International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 03 March 2025
Page No: 540 - 547
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0076

Analysis and Prediction Using Multiple Platform Hub Model and Centralized Network Management Algorithm (CNMA)

Mrs. Buvaneswari M[1], Ms. Jayadurga S[2], Ms. Gayathri D[3], Ms. Harini K[4]
[1]Assistant professor, Department of Computer Science and Engineering, Muthayammal Engineering College, Rasipuram, India.
[2,3,4]UG, Department of Computer Science and Engineering, Muthayammal Engineering College, Rasipuram, India.
Emails: *buvan.jeynesh@gmail.com[1], sjayadurgaskjb@gmail.com[2], gayathri1362004@gmail.com[3], harinikumar004@gmail.com[4]*

Abstract
The system aims to collect data on user behaviour and preferences on various social media platforms such as Instagram and Twitter. The aim is to determine influential users and increase engagement. In contrast to conventional methods that focus on a single platform at a time, the Multiple Platform Hub and Authority Topic (MPHAT) model provides an overall view of users by examining their connections, interests, and favourite networks. The MPHAT model seeks to bring less prominent users into the limelight by overcoming limitations within recommendation systems that benefit popular users. It makes online traffic estimates based on platform-specific posts and user preferences. Furthermore, the MPHAT model excels over conventional techniques such as LDA in topic understanding, influence prediction, and user behaviour prediction. The centralized network management algorithm (CNMA) facilitates smooth integration and processing of user data within various networks.
Keywords: *Centralized Network Management Algorithm (CNMA); Influence prediction; Multiple Platform Hub and Authority Topic (MPHAT) Model; User Preferences*

1. Introduction
Instagram and Twitter are intermediaries in communication with people and community building, especially within this digitally evolving world. It is equally important to understand user's activities and interests as they communicate in different Social Networking Platforms (SNS) [13]. The objective of this project is to make suggestions on what links and posts users might be interested in, predict the sites users prefer in addition to determining key users who can 'move the masses' in one way or another [2]. The traditional method often seems to miscalculate in concentrating on one platform and not looking more closely at one particular topic. In addition, the majority of today's systems that recommend links tend to reward users who are already of high standing, thus reinforcing existing social stereotypes. As a remedy to these problems, we propose the Multiple Platform Hub and Authority Topic (MPHAT) model. The majority of this model brings together users of highly specific topics and authorities of interest so that information is no longer separated by boundaries or islands. The MPHAT model incorporates social influence metrics and web graph analysis to understand user behaviour and influence in a more profound way. This leads to link recommendations being fairer and more balanced. The project aims to make user experiences better, improve content strategies, and build a more connected social media world by guessing site preferences, post numbers, link ideas, and areas people care about. Also, the Centralized Network Management Algorithm (CNMA) acts as the main coordinator, making all activities across many networks run to manage user data well. Early tests using data from Instagram and Twitter show that the MPHAT model does better than old models like Latent Dirichlet Allocation (LDA) in topic modelling. This opens the door to understanding user interaction in the digital world more [8].

2. Objective
It aims to develop a reliable way to spot key users on different social media platforms by looking at

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specific topics and networks. We want to use the tones of content and social info from Facebook, Twitter, and Instagram to boost marketing efforts. We plan to use new methods like the Multiple Platform Hub and Authority Topic (MPHAT) model and the Centralized Network Management Algorithm (CNMA) to fix the problems with current models. This will help us understand better how users have an impact on different networks, showing where they make the biggest splash and how we can adjust our marketing plans. The MPHAT model will look at users' topic-specific hubs, authorities, interests, and likes across platforms, giving us a full picture of how users behave. The CNMA will act as a main hub to handle activities on many networks and treat user data the same way everywhere. This team approach will lead to fairer link suggestions and help improve content plans to make users' experiences better and create a more linked-up social media world. In the end, this project aims to go further than usual approaches that often look at just one platform without thinking about specific topics. This leads to a better and more useful way to find influential users in today's online world [12].

