, that number has risen to 3.35 billion people, as show in figure 2.1[28].

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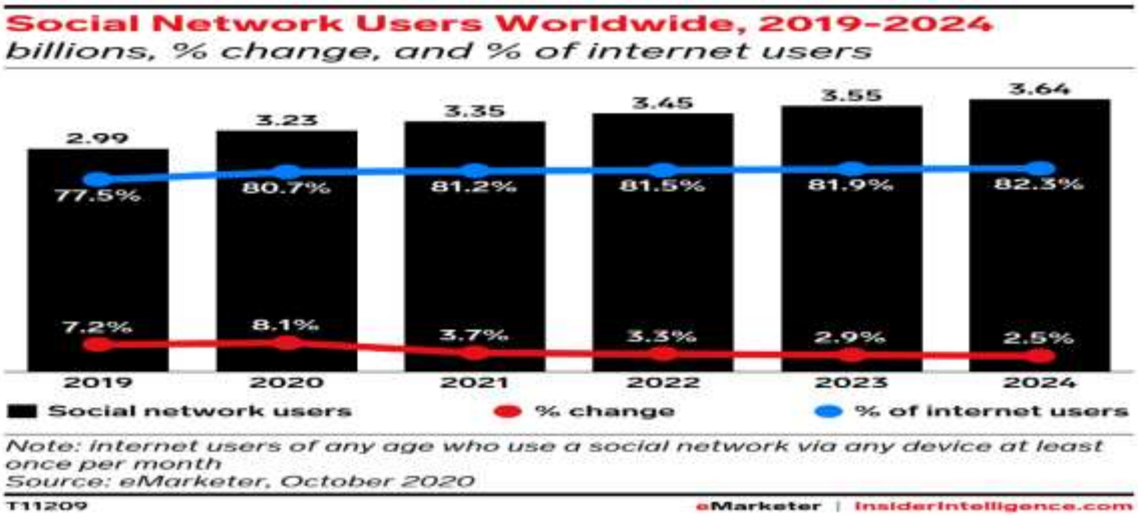


Figure 2.1 Internet Users on Social Media

Twitter is one of the most popular online social media and microblogging platforms. Twitter enables users to interact via posted text messages of up to 140 characters in length, called "tweets". It can be composed of text, images, or videos expressing sentiments about various topics. According to Twitter research, there are around 336 million monthly active users, resulting in one billion unique monthly visits in more than 40 languages. This is demonstrated by Twitter's sharing of monthly active user data through 2021[29].

It has been stated that the social networking service continued to gain traction in its early years. However, since 2010, we have seen constant growth over time, with quarterly increases, as shown in Figure 2.2[30].

Public relationships on Twitter include those between users, between tweets and users [31].

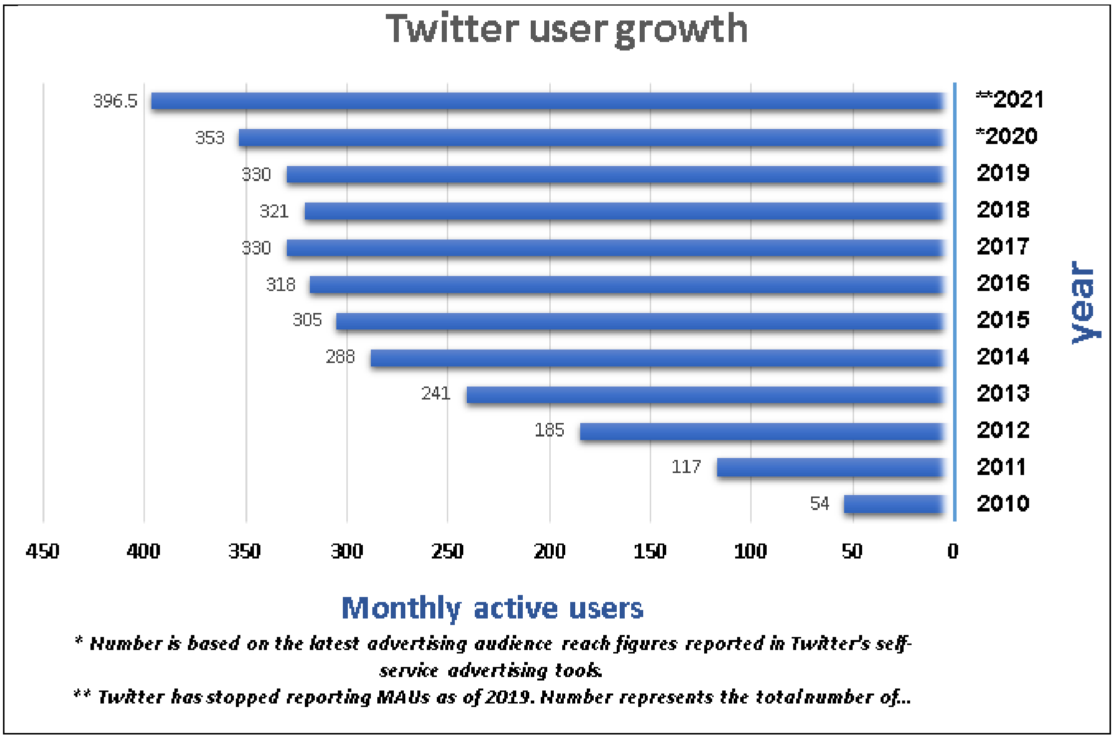
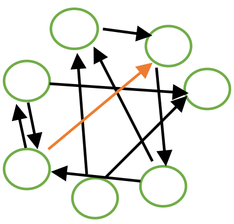


Figure 2.2 The Total Number of Twitter Users

2.2.1 Social Network Representation

A social network is mathematically represented as an Adjacent matrix, Adjacent list and graph, as shown in figure 2.3



$$A=\begin{bmatrix} 0&1&0&0&0&0&0\\ 0&0&0&1&0&0&0\\ 0&0&1&0&0&0&0\\ 1&0&0&0&0&1&0\\ 1&0&1&0&0&0&0\\ 0&1&0&0&0&0&1\\ 0&0&1&0&0&1&0 \end{bmatrix}$$

i :
$1 \longrightarrow \{2,3\}$
$2 \longrightarrow \{1,3\}$
$3 \longrightarrow \{1,2,4\}$
$4 \longrightarrow \{3\}$

Figure 2.3 A representation of graph, adjacency matrix and list matrix

A graph G = (V, E) comprises a set of edges m where E = ((u, v) |u, v) V and a set of nodes (also known as points or vertices) V with |V | = n. The link between nodes I (corresponding to vertex u) and j (corresponding to vertex v) is denoted by the notation (I j) rather than (u, v) [32]"the edges are produced by unordered pairs of vertices." are known as undirected graphs. The degree D of each vertex v, or the number of edges that intersect it in G, categorize them. A collection of nodes v1, v2,..., vk+1 such that there is an edge between vl and vl+1 for all 1 k makes up a walk of length k in an undirected graph. However, there may be other pathways that are shorter than the shortest path between any two nodes. Graph G is said to be connected if every pair of nodes there is a path connecting them. If the edges of graph G comprise ordered pairs of vertices such that (u, v) E = 6 (v, u) E, the graph can also be directed (also known as a digraph). A directed graph's vertex can have two different degrees. A node's in degree in D is determined by how many edges point at it, whereas a node's out degree in D is determined by how many edges point away from it. However, a digraph's definition of the distance d (u, v) between two nodes u, v is "the length of the shortest path between the nodes u, v." D (u, v) is not necessarily equivalent to d when compared to an undirected graph (v, u) [33].

1. **Network:** It is a collection of similar points (nodes) connected by some form of a link.
2. **Node:** an entity in a social network that represents a single user or person.
3. **Edge:** refers to a technique or function that connects each node to the next to form a network.
4. **Neighbor:** Two nodes are said to be neighbors if they are connected by an edge.
5. **Degree:** A contract property indicating the number of edges that link the node. The first node's degree is deg (i).

6. **Walk:** A walk is a collection of connected edges that create a continuous path on a network. Three points stand out:
    1) **Trail**: it is a walk that does not cross an edge more than once.
    2) **Path:** It does not traverse any node (and thus no edge) more than once.
    3) **Cycle:** A path that begins and finishes at the same node. Besides, it does not pass through any node more than once.
7. **Subgraph:** It is a subgraph of the graph that does not contain all of the nodes and edges of the original (bigger) graph network.
8. **Connected graph:** it is the one in which any pair of nodes has a path connecting them (i.e. each node in the graph is a linked node).
9. **Connected component**: When a graph is linked inside itself, it is referred to as a "child graph," and when the graph is connected to the rest of the network, it is referred to as a "connected component."
10. **Complete graph**: It is a graph in which every pair of nodes is connected.
11. **Regular graph:** it is every node has the same degree. Each whole graph is regular [34].

2.3 Influencers Detection

A graph-based depiction of user interactions in a social network is often used to identify influencers. graph theory studies employ the structure information in these graphs to identify the most important nodes in a network [35].

on Twitter, an influence employed for a variety of reasons, including political science [36], human mobility [37], rumor spreading [38], and epidemiology [39]. In a network, an influencer has numerous 'in-degree connections and some 'out-degree connections, as illustrated in Figure 2.4 [40].

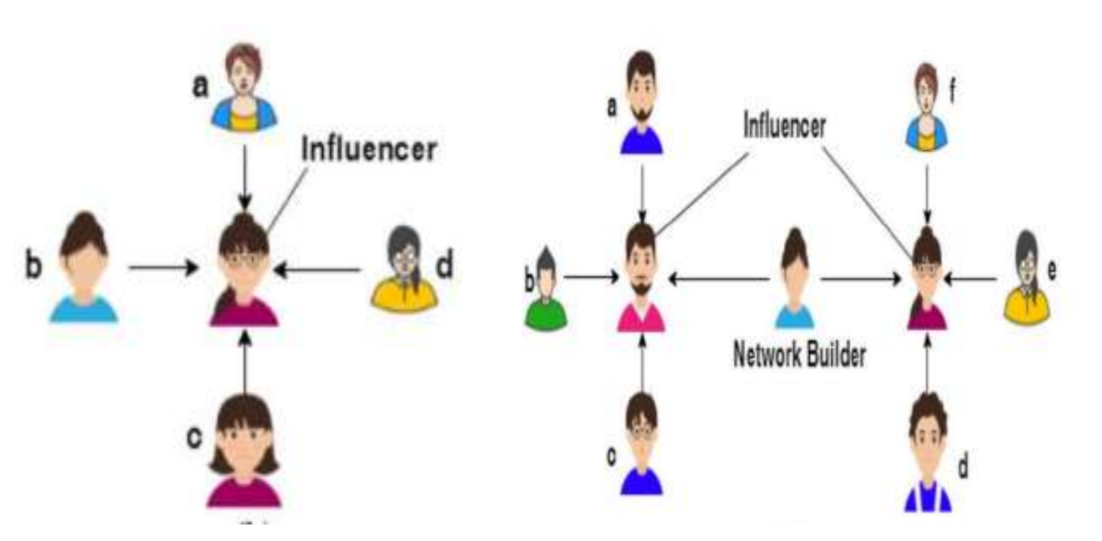


Figure 2.4 Show the influencer in the network

According to certain research, opinion leaders, influencers, and discussants are categorized based on their activity and effect. There is a distinction made in between inventors (those who start a new topic) and spreaders (those who propagate the topic). Disseminators are users who disseminate their influence and avoid structural gaps. Engagers, foster collaborations with third parties, while leaders are classified as leaders of their own teams or organizations (top disseminator-engagers) [41]. There are a several of persons who may be characterized as idea generators (those who have a huge following) and connectors (those who connect starts) [42] [43]. Social Media Influencers build their credibility, and as a result, their target audience notices and supports their particular subject of interest [44].

Influencers should carefully manage and maintain their social media profiles to guarantee that their fans continue to follow them and grow their following. Influencers have large millions of likes and followers. They developed content to meet the expectations of their followers based on their wants. Keeping their profiles up to date and frequently posting and commenting allows them to grow their following and attract constant attention from their followers [45]. The framework of social influence analysis is shown in Figure 2.5 collection of big data from social networks: It is a very important basis of social influence analysis. Big data preprocessing: it is necessary to remove the irrelevant information on the social influence analysis. Selection of evaluation metrics: It is very important to extract a set of evaluation metrics to measure social influence of each user. Measuring social influence: According to the extracted evaluation metrics, evaluation model and computing equations are provided to a specific social network. Design of influence maximization algorithm: is designed to find the most influential top-k nodes. Performance analysis on related algorithm or model: Simulation is made to validate performance [46].

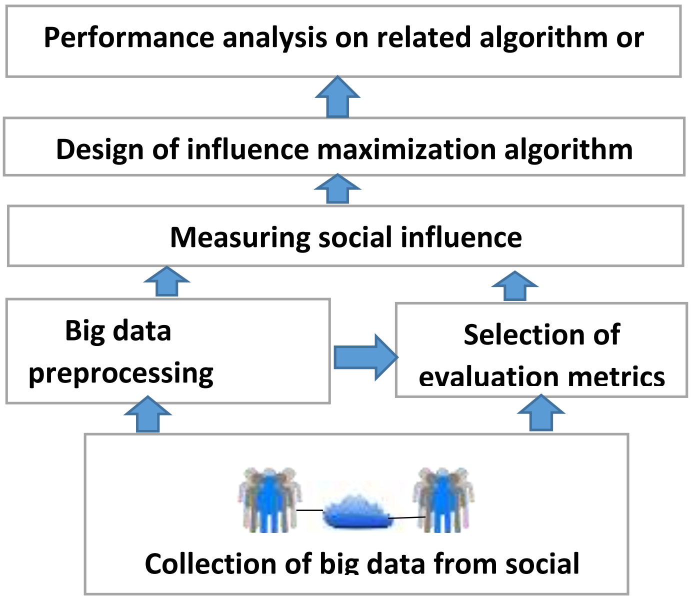


Figure 2.5 Traditional Influence Measure

The most important studies conducted to extract influencers based on specific algorithms, formulas, or patterns:

1. Association Learning Rules

Learning rules to find influencers by knowing the relationships between users suggested in this paper [7]. Erlandsson et al. describe the crawler, acquired association rules can be better understood with the help of a wide range of measurements [47]. As explained in, they supply the SQL database from which this investigation's data was sourced [48].

The supplied metrics (support, confidence, lift and conviction) help in the comprehension of taught rules, in which bigger values for all four measures show that the learnt rule has predictive significance. According to their findings, they conducted a series of experiments on social networks to verify their findings and compare significant persons mentioned in the results based on their degree and page centrality. This approach shown to provide results more quickly than others [47].

