Twitter Account Analysis for Drug Involvement Detection

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***Abstract*—Social media is integral to modern communication, connecting billions of individuals globally. However, this connectivity has also led to negative consequences such as violence, cyber-bullying, cybercrime, and even the promotion of illicit drug-related activities. Among these problems, this paper focuses on an analysis of how drug dealers advertise and drug buyers request drugs using Twitter. For this purpose, we first collect data from users involved in (assumed) illicit drug trade as well as regular users. After monitoring and collecting user data, we store them with our data hierarchy approach and then apply pre-processing, which applies some data cleaning as well as the introduction of additional data from emojis and shared images. This helps better understand and analyze the data. We also apply n-gram analysis to identify patterns and commonalities between sellers and buyers. The results reveal the characteristics of Twitter accounts with (assumed) illicit drug trade including the use of specific words, emojis, and types of photos in their tweets. We observe that Twitter lacks a robust system for consistently monitoring drug-related accounts, with some being suspended while many remain active. Our research and results represent a crucial step toward the development of systems that can effectively identify and address drug-related activities on social media platforms.**

***Index Terms*—social media, Twitter analysis, web scraping, illicit drug, drug trade**

I. INTRODUCTION

Social media has been one of the main mediums for communication and information gathering at a global level [1]. Various platforms contribute to this digital connection and fundamentally strive for the same goal: to serve as an extension of one's presence in the real world and a tool to connect to others for many reasons. The number of social media users worldwide is over 4.48 billion [1]. Given a global population of roughly 8 billion [2], more than half of the globe is connected online. Unfortunately, this great level of connection also brings negative consequences, such as cyber-terrorism, cyber-bullying, and trade of illegal components [3]. Among these activities, one major concern is drug-related activities, including advertisement and promotion [4]–[6]. It has been observed that the previous approach of open-air-markets (where sellers wait at specific locations) was replaced with social media platforms [7]–[10]. Based on survey responses from a past study, drug buyers view these platforms as quick and convenient methods of communication compared to buying at street level and connecting via the complex cryptomarket [11]. Sites such as Facebook, Instagram, and Twitter are very public and can serve as a sort of virtual shop to advertise products while more private channels such as WhatsApp, Wickr, and Facebook Messenger can provide a means of communication.Unfortunately, according to the National Center for Drug Abuse Statistics, fifty percent of people 12 years or older have tried illicit drugs once, including but not limited to marijuana, cocaine, LSD, opioids, and methamphetamine [12]. Just in the United States, 700 thousand overdose-related deaths have been observed since 2000 [12].

With its immense global presence and leniency toward free speech, Twitter has been chosen as one of the platforms. Indeed, based on our initial study, Twitter is one of the primary ones that dealers use to advertise and that consumers use to request drugs and post about their usage. Using this observation, this paper presents a model trained on data from Twitter accounts that can classify them as connected or not connected to drugs. To do so, we conduct comprehensive data collection from users engaged in illicit trade as well as regular users for comparisons. The collected data undergoes pre-processing to ensure data quality and consistency. Subsequently, we employ n-gram analysis to discern underlying patterns and commonalities between sellers and buyers and also classify accounts. The approach discerns whether specific words, emojis, or types of photos within tweets have a discernible impact on the tweet's appeal to potential users or buyers. By investigating these factors, we aim to shed light on the strategies adopted by sellers to attract attention and facilitate transactions in the online drug market. Further, our framework for this study may apply to other domains beyond the online drug market.

The rest of the paper is organized as follows. In Section II, we present the related work with the approach of illicit drug traffic monitoring in social media platforms, websites, blogs, and email lists. Section III-A shows our initial observations from social media platforms, which will be used to create the foundation of our research presented in Section III. We present our analysis results in Section IV. Finally, the paper concludes in Section V.

II. Related Work

There have been multiple studies conducted targeting drug-related activities on social media platforms. In this section, we present an overview of such prior studies.