3. Proposed Work

The project focuses on predicting user behaviour in various Online Social Networks (OSNs), especially on platforms such as Instagram and Twitter[13]. It cover's major aspects, such as identifying users' favorite sites, assessing which site generates the most posts, offering link recommendations, and highlighting the topics that they reveal users are emotional about [2]. The origin of this initiative has many platforms, hubs and authority themes (MPAT) model. This state-of-the-art model originally mixes the analysis of the user's interests, platform preferences and the identity of major effects, referred to as hubs and authorities [5][6][11]. The MPAT model uses the material made to effectively identify these impressive users, validating its accuracy through the user relationship and real-world dataset. The experiments show that MPHAT not only competes well with the key model in terms of analysing user-related materials but also excels in providing link recommendations in both single and multi-platform environments. In addition, tests on various social media datasets suggest that the MPHAT model improves the Latent Dirichlet Allocation (LDA) model in topic modelling. MPHAT complements the model; we have developed centralized network management algorithms (CNMA), which serves as a central coordinator. To streamline activities in many networks, to ensure efficient and harmonious management of user data. From implementing MPHAT on platforms such as Instagram and Twitter to indicate influential users and conduct experiments on synthetic datasets, this project enhances user’s experiences, improving material strategies and creating a more mutually and balanced social media landscape [12]. This innovative approach provides many benefits. Including predictions, no data loss and security and high levels of performance, it creates a strong solution to understand and exploit the user's impact in today's digital age.

4. System Architecture

The architecture comprises several steps and components that help to forecast the behaviour of users in different Online Social Networks (OSNs) such as Instagram and Twitter. The project starts with data gathering and cleaning, which encompasses fetching and purifying unrefined data from different sources. That data is then applied in User Action Analysis, which focuses on actions and interactions that identify users.

The analysis splits into two categories:

- Social influence measurement and identification of influential users,
- Content categorization.

The first category deals with measuring user influence through the segmentation of the Multi-Platform Hub and Authority Topic (MPHAT) model, while the second one relates to the classification of user-generated content [3]. At this level, the analysis is called trend monitoring, as it focuses on the behaviours and actions of the same users over multiple platforms for specific time frames. The system then moves to the Centralized Network Management Algorithm (CNMA), which subsequently acts as the single source of control monitoring all processes and facilitating adoption of measures to manage user information responsibly. At

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this stage, the system is ready for validation and evaluation of the set predictions. The final step is referred to as prediction, where summative inference is done about how to improve the user's experience to maximize the content provided and create a highly intertwined social media sphere, shown in Figure 1.

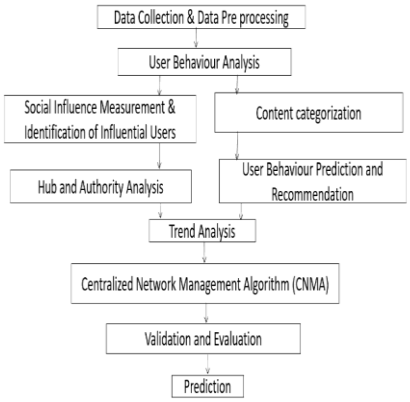

Figure 1 System Architecture

5. Methodology

5.1 Data Collection

The process of data collection pertains to answering research questions, evaluating results and testing hypotheses. Gathering user data from Instagram and Twitter includes all comments, shares, profiles, posts, and likes, which aid in extracting the required information [15]. For the gathering of user data to be successful, it is important to first identify the relevant social networks that are necessary. This information can be extracted via the platforms' APIs while conforming to their terms of service and privacy policies. If the API is restricted, web scraping tools can be employed, but it is important to ensure that legal and ethical boundaries are met. Following the collection of data, its cleansing is done through duplication removal, noise filtering, and adjustment of data formats to achieve consistency. Finally, crucial features like hashtags, keywords, and any other user engagements are marked; they need to be stored in a database or a data warehouse, taking precautions to safeguard privacy. In essence, the entire data collection process needs to be planned out and designed with the objective of enabling analysts to study user behaviour and relations, determine who the key users are, and find relevant topical hubs or authorities. These measures allow for the optimisation of the social network analysis process.