2. Social Network Analysis (SNA)

Recognizing social media influencers in the same way [12]. The dataset used in this study made up. The following formula is used to determine the degree, closeness, and betweenness of a network using Social Network Analysis (SNA) and the weighting of SNA variables:

1. First, the number of edges connecting vertices estimated using Degree Centrality (DC). There is a DC value for each vertex that differs from the other vertices.
2. Closeness Centrality (CC): CC has discovered the shortest distance between all vertices and a vertex destination. The CC value influences the network's relationships; the bigger a vertex's CC value, the more influential it is [50].

3. Betweenness Centrality (BC): The shortest route between two vertices has been identified using BC [51].

The data used in this investigation are weighted SNA measurement data. The findings show who the biggest social media influencers are as well as their connections to other accounts. A distinct set of influencers is produced by each SNA calculation. Finding the main influencer is the goal of SNA data weighting. The min and max values represent the lowest and maximum DC, CC, or BC values, respectively. Each new value of DC, CC, and BC has been weighted and added together to get the vertex's outcome [51].

Associates Tridetti, Stéphane [8], presents during his master's thesis a study on the extraction of influencers and their use in the marketing campaigns of companies or brands for a specific target audience through their permanent activity in continuing to support this brand. To collect his data from Twitter [52], used a step-by-step algorithm to create a graph of who the influencers are and how they can be exploited and used centrality measures (closeness [53] [54], Betweenness [55], Eigenvector [56]). The study analyzes the robustness and qualities of the three fundamental notions using a combination of conceptual and empirical experiments.

3. UIRank Technique

They propose an algorithm called "User Impact Rating Algorithm (UIRank)" to identify influencers among users based on interaction information flow and interaction relationships. This algorithm works through a graph in which it tracks influential users through the content of the Tweet, how the information is disseminated to the user and their frequency of influence. The influence of the user network is determined by the person's position in the network of follower connections. When a user u tweets t, his follower's v will read it with probability p and retweet or comment on it with probability q, causing t to be redistributed among v's followers. The UIRank ranking formulae may be determined using random walk theory when, after reading t, v's supporters retweet and comment on it, causing it to spread again [9].

This shows excellent results in finding influencers according to the above criteria. To validate the UIRank's effectiveness, the references to cross-validation were drawn from four approaches supplied by scholars. The influential individual reference collection contains noteworthy nodes that have been examined using a variety of approaches.

4. Massive Unsupervised Model Outlier Detection (MUOD)

Azcorra shows another use of influencers in FDA. In this study [10], he categorizes some user values into several categories, each of which includes different influencers by applying the " Massive Unsupervised Model Outlier Detection (MUOD)". After testing it on social networks, they found that different influencers identified and distinguished automatically. They also found features associated with each group of influencers, such as the ability to attract the most significant number of likes, attract participation, or attract the largest number of followers. OSNs may profile a collection of parameters that measure users' connection, activity, and other relevant characteristics:

Connectivity measured by using the in-node degree, the out-node degree (which refers to friend or follower ties), the clustering coefficient, and other centrality measures.

Frequently, the activity parameters separated into two primary categories. The user's actions are grouped into a single category. These are often published posts and likes (known as "plus ones" in Google+) given to other users' posts. Likes and comments from other users, as well as re-shares and reposts, constitute extra responses to a user's post (i.e., retweets with Twitter). Each user of an OSN maintains a profile with information about themselves. Depending on the OSN, a user's profile may include the user's name, location (such as the city in which she lives), profession, educational background, and gender. Since its inception in June 2011, Google+ has gathered an official total of 2.5 billion Google account holders who have enrolled for the network. It would make Google+ the most popular social networking site in terms of the user base, followed by Facebook and Sina Weibo (a Chinese-language OSN). These many platforms applied to assess MUDO [57].

5. Machine Learning Algorithms

Influencers' significance in the marketing domain can be detected according to various methods, as Arora et al. state [13]. They provide a formula for determining influencers on social media platforms including Twitter, Instagram, and Facebook. They employ nested learning methods in their work, including Lasso Regression models, support vector regression, K-NN regression, and ordinary least squares (OLS).

1. Ordinary Least Squares (OLS)
   Based on OLS, MLR attempts to minimize the sum of squares of actual and predicted values [58]. The MLR model is predicated on several assumptions. The regression estimators are optimum if they fulfill the

assumptions. The unbiasedness, efficiency, and consistency of the estimators define their optimality [13].

2. Support Vector Regression (SVR)

   Support Vector Machines can solve classification difficulties and regression problems. SVR solves the problem using a small selection of training points, which has huge computing benefits. Using the following formula, they scaled the dataset to train the regression model with a linear kernel.
3. K-NN regression

   Calculating the average of the numerical target of the 'k' nearest neighbors is a straightforward implementation of KNN regression.

   Classification by KNN regression employs the same distance functions as classification by KNN classification in regression.

And then, after obtaining the cumulative results, they calculated to demonstrate the regression index of the influence. Their results proved that communication, admiration, feelings, attraction, and participation play an essential and critical role in determining influencers.

6. Categorical Influencer Detection(CID)

Using a deep learning method that includes VAE and word vectors to imitate the LDA (Latent Dirichlet Allocation) methods, a method for finding themes in microtext devised. This study identifies category influencers using microtext-based topic modeling based on the following factors [16]:

1) Reach score: This metric indicates how many people are reached by the influencer's social media posts. This score is based on empirical evidence:

   Reach score = (total followers + total friends) /2,000,000 × 100 (2.1)

   The value of 2,000,000 chosen based on the real data collected in our database at that time, as most active influencers have a number of followers and friends of over 2,000,000.
2) Resonance score: This score indicates if an influencer in a topic is likely to generate conversation about that issue or not.
3) The average interactive score is the ratio of the number of likes, shares, and comments received by this influencer's posts to the total number of posts published in the last three months.

   avg_interactive_score=(total_likes+total_shares+total_comments)/total_posts. (2.2)

4) Relevance score: This score shows an influencer's importance to a topic. To accomplish this, gathered all the influencer's posts and comments.
5) Sentiment score: They quantify the general opinion expressed about this influencer by other users on social media networks, whether good or bad.

They used two datasets for these experiments: the benchmark dataset [59] [60] and the showcase dataset. It is worth mentioning that the metric for evaluation used in this approach is the Normalized Pointwise Mutual Information (NPMI) [61] as the primary metric for evaluating the qualitative of the topic discovered by the model in this experiment. As a result, they have established that the vocabulary of found themes closely reflects human judgment.

7. Passion Point

The study of influencer detection has been proposed by Huynh et al. [6]. Based on the connections between users and companies, they create a way for visualizing social network influencers. The passion point is a collection of social network links based on a graph that illustrates the relationships between users' influence, speed of information propagation, favorite brand, and the sharing of comparable brand features, according to the next formula:

$$\mathbf{IU(u) = (Impress(u), Popularity(u))} \qquad (2.3)$$

Where $$\mathbf{impress(u)} = \frac{\alpha.SI(u)+\beta.CI(u)+\gamma.Ir(u)}{\alpha+\beta+\gamma} \qquad (2.4)$$

$SI(u)$, $CI(u)$, $Ir(u)$ are computed respectively. α, β, and γ: are weighted numbers. $\mathrm{SI(u)}=\frac{\alpha_1.\#(\mathrm{SU}_1(\mathrm{u}))\ +\alpha_2\ .\#(\mathrm{SU}_2(\mathrm{u}))\ +\ \alpha_3.\#(\mathrm{SU}_3(\mathrm{u}))}{\#(\mathrm{u.ListFriends})\ +\ \#(\mathrm{u.ListFollowers})}$

where SU(u): = $\cup_{\mathrm{t}\in\mathrm{u.Listags}}$ t.Sh: a set of users sharing u's tags.

$SU1(u) := \{v \mid v \in SU(u)$ and friend $(u, v)\}$: a group of users that share u's tags and who are friends with u.

$SU2(u) := \{v \mid v \in SU(u)$ and follower $(v, u)\}$: a collection of users who are sharing u's tags and who are also followers of u.

$SU3(u) := SU(u) \setminus (SU1(u) \cup SU2(u))$: set of users who share u's tags but are not related to u. $\alpha 1, \alpha 2, \alpha 3$: $are\ weighted\ numbers, 0 < \alpha 1 \leq \alpha 2 \leq \alpha 3 < 1$.

CI(u): influence of the user u's comment. It quantifies the effect that comments have on u's tags.

$$CI(u)=\frac{\beta_1.\#(CU_1(u)) + \beta_2 .\#(CU_2(u)) + \beta_3.\#(CU_3(u))}{\#(u.ListFriends) + \#(u.ListFollowers)}$$

where CU(u): $=\cup_{t\in u.Listags}$ t.Com : A group of people who have commented on u's tags.$CU_1(u)$: = {v | v ∈ SU(u) and friend (u, v)}: set of users who have commented on u's tags and who are also u's pals. $CU_2(u)$: = {v | v ∈ SU(u) and follower (v, u)}: set of users who have commented on u's tags and are also followers of u.

$CU3(u): = CU(u) \setminus (CU1(u) \cup CU2(u))$: set of users who have commented on u's tags but are not related to u.$\beta1, \beta2, \beta3$: are weighted numbers, $0 < \beta1 \leq \beta2 \leq \beta3 < 1$.

Where $Ir(u)$: interactor ratio for the tag of the user u.

$$Ir(u)=\frac{\gamma_1.\#(I_1(u)) + \gamma_2 .\#(I_2(u)) + \gamma_3.\#(I_3(u))}{\#(u.ListFriends) + \#(u.ListFollowers)}$$

where $I(u) := \cup_{t\in u.Listags}$:interaction : A group of individuals who interact with u's tags. $I1(u): = \{v \mid v \in I(u)$ and friend $(u, v)\}$: a set of users who engage with u's tags, and who are friends of u. $I2(u): = \{v \mid v \in I(u)$ and follower $(v, u)\}$: a set of users who interact with u's tags and who are followers of u. $I3(u): = I(u) \setminus (I1(u) \cup I2(u))$: a set of users who engage with u's tags but are not tied to $u.\gamma1, \gamma2, \gamma3$: are weighted numbers, $0 < \gamma1 \leq \gamma2 \leq \gamma3 < 1$

while Popularity [62] can compute as:

$$\textbf{Popularity(u)} = 1 - e^{-\lambda.\#(F)} \qquad (2.5)$$

where F: = u. ListFriends, ∪ u.ListFollowers, and λ: is a constant.

8. Soft Rumor Control

Another approach to detecting influencers is Mojgan et al. [19]. However, they use this influencer to spread anti rumors on social media, presenting a novel concept of social network-based soft rumor control. The premise of the suggested model is that as people's knowledge increases, they will make more exact judgments concerning rumors. Anti-rumor communications distributed to increase public awareness through respected authority and trustworthiness. To illustrate this, they calculated influencers in this method:

1. Interest: When assessing if they should regard a user as a trusted friend, it is essential to consider his or her occupation and expertise. They can hypothesize that persons who are interested in a certain topic are more likely to be experts in that field [19].
2. Social intimacy and popularity: Social intimacy quantifies the degree to which the requester user and his/her buddy share mutual relationships [63].
3. Choose dependable consultants: This used to evaluate a requester user trust in a friend for rumor message consulting.

As a result, when a user hears a rumor, he or she rates his or her friends differently depending on the rumor's content. The speaker considers his or her interacting (whether a friend or a neighborhood graph). This approach employs three evaluation metrics: precision, recall, and F1 measure based on the PEME dataset [20].

9. Reliability and Validity

Ebuka et al. [21] explain social media influencers effect on social media users purchasing intentions. They focus on expanding the horizon of source credibility by applying the model experimentally to a diverse group of social media influencers for the first time. With a similar effect, they should use this finding in a formal industrial context to ensure that they meet stated objectives. They composed the population of this study of Anambra state's active social media users. The constructed reliability and discriminant validity [46] tests are conducted using smart- pls. SPSS version 24 is used to compute the data, and SEM using Smart-Pls was used to analyze it. The findings of this study showed that trustworthiness, attractiveness, and influencer product pairing have a favorable and significant effect on buying intention.

2.4 Information Diffusion Models

People's daily lives are increasingly being influenced by online social networks such as Facebook, Twitter, and Google Plus. This emphasizes the significance of researching mechanisms that influence the flow of information through these networks [64]. Social network information propagation has strong temporal features, such as burst updates, which flood all platforms with a carnival of information in a matter of seconds (of course without fact-checking), and a speedy death [65].

The phenomenon of diffusion has received intense emphasis because of its potential impact in domains such as epidemiology [66], marketing [67], and social behavior [68]. Understanding contagious phenomena, product/service uptake, and developing cultural aspects depend on how individuals impact one another, a feature of diffusion models. Better understanding can also help policymakers design policies that optimize benefits, limit risks, and give time control. A simple diffusion process causes two prominent actors and one binding ingredient. The key actors are the transmitter (also known as the adopter and infectious) and the receiver (also known as the potential adopter and susceptible), and different communication and interaction pathways connect them [69]. Four of the most popular models listed here:

1. The Basic Epidemics

Dissemination of knowledge likened to the spread of an infectious disease. Users infected with viruses and those susceptible to infection have a role in the spread of epidemics. Viral information transmitted from communicators to recipients via infected to vulnerable individuals. Learning about information dissemination using simple epidemic models is a good idea. Concomitant Model of Epidemics: SI (Susceptible Infected), SIS (Suspected Infected Susceptible) and SIR (Susceptible Infected Removed) are basic models in the compartment model [70].

2. The Social Influence

This appears to imply that information or designs flow in an orderly method through neighbors. Apart from the infection, this forecasts that a specific center will not gain a slope (or acknowledge a piece of information) unless the number of neighbors who subscribe to that ramp or information surpasses a certain threshold. [71]. They classified the spread of information into three categories depending on influence: individual, community, and influence maximization [72].

3. The Social Learning Appear

Apart from the two fundamental models, the positions represented in this exhibition are supposed to make wonderful decisions. They note what previous adopters in their neighborhood have to say and then decide whether to acknowledge a sizable portion of the data. In real-world social settings, people observe what emerges from previous knowledge regarding early adopters for some time before deciding whether to continue development or disregard these acknowledgments [73].

4. Gossip

Gossip algorithm used as a strong alternative to flooding, which is the practice of re-transmitting information to all of the network's neighbors, or structured broadcast protocols, which frequently require a stable network with a defined topology to perform properly [73].

