The Review of Contemporary Scientific and Academic Studies
An International Multidisciplinary Online Journal
www.thercsas.com

ISSN: 2583-1380 Vol. 6 | Issue No. 1 | January 2026 Impact Factor: 6.53

# A Machine Learning Approach for Detecting and Managing Dormant Accounts on Social Media Platforms

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 **Crossref/DOI:** https://doi.org/10.55454/rcsas.6.01.2026.002



**Abstract:** *In this technological age, connections are maintained through virtual platforms rather than physical interactions. Social media has become an indispensable part of our lives. It allows us to engage, express, and connect with people despite geographical and cultural boundaries. It is very convenient to create multiple accounts across social media platforms. Over time, these platforms have experienced a significant increase in dormant or inactive accounts. Such accounts belong to users who have permanently abandoned their profiles, hacked accounts, fake accounts, or deceased individuals' profiles. These accounts use unnecessary server storage. This paper aims to investigate the growing issue of dormant accounts on social media platforms. A survey was done to discover the trend in usage and the subsequent causes of account abandonment. Based on the findings, a conceptual framework is proposed that aims to build an efficient system that social media platforms can adopt to identify, manage, and notify the users of their inactivity. With user consent, these platforms can delete these accounts, hence creating a cleaner digital space.*

**Keywords:** Digital Footprints, Dormant Accounts, Machine Learning, Social Media, Sustainability

**Article History:** **Received: 28 Dec- 2025; Accepted: 10 Jan- 2026; Published/Available Online: 30 Jan- 2026**

## 1. Introduction

A dormant account is an account on a digital platform that has not been used for a long period. It shows little to no user activity, such as posting or engaging with content or people. Technology and high-speed internet have made people more socially connected than ever. There has been a significant increase in the number of social media users after the COVID-19 pandemic, and this has led to an increased demand for data storage. Activities of users, including posts and stories, to likes and comments, all need to be stored effectively on cloud storage systems.

To interact with a wide range of people, users create several accounts on different apps such as X, Instagram, Facebook, Snapchat, etc. Such accounts are often created with different intentions in mind, like maintaining a boundary between personal and professional life, separating friends and relatives from professional acquaintances, or maintaining an anonymous profile for activities that demand privacy. But problem arise, when users abandon these accounts, unnecessarily consuming storage and digital infrastructure. There are various reasons that lead to the abandonment of accounts, such as gradual loss of interest in the platform, security threats such as hacking, lack of account access details, or personal circumstances that force users to discontinue using their accounts.

It has been noticed that due to the emergence of newer platforms and changing preferences, especially among Gen Z and millennials, users are constantly shifting to trend-aligned and feature-rich platforms. Industry data show that as the older population dominates one of the platforms, younger users move out of the platform in search of new and exclusive spaces. Thus, numerous social media profiles are left inactive or are abandoned altogether. This has been observed in the case of Facebook, where younger audiences have gradually moved towards Instagram or other niche community-based platforms. According to a survey, just 58% of Gen Z use Facebook at least two times a week, but the most active users of this platform are older generations, including millennials (84%) and Gen X (88%) (LaFollette, 2025). There has been a 13% decrease in the number of young users of Facebook in the United States since 2019 (Heath, 2021).

These dormant accounts present a wide range of challenges for social media platforms. They use up server resources, reserve usernames, and disrupt engagement data and even become a security hazard when unaddressed. These accounts lead to an increase in operational expenses and carbon footprints. This digital clutter is causing extra overhead to cloud storage systems and affecting the platform's performance and

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efficiency. To end this, it is wise that platforms should come up with mechanisms for identifying inactive accounts and proper ways to handle them in order to create a sustainable digital ecosystem.

## 2. Literature Review

A considerable amount of research has been done towards identifying fake accounts, spam posting accounts, and social bots across social media platforms (Kavin et al., 2022; Kerrysa and Utami, 2023). These studies have largely focused on detecting harmful or manipulative behavior of social media accounts using AI and machine learning algorithms. Studies have also been conducted on multiple account detection to identify accounts belonging to the same user across online social networks (Shu et al., 2017; Wang et al., 2018). Although these studies have significantly improved the credibility of user interactions on the Internet, they primarily deal with malicious accounts that are in operation. A lack of studies on machine-learning driven systems that monitor and manage dormant user accounts on social media still remains. Although these accounts are not harmful in terms of user activity, they burden the cloud storage systems. This paper aims to fill this gap by proposing an automated detection system that aims to optimize cloud storage.