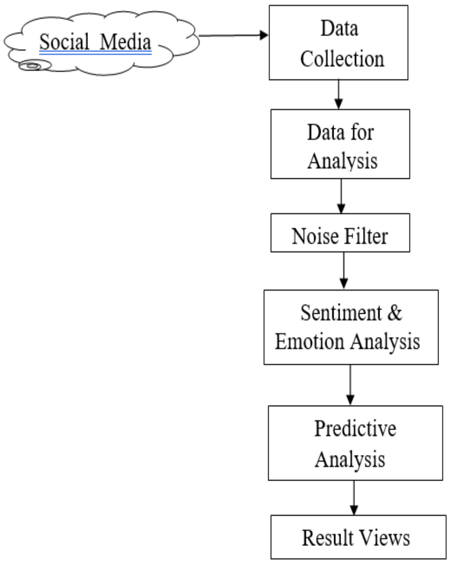

Figure 2 Data Collection Flow

5.1.1 Sources Integration

Social Media Data Integration Process:

- Leverage APIs for collecting data from different sources such as Instagram and Twitter.
- Scraping information for effective collection of data.
- Elimination of metadata, keywords, hashtags, and other data.
- Mapping unstructured data to a predefined schema for effective inclusion.
- Organizing and gathering preprocessed data in a merged single dataset.
- Eliminating contradicting information and retaining correct data.
- Storing compiled dataset in a safe place for greater accessibility.
- Increasing understanding of user behaviour and relationships.
- Connecting the project to various social networks through their APIs, shown in Figure 2.

5.1.2 Data Retrieval

Data retrieval is retrieval of information from data banks or databases for decision-making or analysis.

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- It entails building queries through social network databases and APIs.
- Social network web pages can be accessed in restrictive APIs through legal provisions of scraping.
- Once data has been collected, it eliminates irrelevant or redundant data to retain meaningful data for analysis.
- Data from various platforms is collected into various datasets.
- Standardization of the format is done to produce one dataset.
- The combined dataset is placed in a database or data warehouse to be analyzed.
- Data mining reveals latent topical hubs and authorities, giving information about user influence and interaction [3].
- Data that is gathered is posts, likes, comments, and user interaction.

5.2 Data Preprocessing

The process of shaping and organizing raw data in order to make it suitable for analysis is called data preprocessing. It is an integral part of data analysis. It all starts with cleaning the data, removing duplicates, filtering out irrelevant or noisy data, and even dealing with missing values. Consistency in data formats is then ensured through normalization, where scaled numbers are converted to a common value. Following that is the tokenization process, which divides textual data into individual components. Meaningless stop words are eliminated in the process. Textual analysis helps uncover important topics and sentiments through feature extraction. In this case, hashtags, keywords, user interactions, and metadata all identify key components. The integration of social network data brings together information from multiple social platforms and synchronizes the structures and formats of the data under one umbrella. This is referred to as data integration. The last and final stage is data transformation, which entails combining information into significant categories. Categorical information is then converted into numbers that will be appropriate for machine learning models. Once all these processes have been completed, the data, which can now be referred to as more advanced, in order to determine the hidden topical authorities and hubs found in many social networks, is ready for deeper analysis [1], shown in Figure 3.

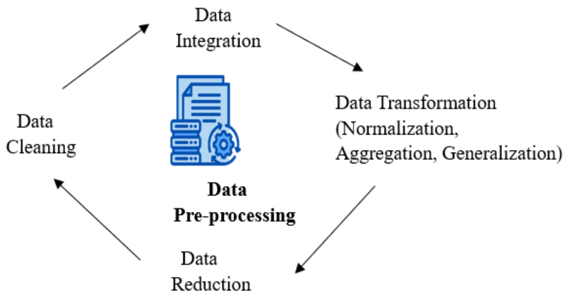

Figure 3 Data Preprocessing

5.2.1 Normalization

Normalization is the process of structuring data to ensure consistency and remove redundancy. It is standardizing data, including conversion of dates, text case, number formats, and 'one size fits all' within data sources.

- Numeric data are scaled to a common value for comparison.
- Duplicate entries are found and removed for data sanity.
- Missing values or incomplete records are filled with suitable amounts or left out.
- User-specified interaction-based platform types or interaction roles are translated into a common classification system.
- It enables researchers to attain normalization across social networking sites and develop a normalized dataset.
- Advanced methods such as topic modelling and user modelling analysis can be used to identify latent topical hubs and authorities.

5.2.2 Feature Extraction

Feature Extraction in Social Network Analysis includes gathering user profiles, postings, comments, likes, and shares from social networks [2].