ALGORITHM 1: Randomized Gossip

$R_v = \{v\}$
WHILE $\Gamma(v) \setminus Rv \neq \emptyset$
    pick $(\theta \log^2 n)$ random edges from $\Gamma(v) \setminus R_v$
        $d = (\log^2 n)$; E' = all (newly) picked edges
        Flood rumors in R_v along E' -edges for d-hops
        add all received rumors to R_v

Gossip is divided into two categories: rumor-mongering procedures and anti-entropy protocols. Anti-entropy protocols are effective for reliably exchanging knowledge among a set of participants until newer information makes them outdated. It is common for rumor-mongering participants to discuss information that picked such that all participants have a high probability of receiving it [74].

Rumor spreading is an extremely effective method of quickly disseminating information. It behaves:

Someone has recently updated if node P for data item x, it will attempt to push the modification to an arbitrary other node Q. However, another node may have already updated Q. In that situation, P may lose interest in disseminating the proceeding update, with a chance of p halt. Hence, it is eliminated, as shown in figure 2.6 [75].

Anti-entropy is, thus, a widely used propagation model. In this approach, a node P randomly selects another node Q and then trades updates with Q. Three methods exist for exchanging updates:

1. P gets only new updates from Q.
2. P transmits just its updates to Q.
3. P and Q communicate with one another (i.e., a push-pull approach)

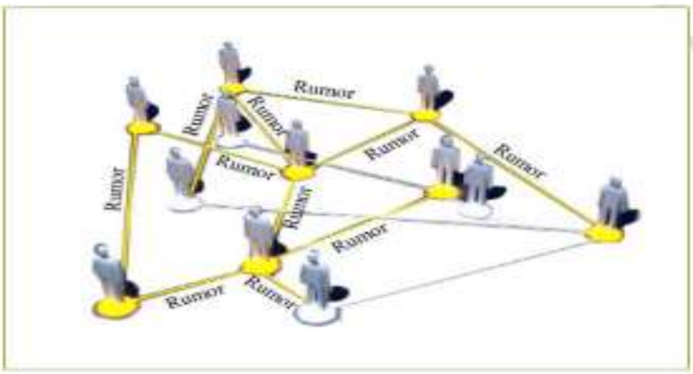


Figure 2.6 Rumors spread on social media

2.5 False information

Photo, blog, message, story, and breaking news are all examples of disseminating false information, which is commonly referred to as "information pollution." Besides to the many formats that are available, there is some heterogeneity among them that helps to classify them. [76]. Using the Venn diagram in Figure 2.7, it shows how various kinds of information pollution may be divided into categories. [76].

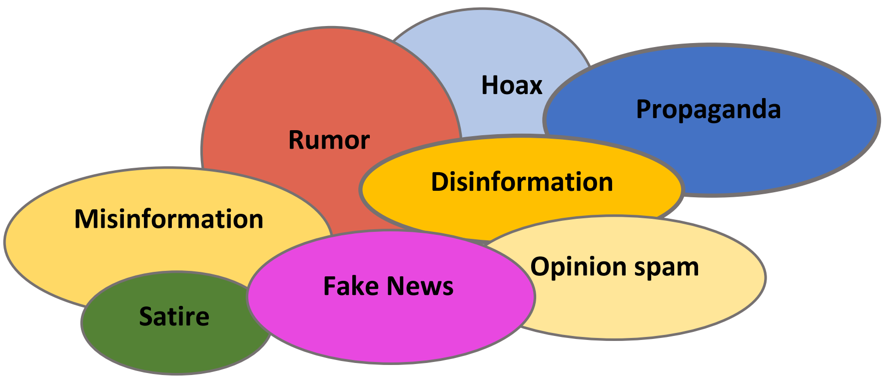


Figure 2.7 Types of information pollution

Rumor is unconfirmed information that goes from person to person and maybe true, partially true, or wholly untrue. Previously, rumors disseminated through word of mouth, but digital technology and the increasing popularity of social media have speed up the transmission of rumors worldwide [5].

Rumors are a part of everyday life, and their spread has a profound effect on people's lives. Rumor propagation begins when some individuals share knowledge with others who follow in the footsteps of their forefathers [77]. The growing usage of social media has facilitated the spread of rumors more successfully than in the past. Thus, rumor identification is a critical field of research for determining the legitimacy and reliability of information on social media. Twitter has developed a reputation as a popular news source over the years, frequently delivering information that is unmatched by traditional media [78].

The Internet remained relatively robust, as did some social networking sites like Twitter. However, Twitter does not always show advantages. It contains a potentially dangerous by-product, such as rumors. The more Twitter is used, the broader and faster the rumors spread. Increasing the number of Twitter users increases the likelihood of new rumors. Such rumors might potentially upset people with inaccurate information and jeopardize primary emergency aid [79].

Detecting accurate or trustworthy information across a network, particularly during critical events, can be extremely beneficial and have practical implications for financial markets, media users, emergency services, and journalists, as well as helping to mitigate the effect of disinformation and false information more broadly. A problem exacerbated by two reasons; namely, (1) anyone can disseminate inaccurate information and (2) determining the source of information is difficult [2].

2.6 Anti-Rumor Propagation Models

Anti-rumor messages that were sent to OSN users are a successful method of preventing rumors [80] from spreading Anti-rumor spread models discussed in this section.

1. The Delayed Start Model

Figure 2.8(b), which depicts the delayed start model graphically, demonstrates how a limited-jurisdiction authority might detect rumor propagation and then combat it by beginning an independent cascade from a randomly selected afflicted node. There is an anti-rumor that spreads from the checkered node. All neighbors, infected or not (node A or node B), receive the information after d. The procedure begins with a random selection of an infected node [81].

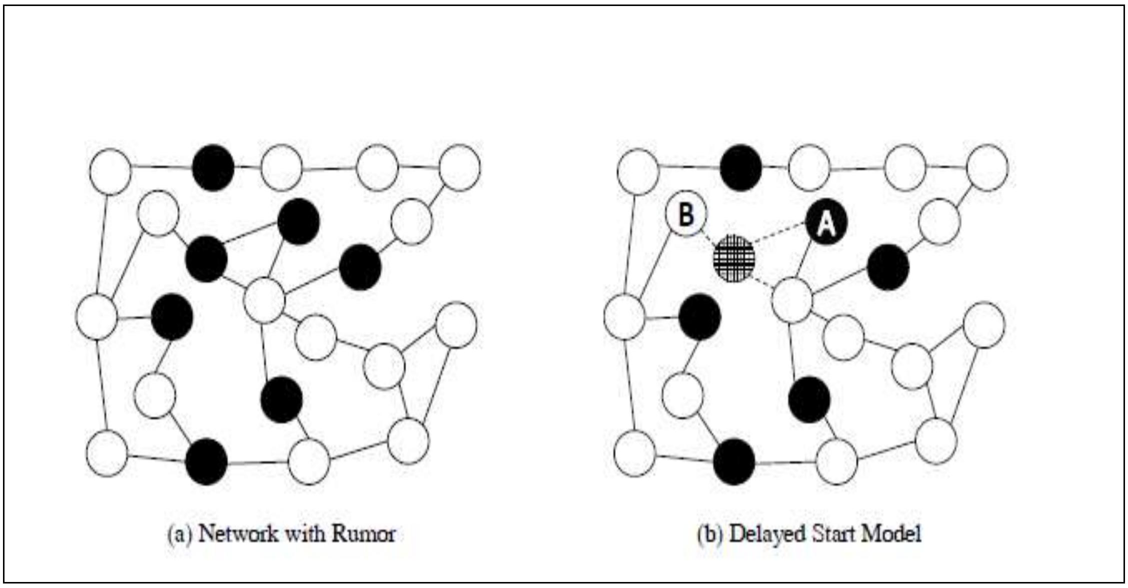


Figure 2.8 Delay Start Model

2. The Model of Beacon

Authorities can implant agents in networks to monitor the spread of rumors and begin anti-rumor operations as soon as they detected, as a proactive means of combating them. Beacons are the name given to these agents. In the Multi-Try Independent Cascade Model(MTICM), the beacons convey the anti-rumor message [82]. Figure 2.9 shows it as a beacon model. Until Beacon B1 receives the rumor, it will stay inactive. This approach differs from the delayed start model in that the anti-rumor operation begins as soon as the Beacon receives the rumor [83].

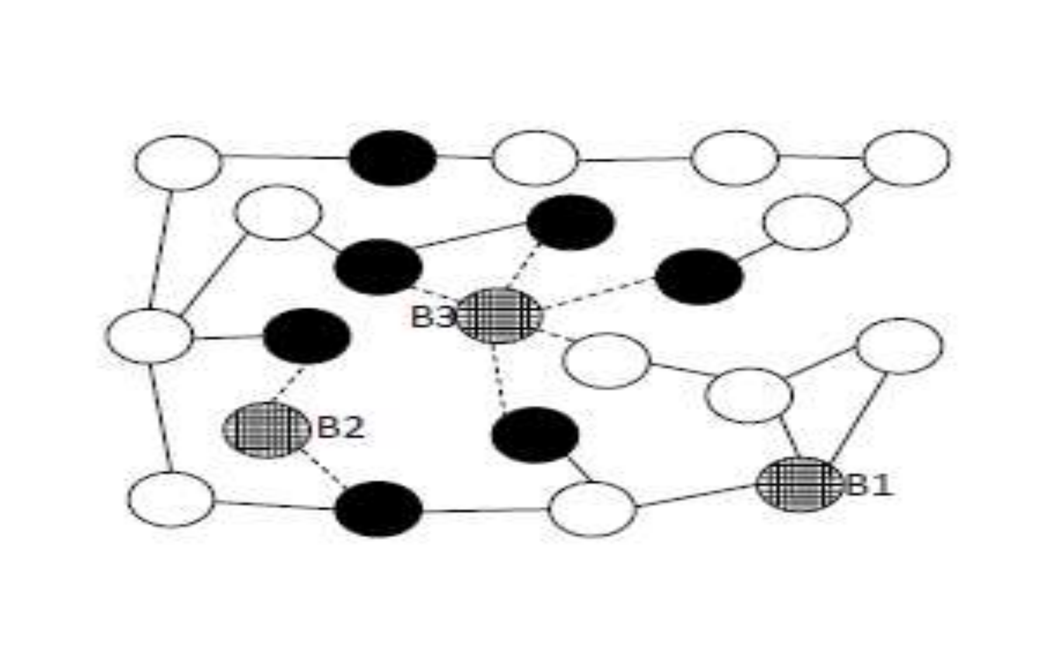


Figure 2.9 Beacon Model

3. The Model of Neighborhood

Previous approaches used nodes picked by an authority either before or after the commencement of the rumor to generate the anti-rumor. Upon hearing a rumor from a neighbor Vj, any node Vi may decide to refute it under this model. Figure 2.10 shows that this model is quite similar to the beacon. The key difference is in the way the first group of beacons is chosen. Unlike in the beacon model, where a central authority chooses the initial set of beacons, in the neighborhood model, beacons spontaneously emerge as the rumor-spreading process progresses [83]. Figure 2.11 classifies some of the prominent technologies used to intervene in the spread of malicious content online [76].

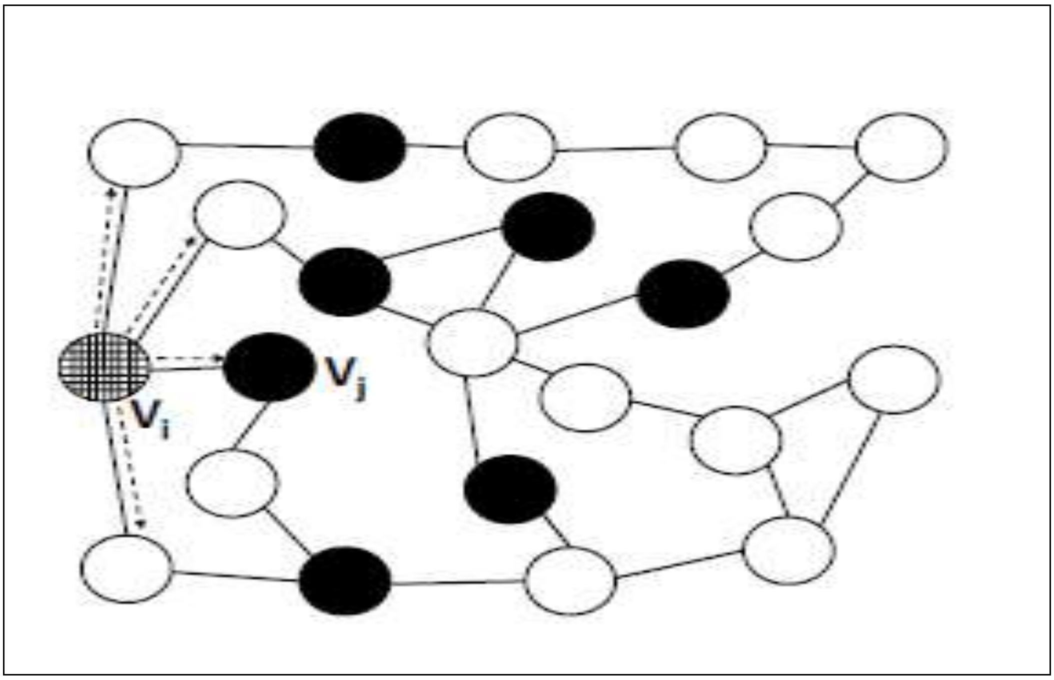


Figure 2.10 Neighborhood Model

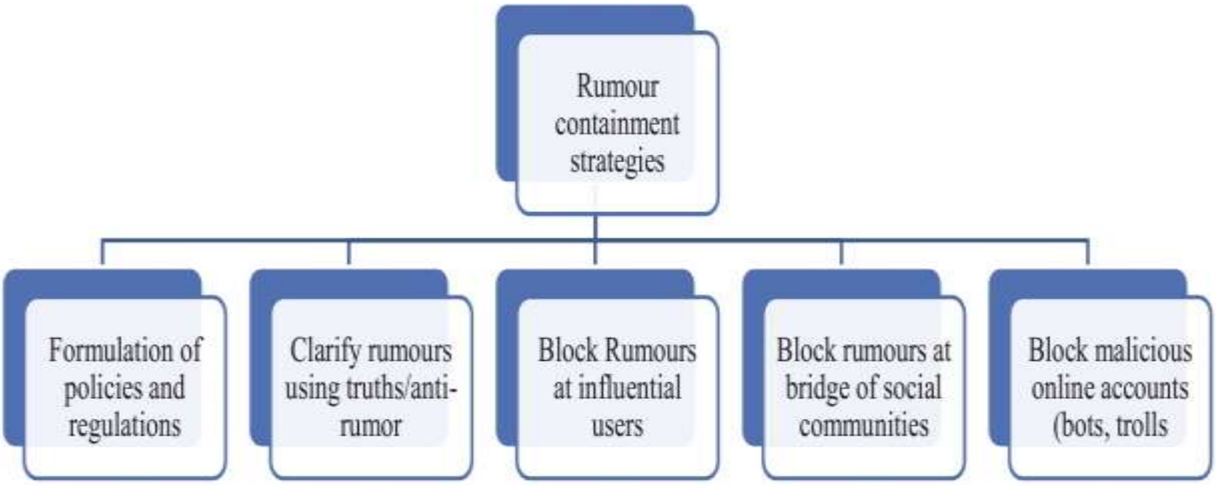


Figure 2.11 Classification of techniques for rumor control

2.7 Classification Algorithm

Recently amount of electronic content extremely growing; due to the internet users' significant growth and its spontaneous access via electronic devices, through messaging, social posts, weblogs, besides other digitized platforms. Technologies misapplication has increased with this rapid growth of online content, which leads to a rise in suspicious activities [84].