## 3. Consumption of Resources by Different Social Media Accounts

Social media platforms accommodate billions of users, which creates vast amounts of data daily. Of the 8.14 billion people worldwide, approximately 63.9% are active on social networks. Around 5.24 billion people use social media worldwide in 2025, double the 2.07 billion users recorded in 2015 (Team, 2025). On average, a typical user interacts with around 6.8 different social media platforms. Meta Platforms like Facebook and Instagram, collectively process over 4–5 petabytes of new data daily, which includes multimedia uploads, text interactions, and metadata (Babu, 2020).

We have classified social media accounts into three types: normal, professional, and dormant, and analyzed how each type utilizes resources, contributes to data load, and impacts the overall system.

### *3.1. Normal Accounts*

Normal social media accounts have frequent logins to connect or post occasionally and do not generate large amounts of media. These users, on average, post three to four images or videos per month, which eat up very little storage, since each image has a storage size of, say, 2-5 MB on average. Profile descriptions and messages have minimal storage requirement. The normal activities like scrolling or viewing feeds are dependent on the cached databases and content delivery networks (CDNs), hence causing minimal load on the server infrastructure. Green Spector calculates that an average 28 minutes daily Instagram session produces about 18.6g of average $CO_2e$ per day, or about 0.56kg of $CO_2e$ per month (Derudder, 2021).

| Social Media Platforms | Monthly Active Users (2025) |
|---|---|
| Facebook | 3065 |
| YouTube | 2504 |
| Instagram | 2000 |
| Whatsapp | 2000 |
| TikTok | 1582 |
| Telegram | 900 |
| Snapchat | 800 |
| X (Twitter) | 611 |
| Pinterest | 498 |

**Table 1: Monthly active users of popular social media platforms in billions**

### *3.2. Professional Account*

A professional or creator account is used by individuals, celebrities, or brands who share content such as reels or promotions with a higher frequency, as this seeks to boost the number of subscribers and increase revenue. Even though they represent the smallest percentage of social media users (around 2.4%), they control most of the content on the platform. The constant posting of high-quality photos and videos, large follower interactions, and extensive use of analytics and promotional data contribute to these accounts consuming gigabytes of storage monthly. The carbon footprint of this type of account will be even higher; a one-hour Instagram session will cause about 37 g $CO_2e$ per day, or about 1.1 kg $CO_2e$ per month, which is twice the footprint of a normal user.

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*3.3. Inactive Account*

Inactive or dormant accounts are the profiles that rarely post and consume very little media content, but they still occupy space in the system. All registered profiles, even those with no posts, leave metadata such as user records, settings, and profile images, stored in database systems. In the long run, millions of such dormant profiles add to storage overhead.

Dormant accounts are vulnerable to security concerns since old or forgotten accounts may have weak passwords, outdated recovery details, or no two-factor authentication, making them easy targets for malicious activity. These accounts can be misused for scams or spreading misinformation without the user's knowledge.



With respect to social-media platforms, idle accounts clutter the digital space, consuming storage capacity and computing power that could otherwise be used to improve the experience of active users. Moreover, these accounts also distort analytical insights and engagement metrics, preventing platforms from obtaining an accurate estimate of the active user base or measuring the success of advertising efforts. In the long run, maintaining these inactive profiles increases operational costs.

The percentage of accounts belonging to deceased users has increased in the past ten years (Lim, 2025). Although a single inactive profile does not consume significant storage, taken together, these accounts form a ghost town in the social graph. Unless properly maintained, such accounts can be intruded upon or maliciously deployed to perpetrate identity theft or fraud. To eliminate this risk, platforms like Facebook and Instagram offer family members or close friends of the deceased the option to request account deletion or memorialization by submitting proof of death. However, only a small portion of people are aware that these options are available on the social media platforms, and very few actually take steps to delete or manage their loved ones' accounts after their passing.

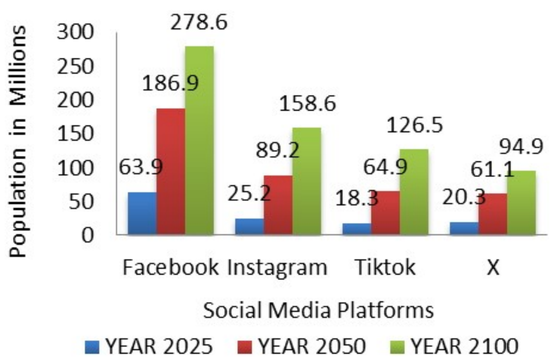


**Figure 1: Express VPN's projection of the growth in deceased accounts in the U.S by the years 2050, 2075, and 2100**

## 4. Methodology

The current research is designed as a mixed-method study embracing an observational and an analytical approach and a structured survey to explore dormant accounts on social platforms.