Prior studies examine drug usage through websites, forums [13], and even email lists [14]. However, these methods became obsolete as more dynamic and up-to-date communication mediums are now preferred as alternatives (e.g., Twitter, Snapchat, Telegram, Reddit); these social media platforms have been gaining interest as they can be used to reach out faster and can also provide anonymity up to a level as defined in the user level agreements [15].

Nevertheless, the current studies are manual, where the researchers provide some keywords and collect data for a period of time using crawlers [10], [16], [17]. Nevertheless, this may result in the potential loss of temporarily posted messages and will not catch potential changes in the messages (e.g., deletion, edits). Hence, we want to create an autonomous social media monitoring toolset that will continuously monitor based on the keywords and users, then automatically add new keywords based on the messages it observes with little to no user intervention. Furthermore, it can also analyze using 1-edit distance-based keywords automatically, which is highly helpful in such analysis [18]). (2) Identification of a seller/user's connections and how much they can propagate: We would like to introduce metrics to understand how users connect to each other. This requires a continuous analysis rather than a single crawling (another difference compared to the existing literature). (3) Further understand the users' details, such as demographics, education, location, and online activities. Such a study can be used for more targeted prevention mechanisms, including advertisements (social media advertisements demonstrated some help in the reduction [19]). Drug trafficking is one of the biggest concerns not only in the United States but across the world. In the United States, multiple government agencies are working to fight against drugs, such as the Combating Illicit Xylazine Act, the STOP Act 2.0, and the PREVENT Fentanyl Act [20]. However, it is not possible to solve this problem just through law enforcement as the sellers always find new ways to reach out to their potential customers, including minors. The existing studies either focus on the websites and blogs and crawl them; this technique is not up-to-trend. Also, the studies do not involve users' connections and reachability, sentimental analysis, etc.

A study conducted in 2022 [21] deals with affordances provided by various social media sites regarding drug-related activity. Posts were filtered to only include those related to the topic, and these were analyzed across the platforms to evaluate drug prevalence in each. Results demonstrated Google Groups had the highest number of drug mentions per post across a group of drug categories based on the longer word limit.

Moyle et. al. [8] conducted a series of three interviews with drug users regarding the utility of social media in their buying activity. These included an international online survey, rapid, in-person interviews, and in-depth, third-party interviews. While each data set provided useful information, all the responses admitted that social media is an important aspect of the modern drug market due to the convenience and relative safety it provides when buying drugs. In-person and dark web transactions still have their place in the market, but platforms like Twitter are clearly an important part of the system for everyday buyers.

Social media platforms are not only useful for studying illicit drug activity but also legal drug activity. Adverse drug reactions (ADR) occur when patients experience negative to life-threatening side effects as a result of taking medication. The great majority of studies related to drug use have revolved around this topic and performing ADR detection. One study [22] from 2015 effectively classified posts as ADR or not using advanced NLP techniques to generate features. Another recent study from 2023 [23] performs a similar detection task for ADR using zero-shot generative AI techniques.

The above studies are all important topics but do not deal with classifying content or accounts from social media platforms as a form of surveillance for illicit drug activity. The first and second deal with comparing prevalence across platforms and gaining a perspective from drug buyers on social media. The final two deal with classification using bodies of text pertaining to ADR and reviews of certain drugs to detect ADR related to that drug. These latter ones do not seek to classify accounts based on text data, and they do not pertain to illicit drug activity at all.

There has also been work to summarize the usefulness of social media to track illicit drug use such as a study from 2017 [24]. The work consisted of a review of many studies related to the topic, and it was concluded that the platforms contain trends and other data that could prove helpful in managing illegal drug activity. Also, more work needs to be done in extracting this data in a systematic manner.

Yang et al. [25] propose a classification system for drug-related and non-drug-related accounts on Instagram using a number of extracted features from text and image data. We extend this work to Twitter with a straightforward classification technique. Further, the social media and drug market landscape changes day to day, so our work analyzes account classification in an actualized manner.

