Multi-modal Deep Learning Based Fusion Approach to Detect Illicit Retail Networks from Social Media

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***Abstract*—Illicit drug trafficking poses a significant threat in today's society in general and in the younger population in particular. Drug abuse has been known to be correlated with car-accidents, crimes, diseases, deaths and many other negative aspects of society. With the advancement of social media being an open platform to express all kinds of social activities, drug use can be encouraged on this platform to lead other people towards drug abuse. Where people abuse drugs on social media, it is a prominent platform for drug dealing as well. Drug dealers post different types of drug images along with their contact information on social media. Tracking drug dealers among millions of social media users can be very challenging for law enforcement agencies. Therefore, automatic detection of drug dealers (along with the type of drugs they sell and their contact information) is crucial. In this article we have presented a state-of-the-art social media analytic algorithm which does multi modal analysis in order to detect drug-related posts and drug dealers from social media. We propose to detect different types of drugs from social media posts which include: pills, mushrooms, LSD, cannabis, cocaine, syrup, hookah and cigars using our drug type detection model. We also propose to extract drug dealer's information from social media and create novel AI algorithms to improve understanding of the operations of Illicit Retail Networks (IRN) that will help detect, disrupt and ultimately dismantle these networks. Our approach is generalizable to detect different illicit networks from social media such as human trafficking, illegal gun sales, money laundering and others.**

I. Introduction

Social media plays an increasingly important role at the retail end of the supply chain networks of illicit drug trafficking. In this paper, we present an AI-Based solution to disrupt illicit retail networks by detecting them from social media. We extract information from Social Media and create novel AI algorithms to detect Illicit Retail Networks (IRN) for drug trafficking in order to help law enforcement agencies to detect, disrupt and ultimately dismantle these networks. Research shows that there are a significant amount of activities related to the selling and buying of drugs [1], [2], [3], [4], [5] using social media sites. Social media is also a venue used for human trafficking [6], [7], [8], [9]. Criminals and cartels engaged in human trafficking and drug trafficking along the US border often use similar methods to get the "product" across the border[10], [11].

According to the National Survey on Drug Use and Health (NSDUH), in 2018, an estimated 164.8 million people aged 12 or older in the United States (60.2 percent) were past month substance users (i.e., tobacco, alcohol, or illicit drugs). The 164.8 million past month substance users in 2018 include 139.8 million people who drank alcohol, 58.8 million people who used a tobacco product, and 31.9 million people who used an illicit drug [12]. According to National Institute on Drug Abuse (NIDA) the estimated cost of drug abuse in the United States including illegal drugs, alcohol, and tobacco is more than $740 billion a year and growing [13]. The total costs related to each type of drug includes: (a) Tobacco: $300 billion, (b) Alcohol abuse: $249 billion, (c) Illegal drug abuse: $193 billion and (d) Prescription drug abuse: $78.5 billion

Apart from the cost of the different drug types, there are more consequences of drug uses in the society such as its impact on health and healthcare systems, impact on criminal and justice systems, impact on productivity and impact on environment[14].

According to Gonzales et al. [15] Socialization Processes such as peer pressure, media influence , social networks , social norms etc. are a dominant relapse theme that influences 65 percent of patients to abuse drugs.

A. Research Goals

Our research goal is to automatically extract illicit network information from Social Media. These illicit networks include illicit drugs being sold, drug types being sold, drug dealer information, human trafficking, money laundering and illegal gun sales via social media. We will ultimately be helping law enforcement agencies to detect and dismantle their networks.

B. Contribution

We have several contribution in this paper which are stated below.

- In this research we proposed a drug type detection model in order to identify different types of drugs from images such pills, mushrooms, LSD, cannabis, cocaine, syrup, hookah and cigar.
- we have employed feature-level fusion technique where we integrated image features resulted from our drug type detection model and text features found from text vectorization technique and employed them into a deep learning model which results higher accuracy in detecting drug-related posts than any other previous studies.

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- We propose to combine detected drug types, drug-related posts and profile, contacts and hashtag information to detect drug dealers and send combined information to law enforcement agency.

II. Related Studies

In this section, we review research on drug dealing related post detection and drug abuse detection because they are most closely related to our research.

A. Drug dealing related studies

Li et al.[3] presented a machine learning algorithm to detect Opioid drug dealers from Instagram posts and they have used texts and hashtags to build a deep learning algorithm. Their objective was to detect illegal drug selling posts from hashtag searches and using deep learning to analyze drug dealing text from posts. They manually annotated 260 images to determine if they were related to controlled substances or illicit drugs. However, their research has several limitations. For example, they did not use multimodal or synchronous approaches to develop a classification model based on both text and images.