*4.1. Objective of the Survey*. It is aimed at the elicitation of both quantitative and qualitative data about user behaviour, preference of the platform, account utilisation patterns, reasons for abandoning accounts, and the participants' level of awareness regarding carbon footprints and their willingness to receive notifications about account inactivity.

*4.2. Survey Platform and Tool.* The data was collected via Google Forms. The questionnaire was shared through WhatsApp, email, and different social-media channels to reach the greatest number of people.

*4.3. Target Audience.* The sample consisted of social media users between the age of 16 and 35 years, which is the most dynamic and active age group in the digital sphere. The respondents included students, working professionals and content creators.

*4.4. Sample Size and Sampling Method.* A total of 100 participants completed the survey. The convenience sampling technique was used. This method was considered suitable to receive preliminary information within the framework of the given investigation.

*4.5. Survey Design and Structure.* The questionnaire consisted of 14 closed-ended questions. For conciseness and better representation, two questions of the original form were combined and presented as a single question in the research paper. The survey included multiple-choice and checkbox questions, allowing the respondents to select several options. Some questions were marked as optional. In questions where multiple responses were permitted, it leads to aggregate response percentages sometimes exceeding 100%.

*4.6. Data Analysis.* The gathered replies were consolidated and analysed via Google Sheets. Elements of descriptive statistics, along with frequency measures, were used to identify patterns and trends of user behaviour.



## 5. Survey Analysis and Results

A total of 100 participants responded to the survey. The demographic profile revealed that there were more females, with 65% as compared to males with 35%. The 78% fell in the age bracket of 18-24, indicating that it is a mainly youthful sample. In addition, 72% of the participants were students, 11% were employed professionals, 9% were self-employed, and 8% were currently unemployed.

The survey questions and insights are given below:

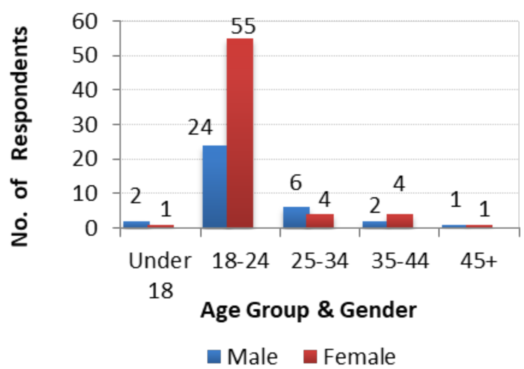


**Figure 2: Demographic distribution of survey respondents by age and gender**

### 1. Which social media platforms have you used? (Multiple responses were allowed)

*Insight:* Over 82% of participants said they have accounts on three or more platforms, with the most prominent ones being Facebook, Instagram, Snapchat, LinkedIn and X.

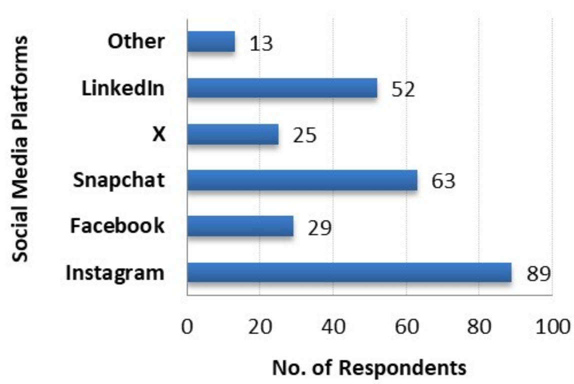


**Figure 3: Graph showing different social media platforms used by respondents**

### 2. Do you have more than one account on any of these social media platforms? If yes, what is the purpose of maintaining multiple accounts? (Multiple responses were allowed)

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*Insight:* Of the total respondents, 61% said that they had more than one account in, as opposed to 39% who did not. Of users with more than one account, 60% said the reason was to separate different social groups (e.g., friends, family, colleagues), 40% created additional accounts for professional work, 38% maintained anonymous accounts to browse content without revealing their identity, while 12% said it was to have a backup.