ML classification model would be used to organize transcripts into unsuspicious or suspicious sets depend on its contents. ML classification would be used on text body with various features, where a set of documents used for training and another set of documents used for testing [84].

2.7.1 Naive Bayes Classifier (NB)

The Naive Bayes classifier is a supervised simple classifier of probability that calculates a collection of probability by counting the frequency and values combinations in a given set of data. The algorithm uses the Bayes theorem and supposes that variables are independent, taking into account the class variable value. This conditional assumption of independence is so seldom valid in real-world implementation, so it is described as Naive, but in a variety of controlled classification tasks the algorithm tends to learn quickly. Theorem of Bayes is a mathematical method for calculating conditional probability, as shown in the Equation (2.6).

$$P(A|B) = \frac{P(A)P(B|A)}{P(A)} \qquad (2.6)$$

Where:

P (A|B) the probability that event A will occur when event B occurs;

P (A) the probability A will occur,

P(B|A) the probability that event B will occur when event A occurs;

P(B) is the probability of B occurrence [85].

2.7.2 Evaluation Metrics of Classification

During the classification training, the evaluation metric plays an important role in obtaining the optimal classifier. The evaluation metric can generally be defined as the measuring tool, which measures classifier performance. Different metrics assess the different properties of the classifier caused by the classification model, thus it is an important step to select the appropriate metric for allowed to discriminate the optimal solution to acquire an optimized classifier [86]. Table (2.1) shows a representation of a confusion matrix for a classification process of three classes, with A, B, and C classes.

Table (2.1) The results of classifying into positive and negative classes

Actual class		**Assigned class**	
		Positive	**Negative**
	Positive	**TP**	**FN**
	Negative	**FP**	**TN**

The main values of this Table are described below [87]**:**

1. True positive (TP): indicates the properly classified positive examples.
2. False negative (FN): denotes to the positive examples that are classified falsely.

3. False positive (FP): denotes to the negative examples that are inaccurately predicted and categorized.
4. True negative (TN): represents the negative occurrences that are properly predicted by the classification model.

The measures accuracy, recall, precision, and f1-score are discussed [87]:

1. Accuracy is the number of correct predictions which is divided by the total number of predictions. The accuracy can be computed based on Equation 2.6.

$$Accuracy = \frac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP+FN}} \quad \textbf{(2.6)}$$

2. Precision is the result of TP number divided by TP and FP number. The precision computed based on Equation 2.6.

$$\textbf{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \quad \textbf{(2.7)}$$

3. Dividing TP number by the number of TP and the number of FN is Recall. This metric could be computed based on Equation 2.7.

$$\textbf{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \quad \textbf{(2.8)}$$

4. F1-score is the 2*((precision*recall)/ (precision + recall)). It is also called the f1- score or the f1- measure. An equation of this metric can be computed based on Equation 2.8.

$$\textbf{F1-Score} = \frac{(\mathbf{2} * \boldsymbol{TP})}{(\mathbf{2} * \boldsymbol{TP} + \boldsymbol{FN} + \boldsymbol{FP})} \quad \textbf{(2.9)}$$

2.8 Summary

In this chapter, the fundamental concepts that related to characterizing a network and finding the most influential nodes of a network are introduced. Besides to the separating them from an influencer, broader notions such as prestige, popularity, and recognition explained. Other topics related to network analysis and information diffusion models are highlighted since the most influential nodes in a network can disseminate information much faster, reaching a greater number of other nodes.

3.1 Introduction

This chapter describes the method used to study influential behavior in the online social network and discusses the phases of the proposed work. Finding influencers in a community is one of the main challenges to benefit from them in several areas. There are several tasks of influencers to attract a larger number of interactions. These tasks are posting important news or putting up advertisements with them, or perhaps take their help in denying negative, false, harmful news or rumors and others. Also, it classifies the new rumor that belongs to any topic. Finally, the system evaluation by the spreading model is used. The first section in this chapter bring to light the architecture of the proposed approach. Then it characterizes the pre-processing of these datasets and also builds the social network from this dataset. In the five-section, rumor classification is used to classify new rumors and highlights the proposed approach for influencer detection in the next section. The final section illustrates the approach that uses to employ influencers to spread information in the network. Some figures and algorithms will be used to depict the system construction method.

3.2 Proposed Approach

The major focus of our method is how to use network information to find influencers in social networks, system architecture illustrated in figure 3.1 consists of five steps. These steps are dataset preprocessing, network generation, rumor classification, influencer detection, and evaluation of this model using spreading.

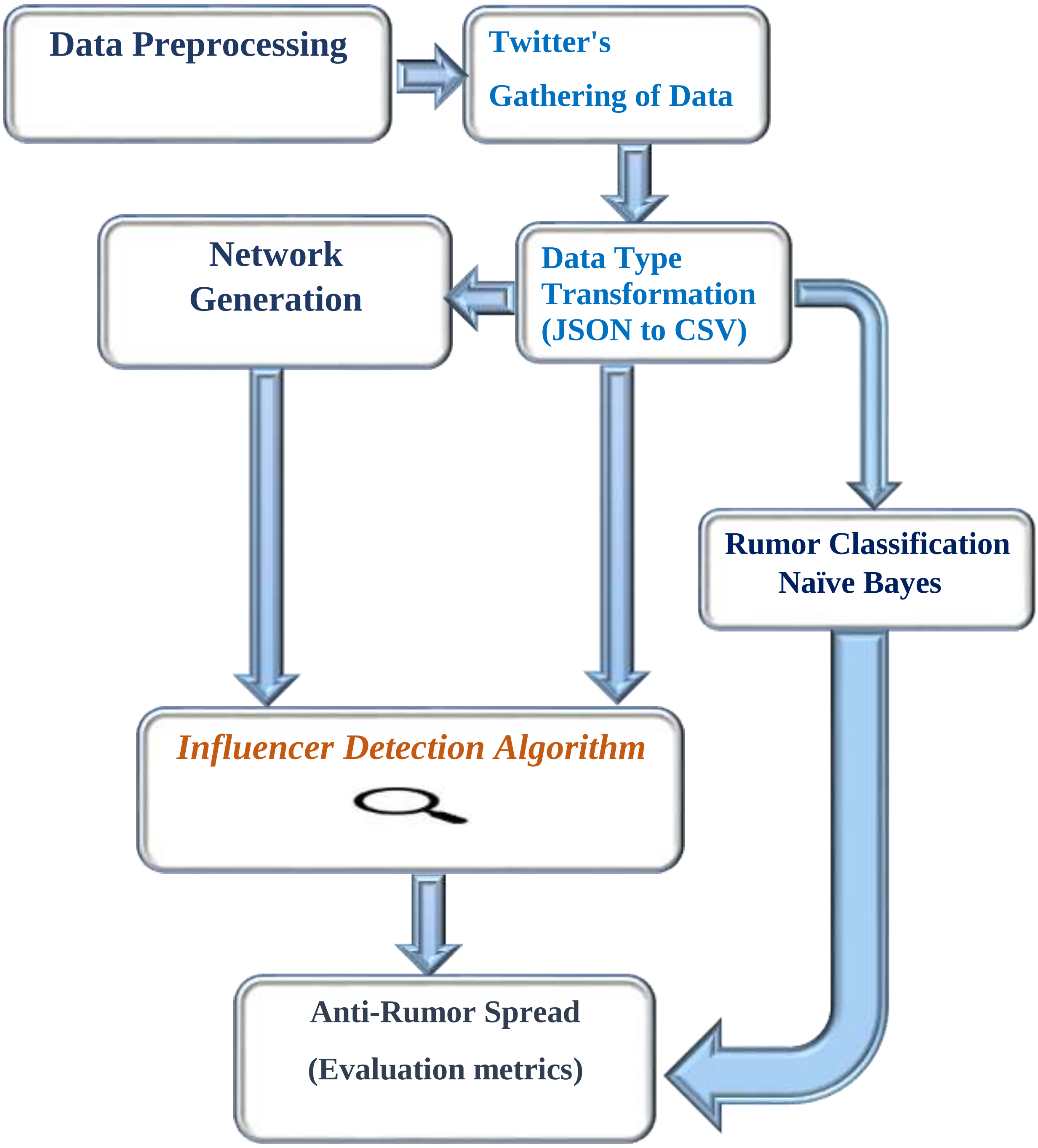


Figure 3.1 Block Diagram of The proposed approach

3.3 Data Preprocessing

The data is high quality if it meets the specifications for its target purpose. This is a list of the key steps to extract pre-processing method. That includes the translation of source data into an acceptable form from tweets, since the raw data was unsuitable for the proposed method. The system comprises pre-processing phases in which it tries to uncover a collection of fundamental features that allow advanced processing algorithms to detect useful contextual information. The preprocessing stage is shown in algorithm 3.1.

Algorithm 3.1: Preprocessing of the Dataset

Input: **Dataset: a set of tweets obtained from the Topics of Dataset**

Output: **A CSV file**

1. ***For*** each Topic ***Do***

    //Twitter's Data Aggregation

2. ***While*** (source tweets exist in Dataset) ***Do***
3. **Let T=** source tweet;
4. **Let R=** tweet reactions;
5. **Let J=** Aggregate tweets and their reactions in one tuple as a LIST
6. header = data. Keys ()
7. ***End While***
8. ***IF* (**count =0**)** ***Then***
9. **he = [**'label', 'contributors', 'truncated', 'text', 'in_reply_to_status_id', 'id', 'favorite_count', 'source', 'retweeted', 'coordinates', 'entities', 'in_reply_to_screen_name','id_str','retweet_count', 'in_reply_to_user_id','favorited','user','geo',

'in_reply_to_user_id_str', 'possibly_sensitive', 'lang', 'created_at', 'filter_level', 'in_reply_to_status_id_str', 'place', 'extended_entities'**]**

10. Write. CSV(he)

11. ***End IF***

// Data Type Transformation

12. **For** (h **to** a header) **Do**

13. Row. append (data[h])

14. **End For**

15. Write**.**csv(Row)

16. ***End For***

17.End

3.3.1 Twitter's Gathering of Data

The data are grouped as explained below. Each event has its directory with sub-folders for rumors and non-rumors. These two directories have a file-specific Twitter ID. The tweets themselves are contained in the "tweet source" directory, but the "reactions" directory contains a collection of tweets that respond to the source tweets. The format of these tweets and responses is JSON (JavaScript Object Notation). During the operating system searches performed for this proposal, the tweets and their responses that correspond to the same primary sub-folders of each event were collected for this study. As a result, there are two JSON files for each event, one for rumors and one for non-rumors. Aggregate data to make sure that the features extracted are appropriate and in compliance with the requirements.

3.3.2 Data Type Transformation

This dataset is a JSON (JavaScript Object Notation) format. JSON is a language-independent data interchange format for representing a variety of data kinds. JSON input can be an array or a single object made up of name/value pairs. To utilize them, the JSON file should be converted into a CSV (comma-separated values) file, which will transform it into a more accessible and organized dataset. Dataset transform from unstructured form to structured form. That makes the next stage of the process straightforward, effective, and successful. As shown in Figures 3. 2 and 3.3 which show the form of the JSON file and its shape after transformation.


```
{"contributors": null, "truncated": false, "text": "Now 10 dead
in a shooting there today RT \"@BBCDanielS: Charlie Hebdo became
well known for publishing the Muhammed cartoons two years ago
\u201d", "in_reply_to_status_id": 552784600502915072, "id":
552785249420447745, "favorite_count": 0, "source": "<a href=
\"http://twitter.com/download/iphone\" rel=\"nofollow\">Twitter
for iPhone</a>", "retweeted": false, "coordinates": null,
"entities": {"symbols": [], "user_mentions": [{"id": 331658004,
"indices": [42, 53], "id_str": "331658004", "screen_name":
"BBCDanielS", "name": "Daniel Sandford"}], "hashtags": [],
"urls": []}, "in_reply_to_screen_name": "BBCDanielS", "id_str":
"552785249420447745", "retweet_count": 0, "in_reply_to_user_id":
331658004, "favorited": false, "user": {"follow_request_sent":
false, "profile_use_background_image": true,
"profile_text_color": "333333", "default_profile_image": false,
"id": 18370911, "profile_background_image_url_https":
"https://pbs.twimg.com/profile_background_images/578554964/clrvc
uc60cp6ce3hqosb.jpeg", "verified": false, "profile_location":
null, "profile_image_url_https":
"https://pbs.twimg.com/profile_images/378800000320937958/abf98da
1430f224cbea0c75c027a178c_normal.jpeg",
```


Figure 3.2 Show the JSON file

retweeted	source	favorite_count	id	in_reply_to_st	text	truncated	contributors	label
FALSE	<a href="http:	0	5.53E+17	5.53E+17	Now 10 dead	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@BBCDaniel:	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@BBCDaniel:	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@BBCDaniel:	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@BBCDaniel:	FALSE		charliehebdo
FALSE	<a href="http:	1	5.53E+17	5.53E+17	@im_a_5H_V	FALSE		charliehebdo
FALSE	<a href="http:	1	5.53E+17	5.53E+17	@GabTarquir	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@S_Jakobsei	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@GabTarquir	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@GabTarquir	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@S_Jakobsei	FALSE		charliehebdo
FALSE	<a href="http:	2	5.53E+17	5.53E+17	@BBCDaniel:	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@GabTarquir	FALSE		charliehebdo
FALSE	<a href="http:	1	5.53E+17	5.53E+17	@GabTarquir	FALSE		charliehebdo
FALSE	<a href="http:	1	5.53E+17	5.53E+17	@BBCDaniel:	FALSE		charliehebdo
FALSE	<a href="http:	1	5.53E+17	5.53E+17	@S_Jakobsei	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@GabTarquir	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@BBCDaniel:	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@lj_kulwicki @	FALSE		charliehebdo
FALSE	<a href="http:	0	5.53E+17	5.53E+17	@neesa_h @	FALSE		charliehebdo
FALSE	<a href="http:	1	5.53E+17	5.53E+17	@lj_kulwicki @	FALSE		charliehebdo

Figure 3.3 Show the CSV file

3.4 Network Generation

After collecting, processing, and storing the data, the elements of the social network are chosen by selecting the nodes and connections from the data set, and then the social network are built, as shown in figure 3.4.