Furthermore, some further studies exist on the analysis of user accounts (with a focus on various concerns) using natural language processing (NLP) and personality analysis [26], [27], graph theory [28]–[32], machine learning algorithms [32]–[34], etc.

In summary, our work focuses on understanding social media platforms and creating an autonomous detection mechanism. To do so, in this work, we analyze different accounts and investigate how they can be tagged with such illicit activities.

III. Methodology

A. Initial Study Observations

Initial Social Media Platform Survey: As a preliminary work, we first investigated multiple social media platforms in terms of their scraping availability and usage for drug trafficking by primarily considering the prevalence of drug-related activities on each platform. We discovered that certain ones, such as Reddit, had relatively relaxed policies on web scraping; however, the drug market on these platforms is limited due to strict surveillance by their moderators, who promptly shut down drug-related discussions. On the other hand, Instagram is one of the largest platforms for drug sales, but it has stringent measures in place to prevent web scraping. After exploring various options, we ultimately concluded that Twitter was the optimal choice for this work.

Early Findings: We initially focused on investigating the accounts connected with fentanyl-related operations because among available illicit drugs, fentanyl is becoming a new trend as it is a cheap but powerful opioid with the highest toxicity level, and it can even be camouflaged as colorful rainbow pills or laced on counterfeit prescription opioids (Percocet, Vicodin, Oxycontin, and Ultram) and sold to minors [35]. Sadly, since 2020, almost 43 thousand overdose deaths have been due to fentanyl [36]. Below we summarize our initial observations:

- During our investigation into finding pure Fentanyl on social media platforms (including Twitter, Reddit, Instagram, etc.) openly, regardless of the platform chosen, we faced multiple challenges. The prevalence of Fentanyl laced with other drugs like cocaine, heroin, Percocet, Oxycodone, and Xanax to amplify its effects makes it difficult for users to be aware of its presence [37]. We observed that those selling one type of drug often deal in multiple substances, indicating a broader network of illicit trade.
- In contrast, users who consume or express an interest in a particular drug tend to solely use hashtags or names specific to that substance, without incorporating numerous other drugs as seen among sellers. This differentiation in hashtag usage suggests that sellers adopt a more inclusive approach to attract potential buyers, while drug users focus on individual drugs, reflecting their specific preferences and consumption patterns.
- Sellers exploit social media to lead buyers to more encrypted platforms such as Telegram, Snapchat, and Kik, where transactions can be conducted with greater discretion. This observation revealed a pattern of users following and connecting with other drug sellers or consumers, facilitating the discovery of additional accounts for data scraping. Notably, these accounts maintain a limitation to evade detection or avoid previous bans, preserving a low profile for self-preservation.
- In pursuit of buyers, sellers employ hashtags, keywords, and emojis to describe the substances they offer, often accompanied by images showcasing the drugs or their effects. Disturbingly, we also identified instances where accounts engaged in this distribution strategy targeted individuals with mental disorders, using hashtags like “mental health” or “ed” (eating disorder) and finding channels targeted towards users struggling with their mental health.
- We also observed that in the realm of the illicit drug trade on Twitter, specific hashtags such as “drugtwt” and “drugstwt” play a dual role, serving as both “trigger warnings” for sensitive content and facilitating buyers in locating sellers.

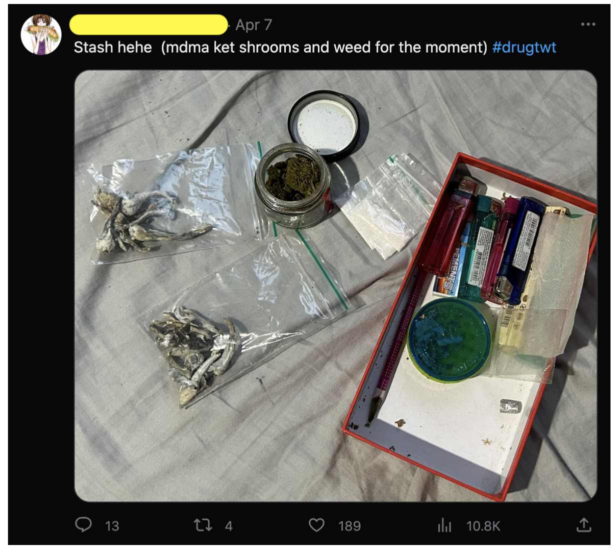

Fig. 1. An example of a tweet from a drug-related account.