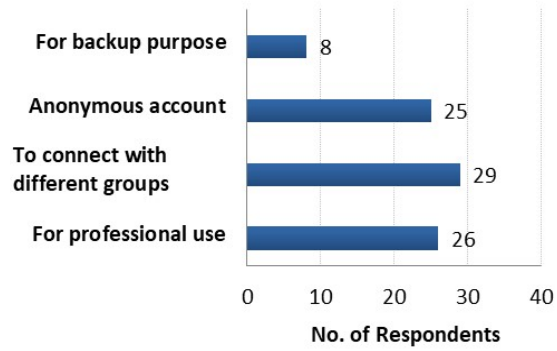


**Figure 4: The graph illustrates the various reasons for maintaining multiple social media accounts.**



**3. Do you have any inactive or rarely used accounts? If yes, what are the reasons for not using them? (Multiple responses were allowed)**

*Insight:* Approximately 43% of participants responded that they did not have any dormant accounts. On the other hand, 46% affirmed that they have such accounts, and 11% stated that they do not remember. The most common reason, with 46% of respondents, was loss of interest in the platform or its content. 39% people stated they had switched to other accounts, 30% stated that they forgot their password and 7% abandoned their account due to privacy concerns.

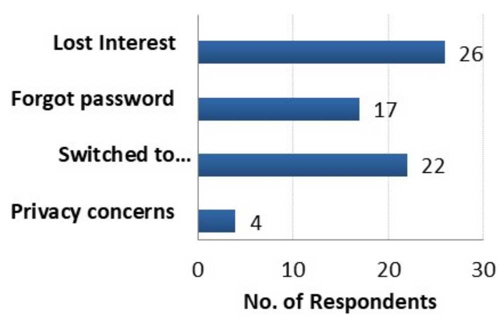


**Figure 5: Graph showing factors contributing abandonment of social media account.**

**4. Are you aware that unused accounts consume storage and resources on cloud servers, contributing to carbon and digital footprints? Would you delete your inactive account if it contributed to reducing environmental impact?**

*Insight:* In terms of awareness, 50% of the respondents realized that unused accounts consume storage and computing capacities in cloud servers; 31% were unaware and, 19% were not sure. In relation to the intention to act, 57% indicated that they were willing to delete their account in order to decrease the environmental impact, 35% said no, while 8% were undecided.

**5. Have you ever received an inactivity alert from any social media platform? Would you be okay if apps notify you to delete inactive accounts based on your activity?**

*Insight:* With regard to previous experience, 55% of the respondents mentioned not having received an inactivity alert from any social media platform, and 20% said yes while 25% could not recall. In terms of the future preferences, 66% indicated that they were comfortable with the notifications reminding them to delete their account, 14% did not agree, while the rest 20% stated that they were unsure about it.

**6. How should you be notified about your inactive account? (Multiple responses were allowed)**

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*Insight:* The respondents mentioned their preferred method of being notified of their dormant accounts, 58% preferred to receive emails, 44% preferred text or SMS, 31% preferred in-app notifications, and 40% preferred to receive a pop-up message on next login.

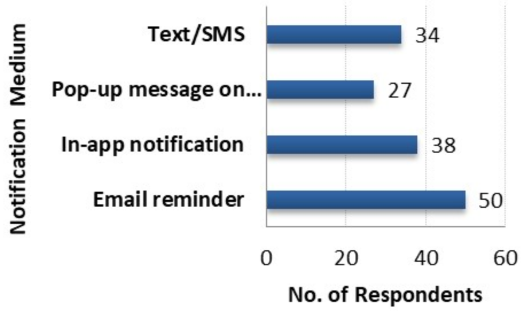


**Figure 6: Graph showing respondent's most preferred medium for receiving notifications regarding account inactivity**

### 7. How long should apps wait before suggesting account deletion?

*Insight:* This question attempted to learn the user preferences about the time duration after which they should be notified. The reactions showed that 26% believed that a suggestion should be made after 1-2 years of inactivity, 46% believed that it should be made after 6 months, and 13% argued that it should never be suggested unless explicitly requested by the user.