- Data is cleansed and normalized to improve consistency and remove irrelevant data.
- Textual information is divided into words or phrases, and principal features such as hashtags and keywords are extracted.
- Data on engagement like likes, comments, shares, and user-specific characteristics are analyzed.

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- Network data like the number of connections and centrality measures are considered.
- Features are employed in constructing models and algorithms for context-specific analysis and information retrieval.
- Features could be user activity including posts and discussions extracted by keyword extraction or topic modelling.

5.3 User Behaviour Analysis

5.3.1 Graph Construction

During the graph construction stage, users as well as topics are depicted as nodes, and their interactions, like follows, likes, shares and comments, are depicted as edges in the graph [9][10]. Weighted edges are additionally granted based on the intensity of each interaction to better define important actors and trends. Furthermore, 20 community detection algorithms are employed that determine the clusters of users within a network that are likely to have particular interests or behave in a similar manner. All these steps allow capturing user behaviour and relations in online social networks in an easy manner.

5.3.2 Model Training and Trend Analysis

While performing model training and trend analysis, relevant methods, such as Graph Neural Networks (GNNs), are selected for their capacity to analyze the graph and learn the structures. The model is then trained on historical data relating users to topics in an optimal manner. The accuracy of the model is then tested using an independent set of data to confirm whether the model works as intended and is indeed useful. These steps are important for forecasting user actions and behaviours in online social networks.

5.3.3 Prediction and Interpretation

The trained model, in this scenario, tries to forecast what is likely to occur in the future and how the users might behave based on the existing data. It anticipates emerging trends by leveraging the previously learnt data and the relationships within the data. These findings are analysed to formulate strategies that, amongst other things, allow for appropriate marketing, suggestive services, and other relevant activities. This step is fundamental in articulating data analysis into activities that increase user interaction and, in turn, increase business opportunities [14].

5.4 Content Categorization

A systematic framework is constructed to forecast user interactions on Twitter and Instagram through the analysis of user behaviour [15]. The methodology starts with data acquisition through APIs, then investigates user actions, engagement, and likes in the "User Behaviour Analysis" stage. The framework applies two fundamental models: the Multiple Platform Hub and Authority Topic (MPHAT) model to discover influential users (hubs and authorities) and a thematic analysis to identify user interests [12]. These findings are combined to segment users and examine trends across platforms. The Centralized Network Management Algorithm (CNMA) provides effective and uniform management of user traffic and data on platforms. Lastly, the system is validated to provide accurate predictions. The framework seeks to improve user experience, enhance content strategies, and promote a more connected social media environment by discovering influential users and making balanced link suggestions, ultimately leading to a more inclusive and engaging online community [12].

5.5 Influence and Authority Analysis

5.5.1 Influence Measurement

Influence Measurement assesses how user interactions on the platform such as likes, shares, comments, and follows affect online influence. Key metrics of centrality are essential in this evaluation: Degree centrality indicates the number of direct connections a user has, reflecting their immediate influence within their network; betweenness centrality highlights a user's role in connecting different parts of the network, showcasing their significance in the flow of information; and closeness centrality measures how quickly a user can reach others in the network, underscoring their effectiveness in spreading information. By integrating these metrics, we can pinpoint the most influential users who drive engagement, shape trends, and act as vital nodes in the network's information sharing [9] [10] [12]. This thorough analysis aids in grasping the dynamics of influence and refining strategies for marketing, content creation, and community management.

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5.5.2 Authority Identification

Assembling authority identification consists of noting the number of occurrences of a particular topic, the frequency of its engagement, reach, sentiment, and consistency over time across social networks. Topics that receive consistent, high engagement and remain relevant are highly authoritative topics leading to the identification of the influential topics that are widely discussed in the network [4] [12].

6. Result

The MPHAT model recognizes influential users, predicts user engagement with high accuracy, and provides more precise link suggestions [12]. The model is also superior to the LDA model in terms of topic understanding. The CNMA algorithm maintains efficient data convergence and security between platforms. MPHAT enhances overall user experience, strikes content promotion, and presents a solid solution for learning user influence in the age of the internet [3], shown in Figure 4.