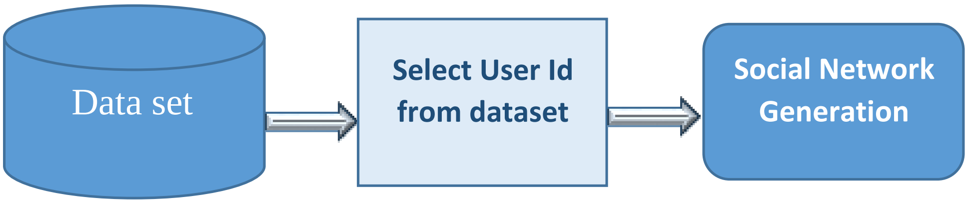


Figure 3.4 Network Generation Steps

In this model, the nodes represent Twitter users, while the links represent the behavior on tweets (mention between users). This behavior is chosen according to the literature and because it expresses more about shared interests between users than a friendship or follow-up relationship. Users in social networks may have a friendship or follow-up relationship because of kinship or reasons other than sharing interests while mentioning behavior on textual content is evidence of people's interest in that content.

Table 3.1: Represent the Relationships Between Users

Tweet Text	**Source (ID The user who mentioned)**	**Mention (ID Referred user)**
Now 10 dead in a shooting there today RT "@BBCDanielS: Charlie Hebdo became well known for publishing the Muhammed cartoons two years agoâ€	18370911	@331658004
@GabTarquini @BBCDanielS @BBCWorld Oh come on. It's a friendly gesture. You quite clearly expected me to be islamaphobic as well.	146142164	@295789381 @331658004 @742143

Nodes must be extracted and then construct relationships between them to collect our data, which entails mapping the network. This network is graph G = **(N, E)** where **N** is a set of users and E edge. The datasets are used to create a graph representation of the social network, with each user's id being a node in the graph and the link between nodes being mentioned, as shows in table 3.1.

After generating the social network. It should be noticed that the social network's nodes and linkages are getting increasingly complex. Therefore, the appropriate communities must be discovered within these networks to extract useful information from them, particularly because the number of social networking site users is so large. Figure 3.5 shows the network generation. In our method, create the graph, then take the largest subgraph in it. The users and their information are used in this subgraph in model, and compute some characteristics for this component such as (the number of nodes and edges, min-max degree, mean degree, and diameter). Diameter the maximum distance between any two points in a metric space.

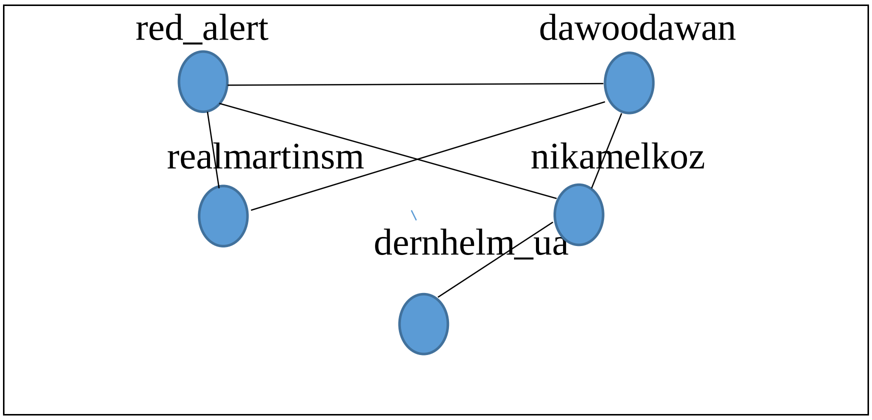


Figure 3.5 The Interaction Relationship Between Twitter Users

3.5 Naïve Classifier

At this stage, the next rumor is classified as belonging to any topic to activate the influencer of this topic. There are two stages in the dataset: one for training and the other for testing, this data was separated into five categories (Charlie Hebdo, Ferguson, Germanwings crash, Ottawa shooting, Sydney siege. Classification is a supervised learning strategy where the algorithms learn from the training input data they collect and utilize this learning algorithm to classify social media data. The Naïve Bayes (NB) algorithm was used. It is a Probabilistic classifier inspired by Bayes theory and considered a simplified version of Bayesian Networks which is a deep and highly sophisticated family of machine learning fields. Among the advantages of this algorithm are its simplicity and generally positive outcomes. This approach takes a little amount of training data to predict the required mediators. Its model is easily adaptable to bigger data sets. The linear time required by Naive Bayes classifiers allows them to outperform more advanced techniques. The classification stage shows the algorithm 3.2.

Algorithm 3.2: Naïve Bayes
Input: **Datasets D with labels class C**
Output: **classifier result**
1. Split the Data into Train and Test Dataset
// find how important a word in the document is in comparison to the corpus
2. Vectorize the corpus by using the TF-IDF vectorizer
// classify out data
3. Train the data by naïve classifier
4. Test the data by naïve classifier
5. Return the classification result
End

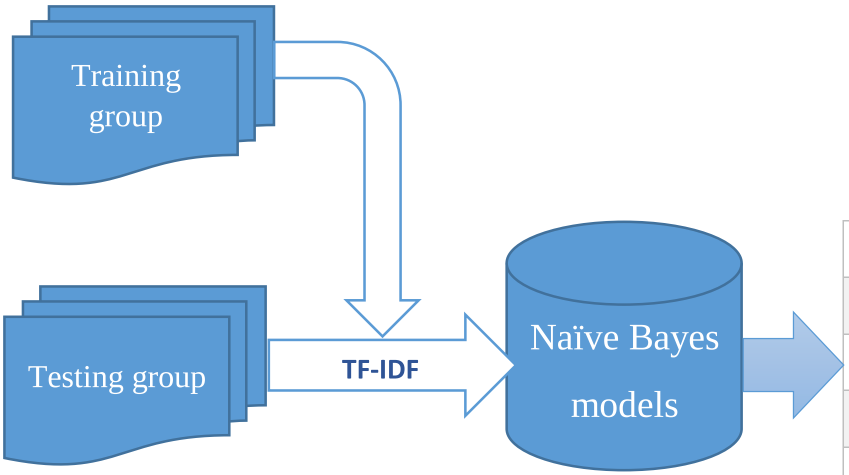
Word frequency can be employed to determine the most frequently occurring terms in a text corpus. This can be useful in a variety of scenarios, such as evaluating commonly used consumer terms or words. The most prevalent technique is TF-IDF.

Term frequency (TF) = (the number of times t it appears in the document) \ (number of terms in the document).

IDF = log (N/n), where N is the total number of documents and n is the total number of documents that include the phrase t. An uncommon word's IDF is high, whereas an often-used word's IDF is low, making it easier to find. The impact of the highlighted words is greater.

The IDF-TF value determine the word as follows: = IDF * TF

A classifier has been developed that can categorize tweets into 5 categories: Charlie Hebdo, Ferguson, Germanwings crash, Ottawa shooting, and Sydneysiege. By training it on a data set of classified documents consisting of 5,802 source tweets classified by content type and we used Naïve Bayes classification algorithms and build a classification model: using the word frequency attributes, as shown in figure 3.6.



Tweet 1	Charlie Hebdo
Tweet 2	Ferguson
Tweet 3	Germanwings crash
Tweet 4	Ottawa shooting
Tweet 5	Sydney siege

Figure 3.6 Classification Model Using Naïve Bayes

3.6 Influencers Detection Algorithm

This is a significant step in the development of the methodology since it determines the results obtained from the suggested method. In this section, an algorithm will be presented to determine optimal influencers. The influencers detection algorithm has been modified to obtain satisfactory and strong results in calculating influencers and using them to combat rumors.

This algorithm calculates several equations to determine the influencers' values in the network, in our model, consider popularity, average interaction, and addition to the reach score. This algorithm was applied to the two datasets (PHEME, Ukraine), as illustrated in the following algorithm 3.3:

Algorithm 3.3: Modified Algorithm Determine Influencers Users
Input: subgraph Gs (N, E) represent the connection between the user ***Output:*** The top n influencer in topic T N=number of nodes T= number of topic **1.** ***For*** each topic T ***Do*** **2.** ***For*** each N in G ***Do*** **3.** **Compute:** popularity, reach score, the average interaction as Eq. (2.5) (2.1) (2.2) respectively **4.** from popularity, reach score, the average interaction **5.** **compute**: ***influence score*** as Eq. (3.1) **6.** ***max Influence score=max [I]*** as Eq. (3.2) **7.** ***min Influence score=min [I]*** as Eq. (3.3) **8.** ***Random Influence score=Random [I]*** as Eq. (3.4) **9.** ***End For*** **10.** ***End For*** **11.** ***Return*** The sets of influencers in the subgraph **12.End**

The influencers detection approach works as follows: for each subgraph node numbers of measures are calculated to conclude the influence score of nodes. Following are detailed explanations of the equations utilized in the algorithm:

1. **Popularity:**

   The great majority of social networking sites are scale-free networks. A scale-free network is one in which the degree distribution is a power law, such that the number of nodes in the network with k connections, represented by P(k), increases exponentially with the increasing value of k, such that P(k) =k^(-y)

   where y is a constant value (2<y> 3).

   A user's popularity can be estimated in a social network based on the number of in-links that they receive from other users, as seen in the previous chapter in equation (2.5).

2. **Reach Score:** This metric represents the number of individuals reached by an influencer's social media posts. This is a quantitative assessment based on empirical evidence, as in the equation (2.1).

The value (2,000,000) in the equation replaced with N, the value of N determines based on the actual data acquired at the time and stored in datasets, where N is the total number of nodes in the network based on dataset features. By selecting this value, we permit large influence to get a score of 100 for reach.

3. **Average Interaction Score:** we measure the average interaction for each node in the subgraph, to get an influencer's average interactive score is how various likes, shares, and comments you receive on each post by how various posts this particular influencer has posted overall,

the value of average interaction score calculated as the equation (2.2) mentioned in the previous chapter.

4. ***Influence Score:*** The following Equation is used to determine the final influence score:

$$\textit{Influence Score} = \alpha \times \textit{popularity} + \beta \times \textit{Reach score} + \gamma \times \textit{Average interaction} \quad (3.1)$$

Where **(α, β, γ)** weighted number **0< α< β< γ<1** these weighted numbers can be determined based on social network characteristics.

$$\textit{Max Influence score} = \sum_{i=1}^{N} \boldsymbol{Max}[\boldsymbol{I}] \quad (3.2)$$

$$\textit{Min Influence score} = \sum_{i=1}^{N} \boldsymbol{Min}[\boldsymbol{I}] \quad (3.3)$$

$$\textit{Random Influence score} = \sum_{i=1}^{N} \boldsymbol{Random}[\boldsymbol{I}] \quad (3.4)$$

After computing the influence score for all user draw and seeing when finds a skew in influence score values, the value of I is determined. Using the equations above, the previous algorithm illustrates how to detect influencers in social networks by calculating the influence of each network node. We view the user with the highest score as a more powerful influence on the network on a specific topic or sector.

We calculate Equations (3.2), (3.3), and (3.4) in this step, focusing them on evaluating a proposed work of detecting influencers.

3.7 Evaluation Metric (Spread Anti-Rumor)

when we detect influencers in multiple topics, one of the most critical tasks was to evaluate these influencers. We examine this proposed approach by utilizing a real dataset of tweets to illustrate the effectiveness of this model. At that step, the results will be compared to other essential work to evaluate them.

For this purpose, we employ the influencers suggested by the previous model to combat rumors by spreading anti-rumor according to the equation (3.5).

$$\sum_{1}^{n} \boldsymbol{U_i} = \mathbf{1} \tag{3.5}$$

where U_i is the node that adopts the message.

The goal finds **n** that represents the number of rounds that require to cover the network**.** The rumor-spreading algorithm explains the steps to spreading information in the network. A mechanism known as "push" is used to spread rumors, where each node in the network transmits a message to one of its neighbors at random until the entire network is covered.

Algorithm 3.4: Rumor Diffusion

Input: **Max, Min, Random Influence score**

Output: **Number of rounds**

// max 100 influence

For i to max influence ***Do***
    Max influence[i]=1
End For
Round=0
while (all nodes do not receive the message) ***Do***
    For i =1 to N ***Do***
        If n =1 ***Then***
            Choose neighbored random of(n)=1
        End If
    End For
    Round=Round+1
End While

// Min 100 influence

For i to min influence ***Do***
    Min influence[i]=1
End For
Round=0
While (all nodes do not receive the message) ***Do***
    For i =1 to N ***Do***
        If n = 1 ***Then***
            Choose neighbored random of(n)=1
        End If
    End For
    Round=Round+1

24. ***End While***
// Random 100 influence
25. ***For*** i to random influence ***Do***
26. Random influence[i]=1
27. ***End For***
28. Round=0
29. ***While*** (all nodes do not receive the message) ***Do***
30. ***For*** i =1 to N ***Do***
31. ***If*** n==1 ***Then***
32. Choose neighbored random of(n)=1
33. ***End If***
34. ***End For***
35. Round=Round+1
36. ***End While***
37. End

After identifying influencers with algorithm 3.3, algorithm 3.4 describes the process of dissemination that occurred in proposed method. They are utilized to spread the message throughout the network. This is accomplished by the following mechanism, where their value is one. And then, in each round, each influencer spread the message to one of his neighbors at random, where the value of Nodes is changing to one. This indicates that the message has been received, and so on until the complete network has been covered. It is worth mentioning these steps are applied three times. Firstly, the maximum influencing score is used to start the spreading from them. Secondly, spreading using a minimum influencing score to clarify the difference in the number of rounds when using the highest and lowest influence score values for spreading. Finally, spreading the message in the network without Influencer Subscriptions. This can be done by choosing N nodes randomly to start the spreading process from them.

3.8 summary

This chapter examines powerful online communities in depth and explores influential online behavior using a variety of methodologies. They can acquire a greater understanding of the online influence process by combining a range of techniques. Additionally, by exploring online groups and researching those objects who have the ability to influence the thoughts and attitudes of others through online means, we can employ them to decrease the impacts of rumor on society.