B. Overview

Based on the knowledge gained in the initial observations (Section III-A), we created our approach as shown in Figure 2 where we first apply web-scraping to gather information from drug-related and regular/neutral accounts on Twitter. After extracting data as a result of web scraping, we store this data in a standardized format for pre-processing and then, for further analysis.

In what follows, we explain the individual components of our approach in detail.

C. User/Account Monitoring

The data collection process starts with the identification of user accounts. As mentioned in the early observations, we first investigated possible accounts to have an understanding of how they behave, what we can collect, and what kind of information can be gathered from these accounts. For this purpose, we did a manual search using different keywords and further dug through the retweets, followers, etc. as well as the hashtags. Thus, during the initial observations, we were able to identify three types of accounts: drug-related accounts, neutral accounts, and accounts that are not related to drugs but are connected to drug-related accounts.

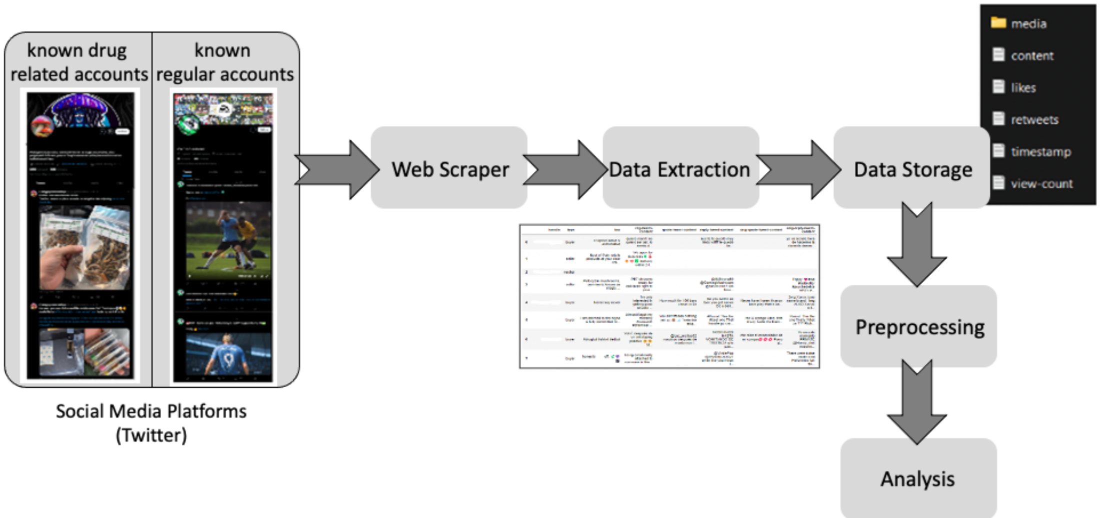

Fig. 2. Overview of our approach.

Twitter includes several types of actions that can be made to interact with content. We choose to scrape tweets, quotes, replies (or comments), likes, followers, and following. Quotes are similar to regular tweets, but they add some commentary to it with the original tweet underneath. Replies appear directly below tweets, and they can be made in relation to regular tweets, quotes, and even earlier replies. The likes include all the tweets that a user has liked. We limit the number of entries for each category of tweets per account to roughly 50 tweets to limit the influence of any one account on our analysis as some accounts can vary wildly in the number of tweets of each type.

In addition, the users can also post photos that can have valuable information, as shown in Figure 1. In this case, image analysis is needed to extract the objects in an image, any text, any faces, etc. Based on these, we created an account monitoring and scraping service that scrapes given user accounts. We limited our scraping with minimal engagement for optimal scraping time. Further, most drug-related accounts we find fit into a low-engagement category.