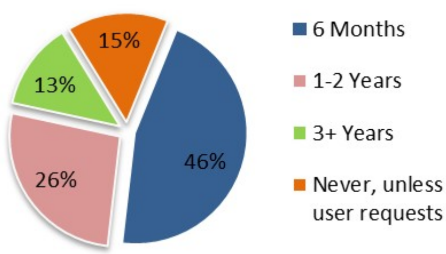


**Figure 7: Graph showing respondent's most preferred duration after which an inactive account should be suggested for deletion**

The results of the survey showed that a significant portion of people have dormant accounts on social-media networks. However, many individuals were unaware of the environmental impact caused by them. Although majority users expressed their willingness to take action and delete such unused accounts. Social media platforms should implement a system that alerts their users about their inactivity via convenient communication channels such as email reminders, SMS alerts, or in-app messages. Creating awareness about digital behaviours will promote the culture of responsible use. These practices can enable platforms to ensure that their resource utilisation is optimised as well as it aligns with environmental sustainability goals.

## 6. Proposed System for Detecting Dormant Accounts

The given research suggests a conceptual machine-learning framework that will help in classifying user accounts into three specific categories, namely active, at-risk, and dormant.

*Feature Extraction*: To build an effective machine-learning model capable of differentiating active, at-risk, and dormant accounts, we need data that have both user-based and content-based feature sets. These properties aid in the estimation of the account activity patterns of each user over a window of observations of W days.

*User-Based Features*: Proper categorization of the user accounts will require that user-based features be derived. They are obtained using the user's metadata obtained via social-media platform APIs and activity records of accounts. There is a huge difference between the patterns of engagement of dormant, at-risk accounts, and active users. The user-based features used in this study are listed below.

- *Last Login Timestamp.* This value is used to capture the last time the user accessed the platform.

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- *Login Frequency.* The count of logins and the number of sessions are the main measures of user activity. Login Frequency measures the number of times a user visits the platform during a particular period of time, W (i.e., 30, 60, 90 days).

$D_u$= count of independent days having at least 1 login in W.
$S_u$= the number of sessions that user u has initiated in W.

$$\text{Login Frequency Ratio (LFR)} = \frac{W}{D_u}$$

The ratio is used to evaluate the level of user activity on the platform.



*Session Duration*: Average session duration is another measure of activity, which shows the duration of time a user spends per session.

$T_u$ = total time spent by user u within W.
$t_u = \frac{T_u}{S_u}$ = mean time spent in each session.

The bigger the value of $t_u$, the more the evidence of active scrolling and interaction.

*Recency of Last Activity*: The recency factor helps in determining when the user last used the platform. It ensures that older activity, for example, interaction that happened several months ago, doesn't falsely suggest that a user is still active.

$$\text{Recency Factor (RF)} = \mathbf{e}^{-\lambda.\Delta}$$

$\boldsymbol{\Delta}$ = number of days since last recorded activity.
$\boldsymbol{\lambda}$ = decay constant that defines how quickly the importance of recency declines.

For instance, if $\boldsymbol{\lambda}$=0.1 and $\boldsymbol{\Delta}$=10 (meaning the user last logged in 10 days ago), then RF = $\mathbf{e}^{-1} \approx 0.37$. A higher RF indicates that the user was active recently.

*Number of Followers*: This metric refers to the number of individuals following a particular account. Active accounts usually have a higher follower count because active interaction and sharing of content help them in retaining followers, whereas dormant accounts show minimal growth in followers because of inactivity or non-consistent usage patterns.

$F_u$ = total number of followers

*Number of Followings*: This refers to the number of other accounts that the user subscribes to. Dormant accounts usually have a static or abnormally high number of following in relation to their followers. This imbalance suggests the possibility of automated behavior or disinterest by followers, both of which are useful indicators.

$FO_u$ = total number of followings

*Content-Based Features*: The content-based features are based on how the user reacts to posts, stories, and other activities shared on the platform.

*Content Creation Activity*: Active accounts are characterized by the creation of content that includes the publication of photos, reels, videos, as well as stories in the time period W.

$P_u$ = number of posts.
$R_u$ = number of videos.
$Y_u$ = number of stories (published in a period W).

$$\text{Content Creation Rate (CCR)} = \frac{P_u + R_u + Y_u}{W}$$

*Engagement Index*: Active users do not simply view the content they also interact with peers (likes, comments, shares, direct messages), which can be considered as one of the most consistent pointers of sustained engagement.