4.1 Introduction

This chapter presents and discusses the performance of the suggested methodology based on the acquired evaluation results and a comparison with another method. The results are grouped for each stage according to their appearance in the third chapter, which begins with the hardware and software prerequisites for implementing the suggested work.

4.2 Hardware and Software Requirements

The proposed system is implemented with an HP device that possesses the following characteristics:

1. **Processor:** @ 1.90GHz and 2.50 GHz, it is powered by an Intel Corei5-4300U CPU
2. **Memory:** 4.00 GB.
3. **Storage:** 321 GB.

Python 3.10 is the software implemented in the proposed approach. That is a flexible, high-level, public domain, interpreted programming language that aims to describe programming concepts with as little code as possible. Python is standard library includes both object-oriented and procedural programming. The great majority of operating systems support this open-source programming language.

Another software googles colab Free GPU server launched by Google is used, the official description is: Collaboratory is a research project and can be used free.

Collaboratory is developed to facilitate the publication of machine learning research and training outputs. It is a Jupyter notebook environment that requires no configuration and operate entirely in the cloud. Keras, TensorFlow, PyTorch and other frameworks make it easily to construct deep learning application. The virtual machine is configured with T4 GPU, 12G memory, and 39G hard disk space.

4.3 Dataset Description

This section will describe the datasets utilized in the proposed study. Two datasets were in use, and their characteristics is detailed below:

4.3.1 PHEME Dataset [20]:

This dataset covers rumors and non-rumors posted on Twitter at times of breaking news. The dataset includes the following five breaking news items:

1. **Ferguson Unrest:** Residents of Ferguson, Michigan, demonstrated on August 9, 2014, in response to the shooting murder of Michael Brown, 18, by a white police officer.
2. **Ottawa Shooting:** On Canada's Parliament Hill, on October 22, 2014, a Canadian soldier was killed by gunfire.
3. **Sydney Siege:** On December 15, 2014, a shooter in Sydney's Martin Place took hostage ten customers and eight employees at a Lindt chocolate café.
4. **Charlie Hebdo Shooting:** On January 7, 2015, two brothers entered the Paris headquarters of the French satirical weekly Charlie Hebdo, killing eleven people and wounding eleven more.
5. **Germanwings Plane Crash:** On March 24, 2015, a Barcelona to Düsseldorf passenger flight collided into the French Alps,

killing all aboard. Eventually, it was established that the co-pilot intentionally wrecked the plane.

Table 4.1 Distribution of Annotations of Rumors and Non-Rumors

Event	Rumors	Non-Rumors	Total
Charlie Hebdo	(22.0%)458	(78%)1,621	2,079
Ferguson	(24.8%)284	(75.2%)859	1,143
Germanwings crash	(50.7%)238	(49.3%)231	469
Ottawa shooting	(52.8%)470	(47.2%)420	890
Sydney siege	(42.8%)522	(57.2%)699	1,221
Total	(34.0%)1,972	(66.0%)3,830	5,802

The JSON (JavaScript Object Notation) file type is used to store the PHEME dataset, which contains 5,802tweets and their relevant interactions with the source messages. There is a difference in the percentages of dividing annotations of events. The percentage of rumors was less than a quarter in all of the events Charlie Hebdo and Ferguson, while the ratio exceeded half in both Germanwings Crash and Ottawa Shooting events, the percentage of rumors was 42.8% in the Sydney Siege Event, as shown in Table 4.1. Actual non-rumor and rumor tweets from the PHEME dataset are shown as screenshots in Figures 4.1 and 4.2.

Series of Blasts Heard At Sydney Cafe

A series of blasts and bursts of ammunition have been heard at the Sydney Café where up to 30 hostages were being held.

Figure 4.1: Screenshot of a Sample of PHEME Non-Rumor Tweets

12 dead in shooting at French Satirical Weekly Charlie Hebdo in Paris

Twelve people,10 journalists and two policemen, have been killed, and 10 others wounded in the shooting massacre at the Paris headquarters of satirical newspaper ...

Figure 4.2: Screenshot of a Sample PHEME Twitter Rumor

4.3.2 Ukraine Dataset

It is NodeXL Twitter Search Network It was generated at a certain time on 3/6/2022 as shown in figure 4.3, between 6 and 9 hours. it is an Excel file with 10 sheets, each of which has several columns such as visual properties, labels, graph metrics, and another column, these sheets are shown in table 4.2. In the same regard figure, 4.4 Describes some of the features in the Ukraine dataset.

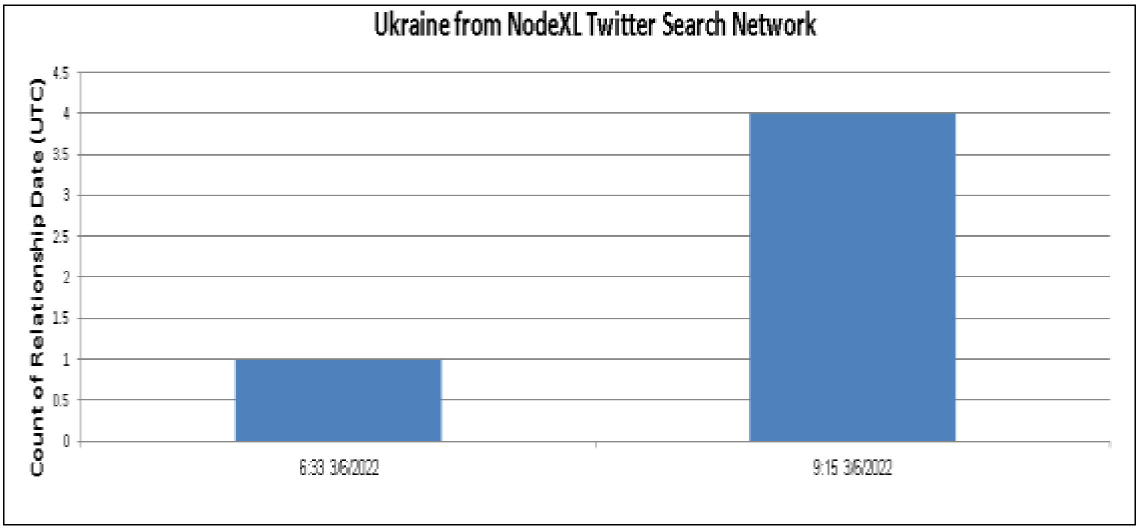


Figure 4.3 Ukraine Dataset

Table 4.2 Sheets of Ukraine Dataset

Edges	Vertices
Groups	Group vertices
Overall metrics	Words
Word pairs	Word list
Export options	Time series

Vertex1	Vertex2	Follower	Friend	Tweets
dawood31298133	dawoodawan99	256	46	426
realmartinsmit	red___alert	8591	8060	2443
dernhelm_ua	nikamelkozerova	82	29	212
hartmutvoigt	knut_knutsson	63	18	116
oigwe3	general_somto	85	61	1047
pedallerpedro	mrjamesob	844	113045	7921
godofvalhalla	tanjamaier17	1736	568	43941

Figure 4.4 Set of Features of the Dataset

4.4 Data preprocessing Results

The first phase of the proposed work involves preparing the dataset for the subsequent phase. Following the execution of the processes below, the pre-processing stage's results are represented:

4.4.1 Twitter's Gathering of Data

The JSON files are collected in the PHEME database, with each JSON file containing the source and reaction tweets, producing the following result:38268 tweets for Charlie Hebdo, ,4489 Germanwings crash, 24175 Ferguson ,12284 Ottawa shooting, and 23996 tweets for Sydney siege.

4.4.2 Type Transformation

After aggregation of data converts JSON files to CSV files Where it's simple to deal with. This allows for the extraction of characteristics from these datasets. Figure 4.5 illustrate some features in the PHEME dataset.

id_str	in_reply	entities	coordir	retweet	source	favorite	id	in_reply	text	truncat
5.53E+17	BBCDanie	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	Now 10 de	FALSE
5.53E+17	BBCDanie	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@BBCDar	FALSE
5.53E+17	BBCDanie	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@BBCDar	FALSE
5.53E+17	BBCDanie	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@BBCDar	FALSE
5.53E+17	BBCDanie	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@BBCDar	FALSE
5.53E+17	im_a_5H_\	{'symbols': [], 'user_m		FALSE	<a href="h	1	5.53E+17	5.53E+17	@im_a_5H	FALSE
5.53E+17	GabTarqui	{'symbols': [], 'user_m		FALSE	<a href="h	1	5.53E+17	5.53E+17	@GabTarc	FALSE
5.53E+17	S_Jakobse	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@S_Jakob	FALSE
5.53E+17	GabTarqui	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@GabTarc	FALSE
5.53E+17	S_Jakobse	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@GabTarc	FALSE
5.53E+17	S_Jakobse	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@S_Jakob	FALSE
5.53E+17	BBCDanie	{'symbols': [], 'user_m		FALSE	<a href="h	2	5.53E+17	5.53E+17	@BBCDar	FALSE
5.53E+17	GabTarqui	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@GabTarc	FALSE
5.53E+17	S_Jakobse	{'symbols': [], 'user_m		FALSE	<a href="h	1	5.53E+17	5.53E+17	@GabTarc	FALSE
5.53E+17	BBCDanie	{'symbols': [], 'user_m		FALSE	<a href="h	1	5.53E+17	5.53E+17	@BBCDar	FALSE
5.53E+17	S_Jakobse	{'symbols': [], 'user_m		FALSE	<a href="h	1	5.53E+17	5.53E+17	@S_Jakob	FALSE
5.53E+17	GabTarqui	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@GabTarc	FALSE
5.53E+17	BBCDanie	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@BBCDar	FALSE
5.53E+17	lj_kulwicki	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@lj_kulwic	FALSE
5.53E+17	neesa_h	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@neesa_h	FALSE
5.53E+17	lj_kulwicki	{'symbols': [], 'user_m		FALSE	<a href="h	1	5.53E+17	5.53E+17	@lj_kulwic	FALSE
5.53E+17	neesa_h	{'symbols': [], 'user_m		FALSE	<a href="h	0	5.53E+17	5.53E+17	@neesa_h	FALSE
5.53E+17	lj_kulwicki	{'symbols': [], 'user_m		FALSE	<a href="h	1	5.53E+17	5.53E+17	@lj_kulwic	FALSE

Figure 4.5 PHEME Dataset Features

4.5 Network Generation

The network is built using NetworkX. It is a Python program for generating, modifying, and investigating the structure, dynamics, and behavior of complex networks; it also enables seamless collaboration with big, non-standard data.

NetworkX is capable of sketching, loading, saving, creating, analyzing and construction in a variety of data forms including standard and non-standard data types, among other abilities. In this experiment, drawing the graph and take the maximum subgraph and computing some characteristics that are needed in this approach. Tables 4.3 explain the network generation results.

Table 4.3 Network Generation

	PHEME Dataset	**Ukraine Dataset**
Number of nodes in the graph	56207	20601
Number of edges in the graph	100274	24229
Number of nodes in the subgraph	54958	9887
Number of edges in the subgraph	99063	14038
Min Degree	1	3
Max Degree	38	6
Mean Degree	3.605	2.83
Diameter	23	28

4.6 Naïve Classifier

In this section, the dataset using the Naive Bayes classification technique will be categorized. The dataset has been separated into two groups:92891 tweets (90%) for training and 10322 tweets (10%) for testing, its percentage was increased to obtain the best results. These tweets were used to build our ranking as the model accuracy has been improved after increasing the number of training data. Table 4.4 illustrate the classification result.

Table 4.4 Classification Result

Topics	Rumors	Non-Rumors
Charlie Hebdo	351	4852
Ferguson	380	1991
Germanwings crash	152	74
Ottawa shooting	433	280
Sydney siege	553	1256

Table 4.5 The PHEME dataset classifier metrics

NO.	Metrics	Result
1	Accuracy	78.54932
2	Precision	0.7892
3	Recall	0.7856
4	F-measure	0.7858

The results shown in the previous table 4.5 demonstrate the superiority in the values of the used metrics. The values that appear in our results represent the average results of the five-event data used in our proposed method.

4.7 Influencers Detection

The main objective of this algorithm is to extract influencers on Twitter and this is done using several equations that were detailed in the third chapter. In this section, the most important results in the account of influencers will be given. the influence score by combining three metrics (popularity, reach, and average interaction) will be constructed and comparing the outcome to that of the passion point.

The following table 4.6 shows the values of the influence score. Figure 4.6 indicates that the values of the two methods are close and follow the same strategy to compute the influence score applies to the PHEME, Ukraine datasets. As observed, the two techniques are equally at the same level of detecting the influencer. This is because both approaches employ the same metric of popularity, namely the number of friends and followers. It is one of the most significant factors in determining the influence score. In addition to other utilized measures.