D. Data Storage

To make data accessible during pre-processing and analysis, we organize it in a standardized system of nested directories and text files. Inside of a top-level *accounts* directory, every account scraped has its own sub-directory. Then within each of these is a group of directories for different types of tweets, in terms of tweets, quotes, replies, and likes. There is also general account information within text files at this level, including followers, following, bio, date joined, and location. Within each tweet type's directory, every tweet has its own directory named by tweet ID, and these each contain the tweet's timestamp, content, likes, retweets, view count, comments, and media (photo or video). Comments are stored in a nested fashion where each comment has its own tweet directory and further sub-directories if that comment also has a reply. Quotes and replies have the same structure described above with the addition of an *original tweet* directory to provide context. Since users tend to like many tweets, we do not scrape liked tweet comments, likes, or retweets to eliminate having to visit each of the tweet's web pages. Figure 3 illustrates the standardized data storage described above.

E. Data Pre-Processing

The scraped tweets contain not only texts but also emojis and photos, which can represent various illegal drugs, enhancing the overall analysis of social media content.

To begin the data pre-processing phase, we initiated an iterative process through directories containing tweet data. Each directory represented a specific user, and within these directories, we have different tweet types: regular tweets, replies, and quotes. This classification enabled us to understand the various ways users engage with social media platforms. Within each directory, we extracted two essential files: "content.txt" to have the textual content of the tweets and "view-count.txt" for valuable information on the view count, aiding us in understanding the popularity and reach of each tweet.

For the tweet types "Replies" and "Quotes," we further processed the data by identifying the original tweets associated with the replies and quoted content. This step involved extracting the relevant information from the "original_tweets_content.txt" file, which allowed us to establish the context and connections between users' interactions.

During this iterative process, we implemented various data-cleaning techniques to ensure that the extracted information was accurate and devoid of any unnecessary noise or any missing information due to scraping. Then, we performed text normalization to standardize text format where emojis are converted to text descriptions as we observed that they are used to represent drugs and intentions. As shown in Figure 1, the users can also share photos in their tweets, which show what they sell. Such photos would provide detailed