Mackey et al.[16] used biterm topic model (BTM) to detect opioid marketing and sale from Twitter posts. Among 213,041 tweets 0.32 percent were identified as online marketing for prescription opioids. After manually analyzing those tweets, they found 34 live hyperlinks of the sale of opioids. Some of their limitations include not collecting street/slang names for drugs and only using text features.

Yang et al. [4] proposed an approach to detected drug-related posts by both image and text analysis and detected drug dealer account by account pattern analysis. They have used percentage of drug-related posts, ratio of the number of followers, frequencies of drug-related posts in hours of a day and the evidence of transaction to detect the drug dealer. They have achieved 88 percent accuracy detecting drug-related post recognition and an F1 score of 0.51 on drug dealer detection. They do have few limitations such as, they have only used 3 categories of drugs to train their image based classifier which are pills, syrup and weed.

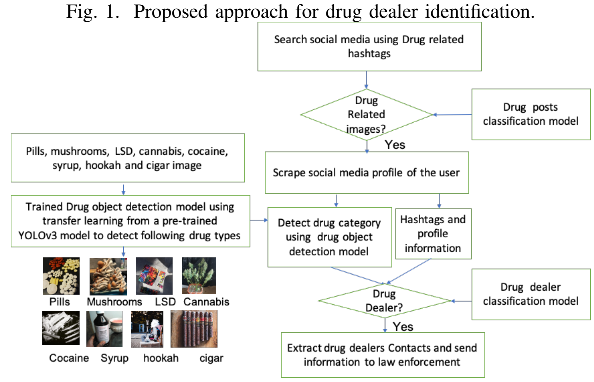
Demant et al. [5] conducted an interview consist of 107 drug buyers and sellers found high degree of drug-dealing activity on Facebook and Instagram, as well as on Snapchat and Facebook Messenger. Buyers and sellers also make use of encrypted platforms, such as darknet forums and the Wickr application.[17] Tyrawski et al. examined how pharmaceutical companies use social media to interact with the general public and market their drugs and found 40.7 percent companies do direct-to-consumer advertising. Moyle et al. [18] conducted interviews and surveys to explore the supply and access of drugs using social media and found mobile apps such as Snapchat, Instagram, Wickr, Kik, Whatsapp, Facebook are mostly used for drug dealing.

B. Drug abuse related studies

Zhou et al.[19]used Instagram data to detect illicit drug Use Patterns at fine granularity with respect to demographics and they also extracted common interests shared by drug users. Hu et al. [2] used an ensemble deep learning model which combines word-level CNN models and character-level CNN models to classify drug abuse related tweets and their model performs better than traditional machine learning models, especially on heavily imbalanced datasets. Sarker et al. [20] collected twitter posts about three commonly abused medications (Adderall, oxycodone, and quetiapine), annotated 6400 tweets and designed an automatic supervised classification technique to distinguish posts containing signals of medication abuse which acquired 82 percent accuracy. They have identified 3 research questions which are increasing annotations, visualization and real-time monitoring and natural language processing-oriented improvements. Ding et al.[21] employed unsupervised features learning to take advantage of a large amount of unsupervised social media data, employed multi-view feature learning to combine heterogeneous user information such as "likes" and "status updates" to learn a comprehensive user representation, build SUD prediction models based on learned user features and employed correlation analysis to obtain human interpretable results(80 percent prediction accuracy based on AUC). Phan et al. [22] used five-year dataset from Instagram to analyze what machine extracted textual and visual cues reveal about trends of casual drinking and possible negative drinking and found that possible negative drinking occur more frequently in party occasions and nightlife locations, with a higher presence of people, while casual drinking posts occur at food locations. Hassanpour et al. [23] used 2287 active Instagram users data to develop a deep-learning method to classify individuals' risk for alcohol, tobacco, and drug use. Zhang et al. [24] collected hookah images from Instagram and used CNN to extract unique hookah features and classified hookah and non hookah images using SVM, their method 99.5 percent accuracy classifying between hookah or non hookah images.

III. Methods and Results

Fig. 1. Proposed approach for drug dealer identification.