Table 4.6 Influences Scores

Influence score	PHEME Dataset	Ukraine Dataset
Min	0.3	0.3
Max	67860351	52865113
Average	6733	92678

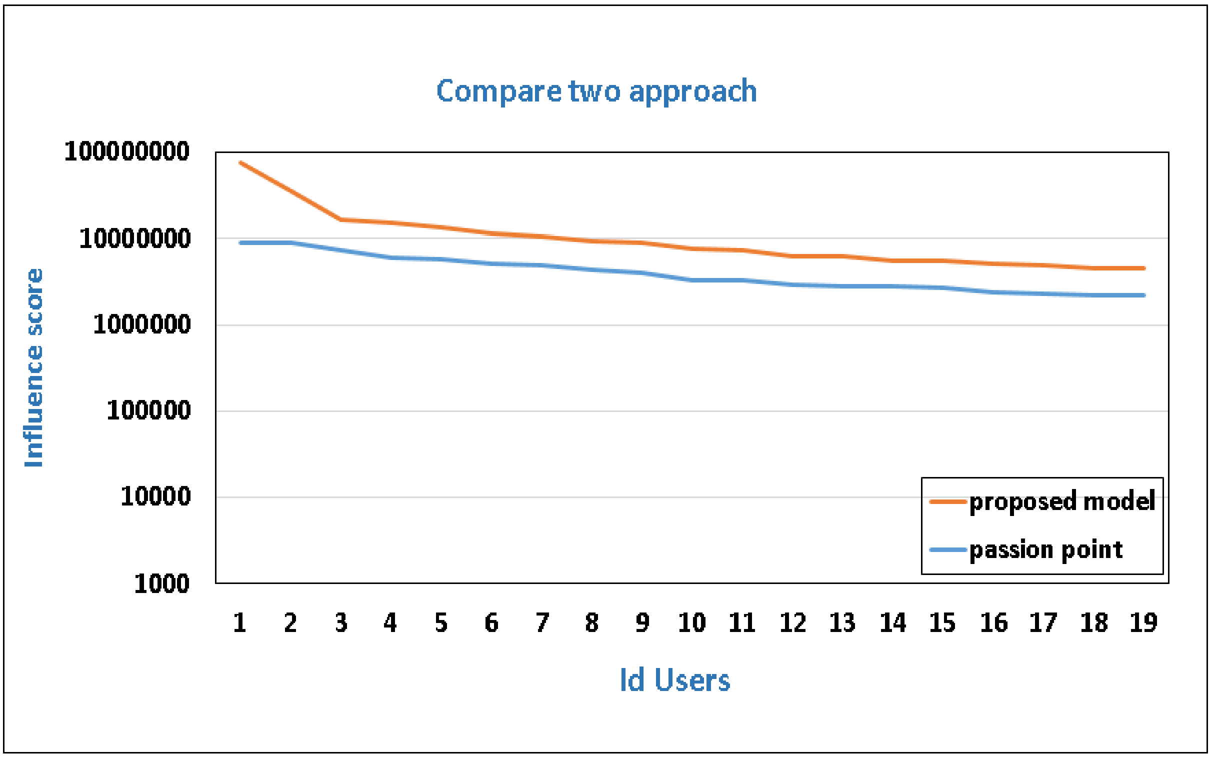


Figure 4.6 Result Comparison between Two Model

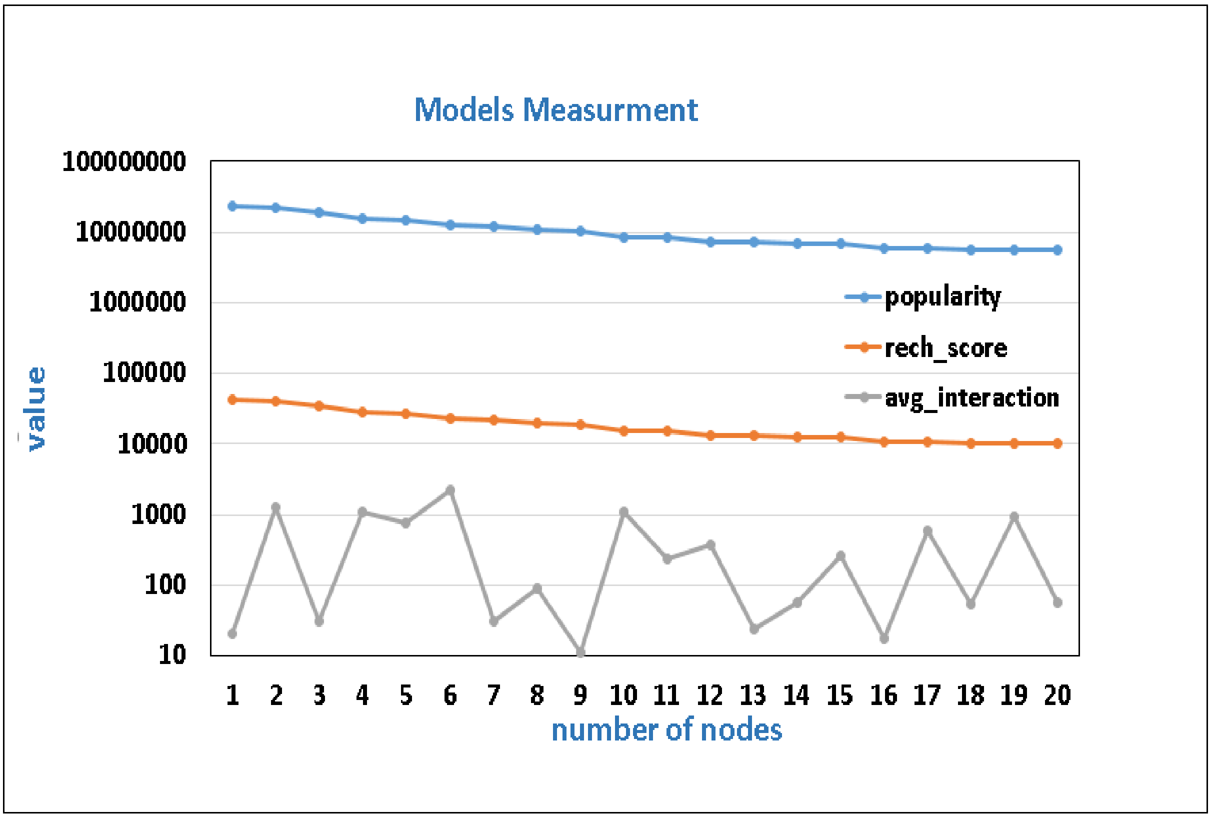


Figure 4.7 Result of Three Measure

Figure 4.7 explains the values of the three measures that were used to calculate the degree of influence. The figure demonstrates that the values of popularity and reach score are stable. This is due to the fact that the values them is the number of friends and followers of the object, and caused them the number of followers of the influential object on Twitter is always large. Whereas, the values of the average score fluctuate because it measures the rate of effectiveness of the influencer on Twitter. Some influencers despite their large number of followers, their interaction (Shares, likes, comments) on Twitter is low, and this shows the fluctuating line in the figure. Figure 4.8 illustrates the influence score according to the topic where the influencers are detected in each topic.

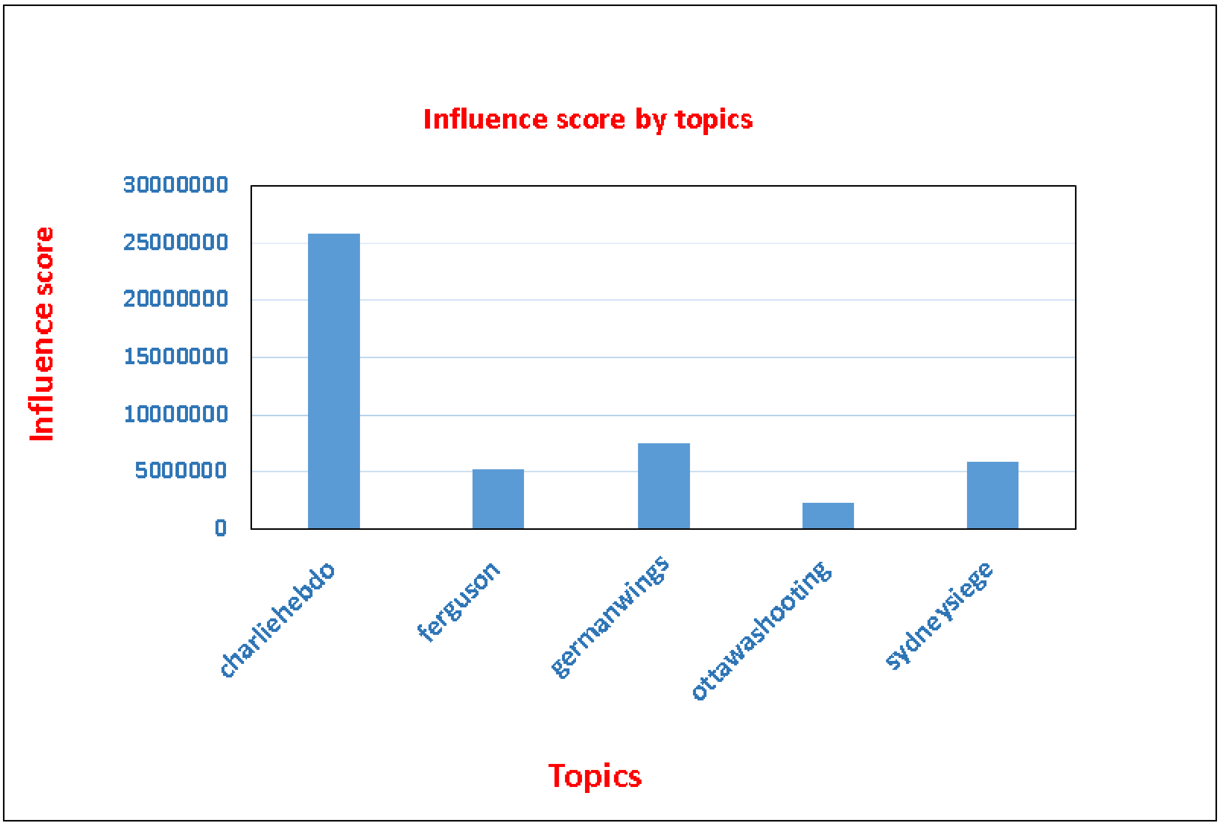


Figure 4.8 Influencing Score According to Topic

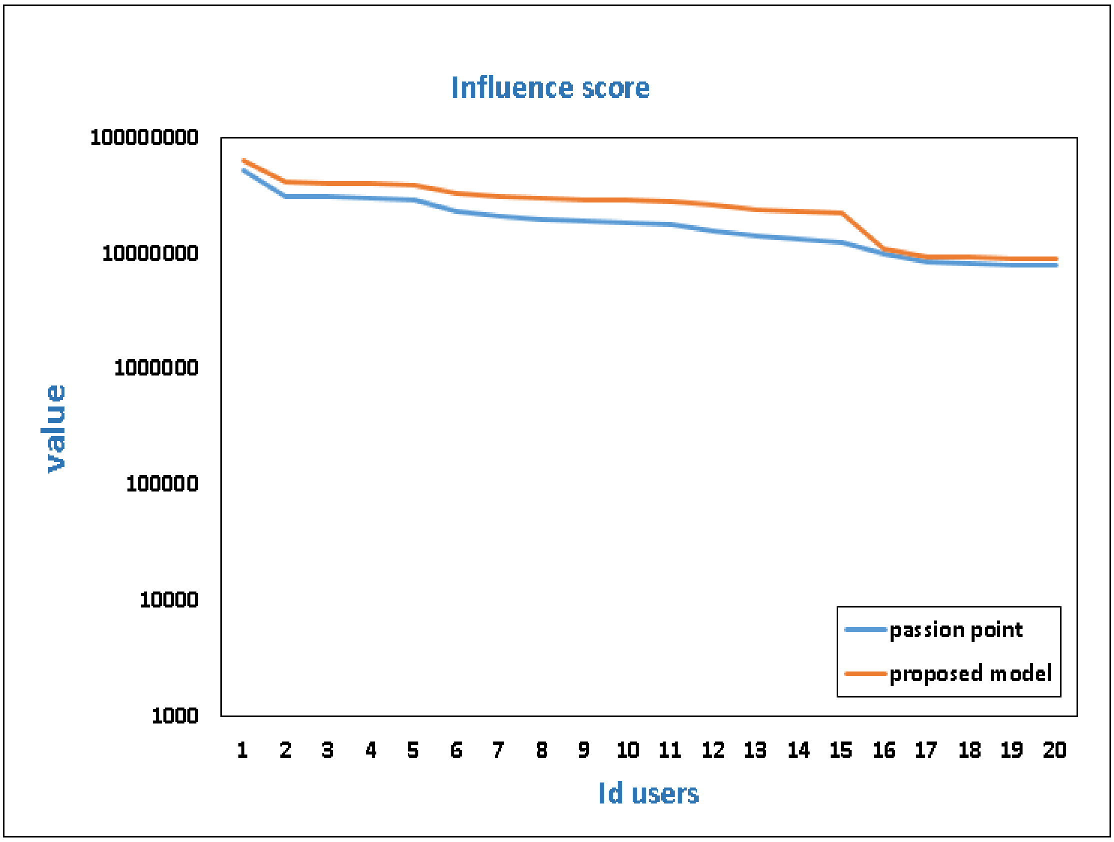


Figure 4.9 Influences Score by Ukraine Dataset

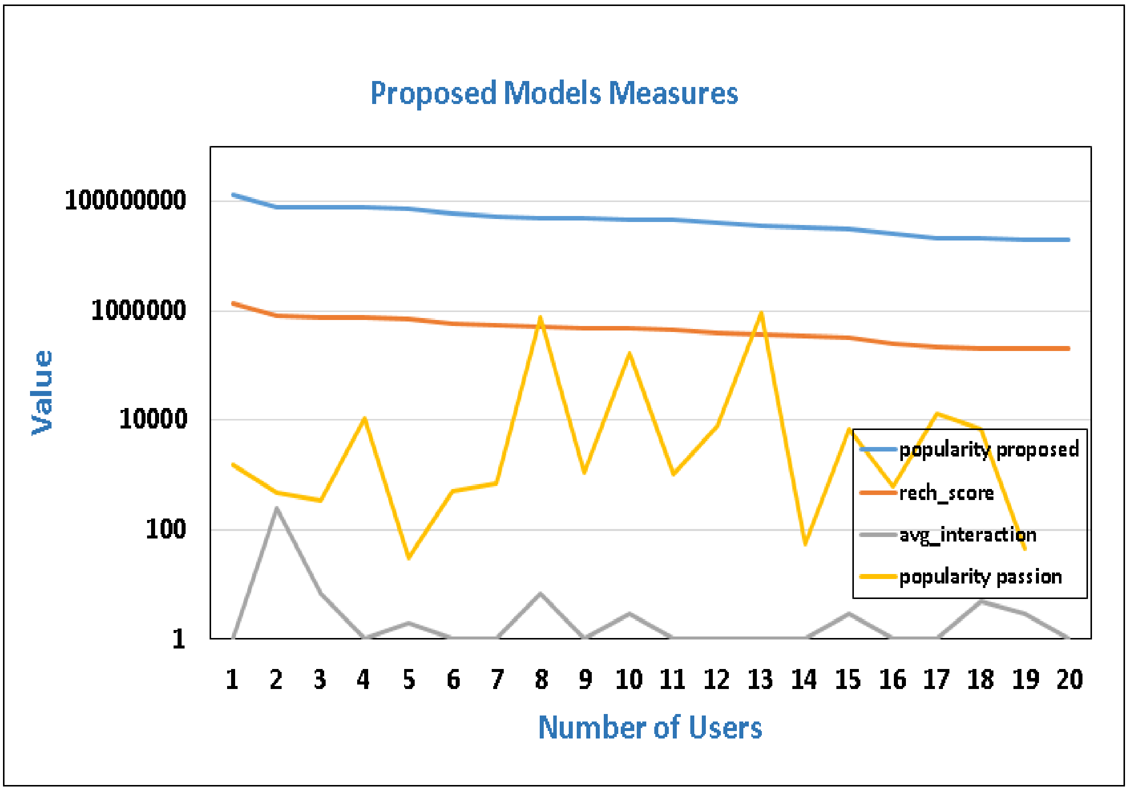


Figure 4.10 Result of measure *by Ukraine Dataset*

This approach was applied with another dataset, the Ukraine dataset, producing the results in figure 4.9 illustrates the influences score of the proposed approach and the passion point model.