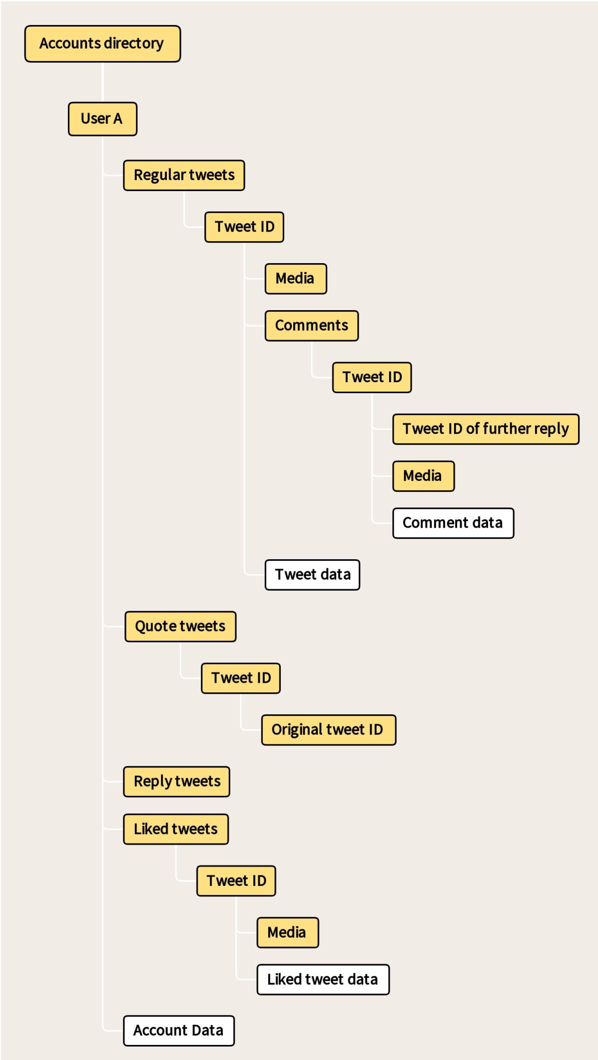

Fig. 3. Data storage structure

information if they are processed carefully. Therefore, we applied computer vision to extract textual data from images – the steps and used APIs are explained in Section IV. Each data frame represented a unique user, enabling us to gain insights into individual users' posting habits, engagement levels, and content preferences.

F. N-Gram Analysis

To identify linguistic elements employed by sellers in the context of online drug distribution, we conduct an n-gram analysis of our data, aiming to uncover prevalent words, hashtags, and emojis utilized by sellers. Initially, we categorize tweets into "popular" or "non-popular" based on their average view count within our tweet pool. Subsequently, we establish the independent variable as the tweet content and the dependent variable as the view count, allowing us to predict the popularity of tweets by analyzing their content. To accomplish this, we divided the data into separate training and testing sets and constructed a logistic regression model, which is then trained and used for predicting tweet popularity. This approach provides valuable insights into the key linguistic factors considered by the model when determining a tweet's popularity. As a result, we gain valuable knowledge of the words and expressions commonly employed by drug dealers in their tweets, enabling us to discern the prevalent vocabulary and patterns used in the online drug trade.

To perform effective classification of accounts, we are working to increase the size of our data set and planning how to best use all the different bodies of text associated with each account. These include bios, usernames of followers and following, comment text, text from each type of tweet, and more. We hope to complete this classification work in the near future.

IV. Experimental Results

A. Implementation Details

In this section, we introduce challenges in this work and explain design decisions we made.

a) Twitter and Limitations: During our study, Twitter placed new limitations on searches and content access. The search limit created a timeout on navigation every few minutes when scraping a large number of tweets. Twitter also made a change limitation that dealt with blocking access to the Twitter API without providing login credentials. The first slowed down our data collection considerably, and the second forced us to alter the way we searched for tweets. Originally, we used snscrape [38] that leveraged the Twitter API without having to log in, searched for different kinds of tweets from a user, and then gathered any missing data using our manual scraper. Nevertheless, Twitter enacted the API changes, and we decided to switch the entire scraping pipeline to Selenium, including searching for tweets.

b) Selenium: The Selenium framework is employed to control a web driver that can process HTML and extract the desired data. Twitter has an available paid API that can search for tweets and provide data on them, but it was unclear if this would yield the volume and type of data we needed. Thus, using Selenium, our script roams from web page to web page, gathering relevant data along the way.

c) XPath: HTML as the building block of websites can be processed in a variety of ways, and one of the most common is with XPath. Selenium provides searching functionality based on XPath, and this was our main method of performing the actual scraping. As Twitter is a high-traffic and volatile website, there are many factors that need to be accounted for to successfully navigate without causing the web driver to throw errors. To avoid these, we employed a variety of XPath techniques including searching for elements with a specific attribute value, finding an element with a specific attribute value and navigating from there, using absolute paths when a piece of data exists in a stable format across accounts, and much more. However, Twitter's structure is being constantly updated, which ends us not having consistent structure across web pages, and we frequently encountered errors with XPath (i.e., XML Path Language used for path definitions in an XML document) while searching for elements such as buttons to expand sections, webpage scrolling, missing elements, and non-existent elements. Therefore, in our web scraper implementation, we included all these corner cases to improve the data extraction quality.

d) Microsoft Azure Computer Vision API: In order to analyze the images from tweets, we decided to use the Microsoft Azure Computer Vision API for extracting tags from images. Nevertheless, while working with the free tier version, we encountered certain limitations. One notable constraint was the "image per minute" limit, which restricted the number of image tags we could generate per minute to 25. To overcome this limitation, we strategically incorporated a timer function to maximize the number of image tags per minute without breaching the limit, ensuring smooth and efficient processing. Additionally, we confronted a credit limit constraint for generating image tags. This credit limitation meant that we were unable to obtain the complete number of image tags per minute, adversely affecting the overall performance of our pre-processing pipeline. As the image tags provide detailed information and help us enhance the performance of our analysis and machine learning model, we will either use a different API or upgrade our subscription to the paid version to overcome the limitations of the free tier version.