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$L_u$ = total likes given by user u.
$C_u$ = total comments made.
$M_u$ = total direct messages sent.
$F_u$ = total number of followers.

$$\text{Engagement Index (EI)} = \frac{L_u + 3C_u + 5M_u}{F_u + 1}$$

Here, higher weights are assigned to comments and messages since they reflect deeper user interaction. Plus 1 is added to the denominator to avoid division by zero.



*Composite Activity Score (CAS)*: A combination of all the indicators mentioned above can be transformed into one single measure, called the Composite Activity Score (CAS). It is a value that expresses how active an account is on a scale of 0 to 1.

$$CAS = w1(LFR) + w2(t_u) + w3(CCR) + w4(EI) + w5(RF)$$

Classification criteria: In the case of an active account, CAS ≥ 0.6. In the case of at-risk accounts, the CAS is supposed to be between 0.25 and 0.60, and for dormant accounts, the CAS should be less than 0.25. These limits can be adjusted depending on the dataset or user base behavior.

*Data Pre-processing*

Before using the data for classification, it has to be pre-processed in order to be clean, consistent, and ready to analyse. The raw data is supposed to be converted into a standard tabular format, which is easy to consume by algorithms. Attributes concerning dates need to be transformed to numbers, and textual and nominal information should be changed to a homogeneous format. Where records have missing data either due to incomplete activity records or undefined user statistics, such as the number of posts, there is a need to impute these values manually, e.g., a user who has never posted has a classification of 0 posts. To protect privacy, any sensitive information, including usernames, emails, or IP addresses, should be deleted. Lastly, numerical characteristics must be normalized to fall within the same range, thus increasing the performance of a model. After doing the pre-processing, a dataset must be further broken down to have training and testing subsets in order to develop a model.

*Classification Criteria.* This criterion of classification makes sure that the active accounts are not mislabelled as inactive.

*Dormant Accounts*: Dormant users are those who have deserted the platform or those who are not very active. Their last login timestamp is greater than 365 days and the average session time ($t_u$) is less than 60 seconds meaning that they are engaged in a negligible way. The characteristics of such accounts are login frequency rate (LFR) ≤ 0.2, total time spent ($T_u$) = 0, and no content creation (CCR = 0) in the last 365 days. They have an engagement index (EI) of less than 0.25 and activity metrics like likes (Lu), comments (Cu), and messages (Mu) are usually valued at zero. They have a recency factor (RF) of 0.1 indicating an inactivity of more than 240 days. On the whole, the composite activity score (CAS) is below 0.25 in these accounts, which puts them under the dormant category.

*At-Risk Accounts*: At-risk accounts are those that exhibit a gradual decline in activity and will eventually go dormant. The last login timestamp is between 200 and 365 days, and their mean time ($t_u$) of the session is less than 5 minutes. They still exhibit some form of activity, such as responding to posts in the form of likes, comments, or story views. Their frequency of logins (0.2< LFR < 0.6) and content creation rate (0.05≤ CCR < 0.14) which indicates they are not used regularly. The engagement index (0.25 ≤ EI < 0.50) and recency factor (0.1 < RF < 0.5) serve to further support reduced interaction and activity over the past 120 days. To this effect, a composite activity score (CAS) of between 0.25 and 0.60 is registered with such accounts, thus classifying them as at-risk. On the whole, these users are partially active but show signs of disengagement, which makes them the most suitable ones when considered for re-engagement efforts.

*Active Accounts*: Active accounts are those accounts that are regularly used by a user with frequent logins, creation of content, and usage. The last login timestamp of these users is less than 30 days, and the average time per session ($t_u$) is more than five minutes. They also have a stable content creation rate (CCR ≥ 0.14), a high level of engagement (EI ≥ 0.5), and are able to maintain or improve the follower-following ratio. In

 https://doi.org/10.55454/rcsas.6.01.2026.002

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combination with a high login frequency rate (LFR ≥ 0.6) and a recency factor (RF ≥ 0.5), such accounts have a composite activity score (CAS) of at least 0.6; thus, these accounts are in the category of active.