In figure 4.10, the values of the metrics used in the algorithm for detecting influencers have been clarified. It must be emphasized that the popularity and reach values change steadily, but the average values are also fluctuating. Furthermore, the variation is explained between the values of popularity in the proposed method and the passion point approach. It is noted that the method of passion point, popular is not at one level. That is, the values of influencers, the number of their friends and followers, differ by a large amount compared to the values of popularity with our proposed method.

Table 4.7 The Weighted Use in Influencers Detection

α	**β**	**γ**	**Influence score**	**Spread**		
				Max	**Min**	**Random**
0.4	0.3	0.3	67860351	5592	6301	6554
0.3	0.3	0.4	90479429	6064	6400	6067
0.6	0.2	0.2	45241717	5660	6173	6264
0.2	0.2	0.6	135718029	5811	5671	6267
0.2	0.6	0.2	45239940	6164	6163	6145

Table4.7 includes the values of the weights that are evaluated in the influencers detection algorithm. The weights are update and evaluate in the diffusion algorithm, where it has been determined that the first weights are higher to spread.

The previous table shows that the dissemination of information is faster in the social network when the weight of popularity is higher compared to other weights. This shows that increasing the number of followers for each user has a significant impact on spreading information on the network. This explains the greater the number of followers of the influential object, the greater its ability to spread information faster

4.8 Anti-Rumor Technique

In this study, use spreading to evaluate the proposed approach, validating performance using various values of influence score.

Figure 4.11 illustrates the difference in spreading between the proposed algorithm and the passion point algorithm. It must be pointed it, that spreading in two approaches takes the maximum [N] influence score and the minimum [N] influence score. In addition, spreads without influencers according to the equations mentioned in the previous chapter, respectively, as show in table 4.8. It should be noted the value of N=100.

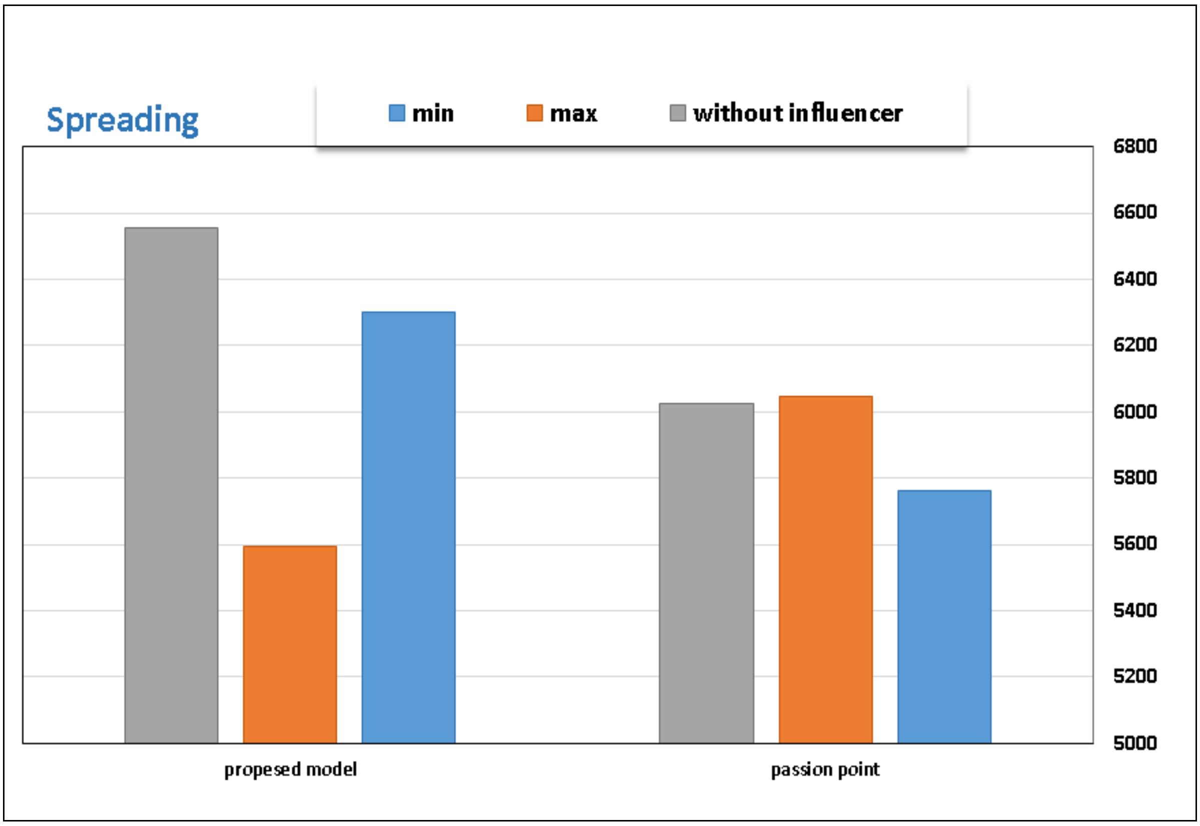


Figure 4.11 Show the Spreading between the two approaches using the PHEME Dataset

Table 4.8 Show the Values of Spreading PHEME Dataset

influencers	Proposed method	Passion point
Max	**5592**	**6047**
Min	**6301**	**5760**
Without	**6557**	**6025**

It is concluded, from the above figure that the method required fewer cycles and less time to spread the information using max influencers than the min influencers to cover the network. At the least spreading the information without using influencers on social networks notice that spreading takes more round to cover the network as a whole. The difference between using influencers and not using them was obvious also the figure shows that spreading by passion point there is a difference between min, max, and without influencing score. This is how it turns out the maximum influence that takes more rounds than the minimum and without an influencer spreading. To discuss the results of the spreading, it is noted that the role of influencers in disseminating information on social networks and their turn in controlling rumors when they spread denial compared to other users.

It may be useful to emphasize the result of the spread by applying it to the Ukraine dataset, as show in table 4.9. The same level of results was obtained previously; without a doubt, the influencers need fewer rounds to cover the whole network with information. As shown in figure 4.12

Table 4.9 Show the Values of Spreading Ukraine dataset

influencers	Proposed method	Passion point
Max	2108	2278
Min	2143	2149
Without	2197	2228

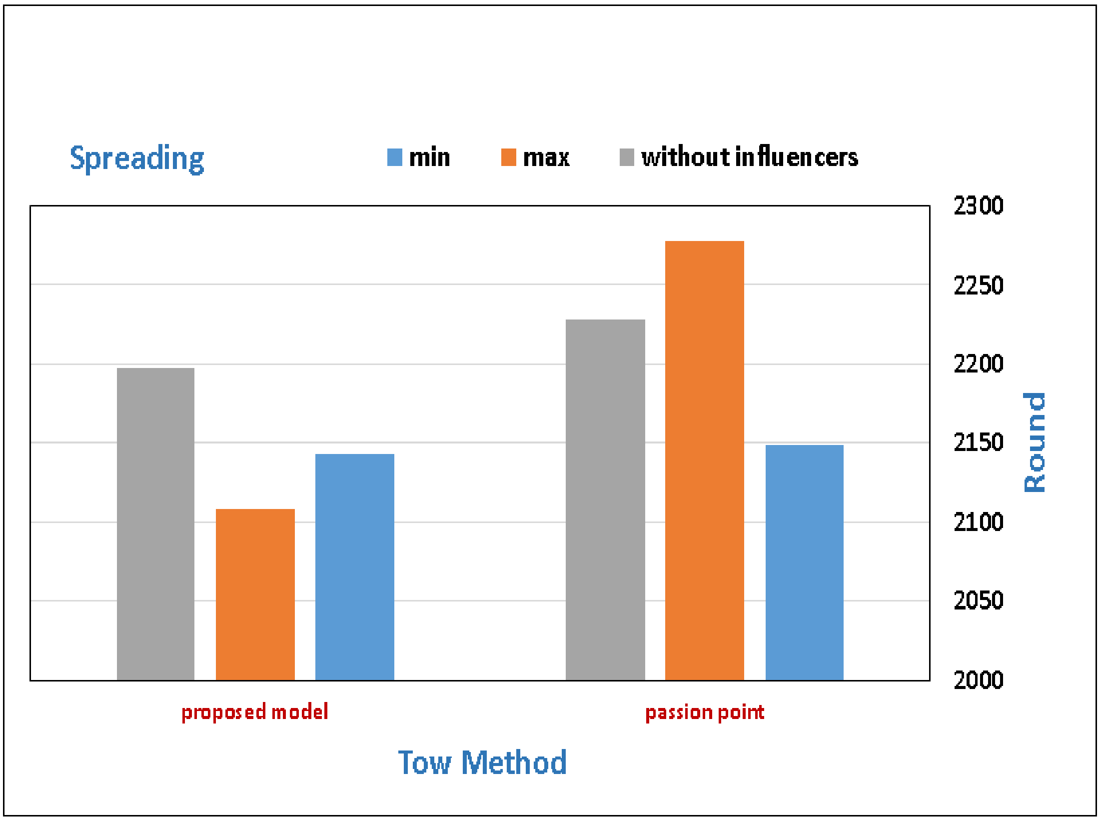


Figure 4.12 Show the spreading between the two approaches using Ukraine Dataset

The values of the influencers utilized in the spreading are shown in Table 4.10 it is observed the difference in the number of rounds coming from the various influencing values, and the best diffusion results with 100 influencers as compared to alternative values.

Table 4.10 Spreading Using Influencers

Number of Influencers (N)	Round		
	Max	Min	Without Influencers
50	6022	6283	6177
80	60297	6297	6081
100	5592	6301	6554
200	6356	5902	6314

5.1 Introduction

Researchers have given social networks great attention, and they have investigated them from a variety of angles, including looking at their effects on the economy, security, health, and education systems, as well as financial markets. Where it has a large user base and a huge store of information and news. It quickly became a platform for spreading rumors and false information, prompting us to focus on the problem of controlling rumors on social networking sites. This chapter provides a summary of the method's extracted results.

5.2 Conclusion

The results obtained in this research can be summarized as follows:

1. This proposed works produces an approach to combat rumors on social media platforms (Twitter) by utilizing influencers to spread anti-rumors. It tries to educate the public about rumors, and anti-rumors are circulated via Twitter by influential individuals. When the user hears any rumor, the model selects several influencers whose values we have calculated according to certain criteria to block the rumor.
2. The pre-processing of the dataset is one of the very important steps that will affect the outcome of the proposed system. It transforms the data into a structured form.
3. Classifying the tweets using a large training group gave better results than the training group Small.
4. It is worth noting the importance of choosing the weights used in this study, as this has been proven through experience to reach the weights that give the best influence score. Also, choosing the number of

influencers for disseminating the information plays an important role in obtaining satisfactory results.

5. Experiments were performed on Twitter datasets containing more than breaking news, as well as journalists' comments on rumors and non-rumors. Different properties of these publicly available annotated datasets (PHEME dataset) have been significantly invested in the suggested system to improve the performance of the proposed approach.

5.3 Future Works

The Future work suggestions can be described as follows:

1. It is possible to expand this work to include other social networking applications, such as Facebook or Instagram.
2. Optimization of the weights is utilizing in the formula for computing the influence score to select the optimal weights for selecting influencers.
3. For the first challenge of identifying critical nodes in information propagation, the current works given in this study is constrained since they can only deal with unweighted networks with a single type of node. Bipartite networks and heterogeneous networks that are even more complex are beyond the scope of this work. In the future, more emphasis will be placed on heterogeneous networks.
4. Deep learning learning methods may be used to take full advantage of unlabeled social media data to cluster posts into rumor and non-rumor.

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Publications

1. A. A. AbdulAmeer, M. A. Salman and M. A. Mahdi, "Influencers Detection Algorithm to Combat Rumors in Social Networks," 2022 5th International Conference on Engineering Technology and its Applications (IICETA), 2022, pp. 32-36, doi: 10.1109/IICETA54559.2022.9888361.

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Dear Ansam Ali AbdulAmeer , Muhammed Abaid Mahdi & Mahdi Abed Salman / **Dept. of computer science / College Science for Women /University of Babylon /Babylon, Iraq**

We are pleased to inform you that your paper " **Detection of Influencers in Social Networks: A Survey** " is accepted for publication in Journal of Kufa for Mathematics and Computer (JoKMC).

Prof. Abed Al-Hamza Mahdi Hamza,
Managing Editor of JoKMC
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الملخص

على الرغم من أن الشبكات الاجتماعية عبر الإنترنت يمكن أن توفر فرصة محتملة لتبادل المعلومات بين الأفراد. يعد تلوث المعلومات على الإنترنت أحد أهم الاهتمامات العالمية. منذ أن نمت شعبية وسائل التواصل الاجتماعي ، أصبحت أكثر صعوبة. يجعل تلوث المعلومات الناس يفكرون ويتصرفون بطرق غير صحيحة. على شبكة الإنترنت ، هناك العديد من أنواع تلوث المعلومات ، ولا تزال الشائعات تمثل تحديًا هائلاً. إنها ظاهرة اجتماعية ضارة يجب الانتباه إليها. يهدف هذا العمل إلى مكافحة الشائعات على الشبكات الاجتماعية عبر الإنترنت من خلال إشراك المؤثرين الموثوق بهم. إنهم أعضاء في شبكات التواصل الاجتماعي عبر الإنترنت ((OSNs ولديهم تأثير كبير مقارنة بالآخرين. يمكن أن يلعبوا دورًا مهمًا في تقليل تأثير الشائعات. يستخدم النموذج المقترح لكشف المؤثرين من خلال استخدام بعض المعايير لتحقيق هذه المهمة. الخطوة التالية بعد عملية الكشف هي تصنيف الإشاعة الجديدة حسب الموضوع باستخدام مصنف Naïve Bayes.أخيرًا ، وظف هؤلاء المؤثرين لمكافحة الشائعات. لتقييم النموذج المقترح ، تم استخدام مجموعتي بيانات (PHEME ومجموعة بيانات أوكرانيا) ؛ يوضح هذا أن النموذج يمكنه تحديد المؤثرين ذوي التأثير العالي الذين ينشرون مكافحة الشائعات في الشبكات الاجتماعية. وتؤكد النتائج أن النموذج له أداء جيد في اكتشاف المؤثرين وكذلك نشر مناهضة الشائعات مقارنة بأساليب نقاط العاطفة.

وزارة التعليم العالي و البحث العلمي
جامعة بابل كلية العلوم للبنات
قسم علوم الحاسوب

مكافحة الاشاعه في وسائل التواصل الاجتماعي بأستخدام خوارزمية أكتشاف المؤثرين

رسالة مقدمة الى مجلس كلية العلوم للبنات في جامعة بابل وهي جزء من متطلبات الحصول على درجة الماجستير في علوم الحاسبات

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