B. Analysis and Results

In our analysis, we targeted three classes of accounts: presumed sellers, presumed buyers, and presumed neutral accounts. We were able to find 15 seller accounts and 13 buyer accounts with drug-related activities and added 11 neutral accounts. In total, we had 1964 total tweets, 200 quoted tweets, and 783 reply tweets. During our data collection, pre-processing, and data analysis, we not only validated our initial insights but also unearthed novel attributes associated with these accounts. Upon closer examination of the registration dates for the collected accounts, a significant revelation emerged: an impressive majority of the accounts we gathered were of recent origin, indicating their creation within the current year as shown in Figure 4. This pattern is noteworthy, particularly within the context of individuals involved in illicit drug distribution. It has been observed that those seeking to engage in such activities tend to establish accounts at frequent intervals, presumably to maintain a low profile by keeping their follower count minimal and evading detection from vigilant moderators and potential criminal inquiries. We show some of the stored data in Figure 5 showing the usernames, the tweet type, tweet ID, and content information. We also stored the view count and original tweet (if they are just a quote or reply) and if there exist any possible further comments, which can allow us to analyze the comments as well.

We have uncovered tweets bearing identical content, originating from distinct accounts that share a similar join date. This suggests a pattern where vendors maintain multiple accounts to facilitate their product sales. Moreover, the dynamic nature of these accounts enables them to saturate their feeds with posts concerning the substances they are vending, often

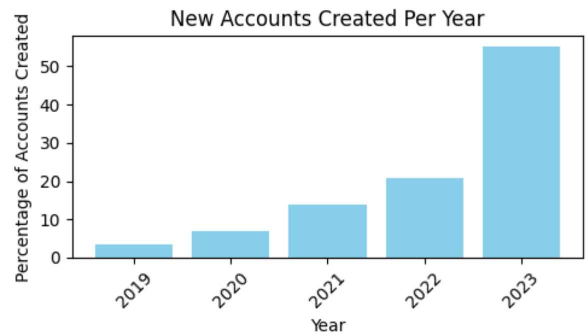

Fig. 4. The majority of the accounts we scraped from were created this year.

employing a strategy of repetitively retweeting their own content. Employing this "spamming" technique significantly broadens the reach of their merchandise to a larger audience. Furthermore, our investigation has revealed that these accounts actively engage with other tweets pertaining to drugs, effectively advertising their wares. This approach simplifies the process for potential buyers to access a broader market, all from a single post.

Our analysis is limited by the number of accounts at our disposal. As our dataset consists of a small number of accounts with drug-related activities, our analysis represents a small sample of such accounts (we are hoping to extend the number of accounts we can monitor in future studies). Despite the current limitations in the size of our dataset, the n-gram analysis has draught valuable insights, reinforcing our initial findings. Notably, our analysis confirms that sellers employ specific strategies to enhance the popularity and reach of their tweets among potential buyers. Hashtags, particularly those related to drugs, such as "*drugtwt*" and "*drugstwt*," emerge as key elements for generating traction in the online drug distribution landscape. Furthermore, sellers make ample use of emojis to complement their messaging effectively. For instance, we observed a consistent use of the *snowflake* emoji when dealing with users primarily interested in purchasing *cocaine*. Although further data is essential to improving the accuracy of our analysis and classification, we have discerned the vocabulary and format utilized by sellers to connect with their target audience. These preliminary findings lay the groundwork for future investigation, allowing us to unravel deeper insights into the online drug trade dynamics and contribute to developing more effective strategies for monitoring and addressing this critical issue.