*User Notification and Decision-Making*

According to the survey results, it was noted that most users preferred to get notifications via email and text messages (SMS). Email is thought of more as a formal and safe way of communication, whereas SMS guarantees immediacy and access to the user. Therefore, the system must include a multichannel notification strategy to ensure that the chances of missing out on the alerts are minimal. When a user receives the notification, he or she must get a clear option to approve or reject the deletion request. It is possible to make this decision process easier by offering interactive buttons or links that are directly in the email and SMS, which redirect them to a secure page on the platform. In terms of system logic, the social media application should be designed to:



- Issue an alert when the account inactivity threshold has been met as per the system rule.
- Send notification in email and SMS at the same time.
- Keep a user-response tracker and capture the response of an individual who has accepted or rejected the deletion request.
- An automated deletion process must start if the user gives approval for the request. Users can be provided with a grace period of seven days before final removal, in case of accidental deletion. Upon completion of the grace period, the account data should be removed permanently from the active storage. This will help in storage optimization and system efficiency.
- In case the user declines the request, the account would be pre-marked as active under the system.

This two-way decision process not only follows ethical practices, it gives users the right to manage their digital presence, which minimizes resistance to account deletion and enhances compliance.

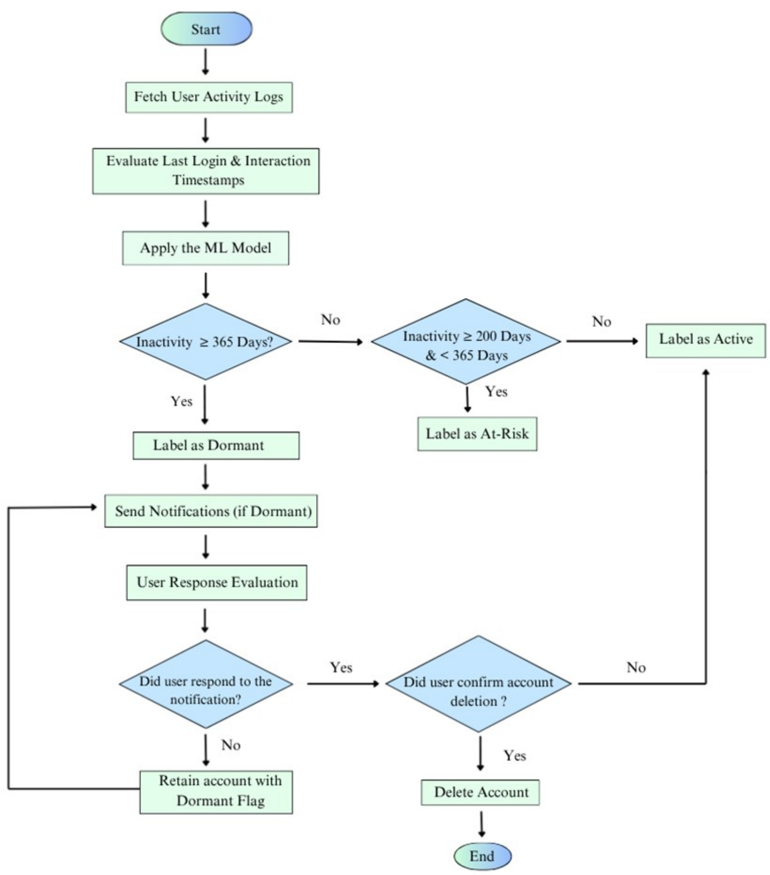


**Figure 8: Workflow of dormant account detection system using user activity logs and an ML model**

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*Machine Learning Model*

In order to enhance user account categorization, a classification model based on machine learning can be created. This model works with user-based and content-based feature records as input. Supervised machine learning methods such as random forest, decision tree, logistic regression, and support vector machine (SVM) methods can be employed effectively. These can pick and learn patterns from available labeled data that are in the form of behavioral criteria of accounts such as login frequency, session duration, engagement rate, and content creation rate. In case labelled data is not available, unsupervised models such as k-means clustering or hierarchical clustering can be employed. The classification model performance can be judged through accuracy, precision, recall, F1 evaluation scores to characterize the requisite quality benchmarks as per need in the classification task. By implementing such models, social media platforms can easily identify user activity patterns and effectively categorize accounts.



## 7. Future Scope and Conclusion

The theoretical framework presented in this paper provides a basis for a dormant account detecting system that uses machine-learning algorithms. Combining parameters such as frequency of logins, engagement rate, session duration, and content creation rate, future researchers and developers will be able to operationalize this conceptual model into an effective detection system. When developing such systems, one can sample information from social media platforms through APIs and integrate it into machine-learning models that can be used to classify users and their accounts. The model is capable of being trained on massive data to maximize prediction precision. The paper therefore provides the foundation for future research and practical developments aimed at creating an optimized and resource-efficient social media ecosystem.

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**Conflict of Interest**: The authors declare "No conflict of interest".