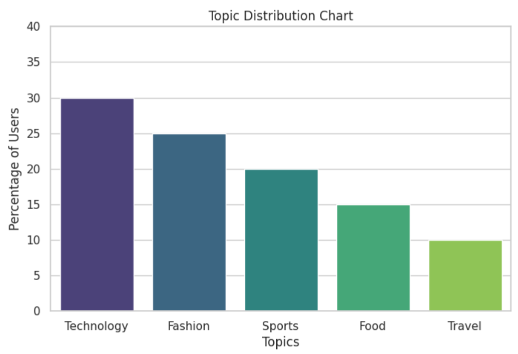

Figure 4 Topic Distribution Chart

The graph indicated the most significant data on what the social media audience wants. According to it, technology was the most preferred topic and concerned nearly 30% of the users, followed by fashion with 25%, sports with 20%, food with 15%, and travel with 10%. This information allows marketers and content providers to adjust their strategy to suit their audience better by knowing what concerns the users most. This data-driven strategy results in more relevant and engaging content with increased engagement and satisfaction. The line graph illustrates the trend of the engagement of users on Instagram and Twitter within a period of 30 days [15]. It provides insightful information about the time of maximum engagement that accompanied the overall activity of users on both websites.

- The x-axis is the 30 days span which are labeled one by one.
- The y-axis is the levels of engagement, which illustrates the trend of the engagement of users on the websites, shown in Figure 5.

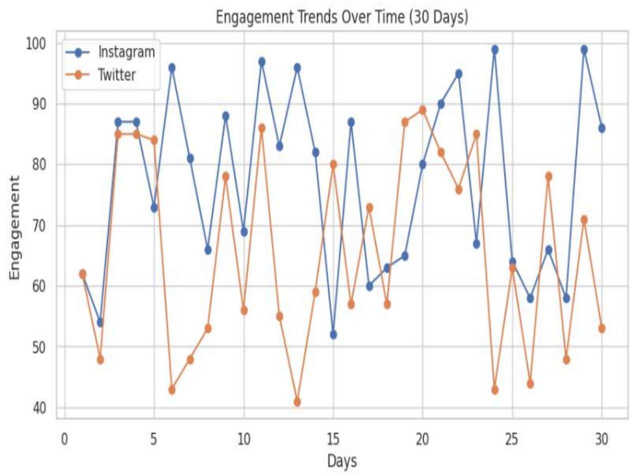

Figure 5 Engagement Trend Over Time

The blue line is the engagement on Instagram, and the orange line is the engagement on Twitter.
Both lines show ups and downs in the level of engagement, with Instagram showing higher highs compared to Twitter.

Table 1 Prediction Rate

User ID	Predicted Engagement Score	Predicted Influence Score	Recommended Topic
User 123	85%	78%	Technology
User 456	72%	65%	Fashion
User 789	68%	60%	Sports

The table 1 shows statistics about a sample of three users' social media engagement and influence. The users were specifically identified and have been associated with their engagement scores and their predicted influence scores, which state the level they are interacting with the posts on and how powerful they are with respect to influence within their groups, respectively. User123 is, for example, an 85% engaged user and has a predicted 78% influence, and thus a trending member of the social networking website. Suggested content topics are created to match each user's interest, i.e., Technology for User123, Fashion for User456, and Sports for User789.

Conclusion and Future Enhancement

The system focuses on data gathering and preprocessing to turn raw user data from sites such as Instagram and Twitter into a structured dataset that can be analysed. This is done through the use of APIs and web scraping, in compliance with legal and ethical requirements. Data will be checked against each other, duplicates eliminated, noise removed, and uniform data format preserved. Feature extraction and text mining will identify relevant features like hashtags, keywords, and user activities. The integrated approach ensures uniformity of data and resolves conflicts so that higher-level analytics can identify important users and hidden topical hubs [1]. Data obtained from processing will facilitate social network dynamics, trend strength analysis, and prediction. The application of the Multiple Platform Hub and Authority Topic (MPHAT) models for user behaviour analysis, such as influence and authority analysis, forms a solid basis for trend analysis and prediction in online social networks. In-depth interaction graphs are built, and sophisticated algorithms such as GNNs train models to accurately quantify user influence and topic authority [3][7]. This leads to accurate marketing targeting, customized recommendations, and enhanced decision-making, resulting in high user activity and enhanced business revenues. This integrated system has strong potential for future studies and use in modelling and analyzing social network activity.

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