Using all the text from each content type, we vectorized these corpora into 1-gram, [1,2]-gram, [1,3]-gram, 2-gram, and [2,3]-gram sets. N-grams analysis uses a sequence of n words that have a frequency. Every n-gram's frequency can be used as a feature for use in machine learning algorithms. For example, with $n = 1$ and the phrase "quick fox," we would have the 1-grams "quick" and "fox." With $n = [1,2]$, we would have the same 1-grams as before and the 2-gram "quick fox" additionally. The number of times these sub-phrases appear in

	Username	Tweet Type	Tweet ID	Content	View Count	Timestamp	Has Original Tweet (Quotes)	Original Tweet Content (Quotes)	Comments (Quotes)
184	popyerc	QUOTES	1673612927520108547	I wish I had realized dis before hand but hey ...	191	2023-06-27T08:43:10.000Z	Yes	I think some people come into our lives to act...	[]
185	popyerc	QUOTES	1674200053190098945	Ain't NOBODYYY gone have yuh bacc no cap!!!! I...	77	2023-06-28T23:36:12.000Z	Yes	I don't ask for much, I just be needing to kno...	[]
186	popyerc	QUOTES	1674202253794607106	I feel bad but I have to, I jus hate the feel...	121	2023-06-28T23:44:57.000Z	Yes	Scorpios dont take revenge. We erase your exis...	[]

Fig. 5. A sample data set of tweets and their associated data.

the corpus would form the feature.

From our data analysis, we concluded that regular tweet content is the most meaningful in terms of predicting an account as drug-related.

For our classification, we trained a logistic regression model. We demonstrated the accuracy scores for our classification in Table I. These scores represent the percentage of accounts correctly predicted as a drug seller, drug buyer, or neutral. A higher score indicates that the body of text used in that training and testing is more separable based on the account type, and that text is thus better for classifying for our purpose. From the scores, we observe that the bio and the regular tweet content (i.e., the text of the tweet) are able to provide the best data for the classification of Twitter accounts based on drug involvement with almost all n-gram sizes in our evaluation. For the bio, we observe that for n=1 (score of 0.617) and n=[1,3] (score of 0.669), we obtain the highest scores. For the regular tweet contents, n=1, n=[1,2], and n=[1,3] all provided 0.569 in score, which provides a good understanding. Nevertheless, the replies are not able to provide many results as they do not discuss the drug-related activities too much, similarly the quoted content and reply content. From the observations, we can summarize that n=1, n=[1,2], and n=[1,3] are able to score a high confidence threshold of 0.5 for both bio and regular tweet contents.

TABLE I
AVERAGE SCORES FOR N-GRAM ANALYSIS OF THE DATA.

n-gram size	Bio	Regular Tweet Content	Quote Tweet Content	Reply Tweet Content	Original Quote Content	Original Reply Content
n=1	0.617	0.569	0.407	0.411	0.320	0.537
n=[1,2]	0.583	0.569	0.327	0.417	0.400	0.506
n=[1,3]	0.669	0.569	0.340	0.357	0.460	0.494
n=2	0.406	0.333	0.226	0.226	0.460	0.360
n=[2,3]	0.337	0.5423	0.407	0.229	0.400	0.346

V. CONCLUSION

Illicit drug use has become a major problem in our world today. Social media platforms provide an accessible medium of promotion and communication. First, we investigated multiple social media platforms and decided to focus on Twitter because of its popularity in global usage. Hence, our work aims to provide a straightforward method of classifying accounts on Twitter for regular surveillance and detection of drug-related accounts. We first studied the characteristics of (assumed) illicit drug-related Twitter accounts and then applied n-gram analysis to identify common words, phrases, emojis, and images associated with tweets involved in illicit drug trade. Nevertheless, due to the changes in the platform, we lack the large amount of data to analyze them in great detail. Therefore, our future work will extend our framework to examine larger sets of data or to analyze characteristics of social media accounts and content for other categories of social media usage.

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