A. Categorization of Drugs

In order to develop a better image detection model, our categorization of drugs is done based on the looks and forms

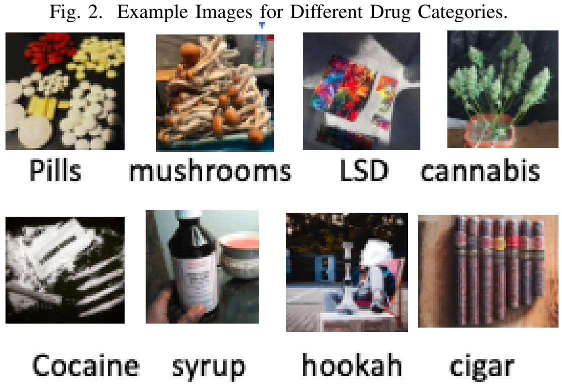
TABLE I
USDEA DRUG NAMES AND FORMS

Drug Names	Drug Forms
Amphetamines, Barbiturates, Steroids	pill, injection
Benzodiazepines, Methadone	pill, syrup, injection
Cocaine, Heroin, Bath Salts	powder
Ecstasy Or MDMA (Molly)	pill, powder
Fentanyl	pill, patch, powder, crystal
Flakka (alpha-PVP)	crystal
Gamma-Hydroxybutyric Acid (GHB)	powder, liquid
Hydromorphone	injection, powder, pills
Inhalants	household products
Ketamine	injection
Khat	leaves and twigs
LSD	paper sheets
Marijuana,Salvia Divinorum	plant leaves
Methamphetamine	powder, pill, crystal
Morphine	injection , pill
Opium	solid, powder, injection
Oxycodone, Rohypnol, Kratom	pill
Peyote, Mescaline	small spineless cactus
Psilocybin	mushrooms
Spice/K2, Synthetic Marijuana	potpourri
U-47700	powder, pill

of drugs. Yang et al.[4] used three categories such as weeds, pills and syrups to train their image based classifier. We have found there are more substances and drugs are being sold on social media that do not fall into those three categories. From the United States Drug Enforcement Administration, [25] we found a list of drugs being sold in USA which is displayed on table 3.1. Drugs are found in different forms such as pills, injections, powders, syrups, crystals and plants. We combined injections, syrups and other liquids into one category titled, 'syrup' because these substances look similar. Again, raw cannabis and processed cannabis looks different so we kept them in a different category. Also we added hookah and cigar because they are sold together with other drugs. So, our nine initial substance categories are: pills, mushrooms, LSD, cannabis, raw cannabis, cocaine, syrup, hookah and cigar.

B. Drug Category Recognition

Fig. 2. Example Images for Different Drug Categories.



We have trained a drug type detection model in order to identify what type of drugs are being sold via social media. This section consists of the following subsections: data collection, data processing, Model training and results.

TABLE II
HASHTAG LIST

Drug category	Hashtags used to scrape social media posts
Syrup	#promethazinecodeinesyrup, #alpharma
Mushrooms	#magicmashrooms, #shrooms
Pills	#fuckxanax, #stopdoingxanax2017, #xanaxbaseball
LSD	#lsdtrip, #acidtrip, #lsdtrips, #acidtabs
Hookah	#hookah
Cigar	#cigar, #cigars, #cigarlife
Cocaine	#lacocaina, #pleasedontdococaine, #whitecocaine
Cannabis	#mariuana, #cannabis, #pullandsnap, #propanehashoil #trimrun, #butanehashoil

1) Data Collection: To scrape Instagram images we employed Instaloader [26] and Instaphyte [27] hashtag scrapper. Multiple hashtags has been used to collect different types of drug images from Instagram which is shown below in table 1. We have selected these hashtags because they are most commonly used among drug dealers. Data collection happened between February 2020 to May 2020. After collecting images using scrapper, we have manually selected images for each category of drugs.

2) Data Processing: In this phase, we have labelled images into nine categories using LabelImg [28] which allows us to draw visual boxes around the objects in the images and label them as well. After labelling each image using LabelImg, it automatically saves the coordinate information of the drug category found in that image into an XML files. We have used 1074 labelled images in total where 84% were used for training and 16% were used for validation.

3) Model training and Results: We have trained drug type detection model using ImageAI[29] and leveraging transfer learning from a pre-trained YOLOv3 [30] model to detect drug categories. YOLOv3 is an improved version of the YOLO model. The YOLOV3 model has 53 convolutional layers, so it is called Darknet-53. YOLOv3 runs significantly faster than other detection methods and it uses independent logistic classifier. We have trained our model using nine drug categories which are mushrooms, pills, LSD, cannabis, raw cannabis, cocaine, syrup, hookah and cigar. Precision values found from the validation set is shown in table III. The precision of Cocaine is the highest (79 percent) and the precision of LSD is the second highest (73 percent). One of the examples of how our model can detect drugs from images is shown in figure 3. This is an example of our model detecting pills from an Instagram post with 79.76% accuracy.

4) Challenges: There are many challenges opposing us to achieve better accuracy in our drug type detection model. For example, raw cannabis and mushrooms can be confused with other plants and fungi and snow can be misidentified as cocaine. Another challenge is that we could not train our model for more than 8 epochs in Google Colab Pro [31] due to session time out.

TABLE III
PRECISION OF DRUG TYPE DETECTION MODEL

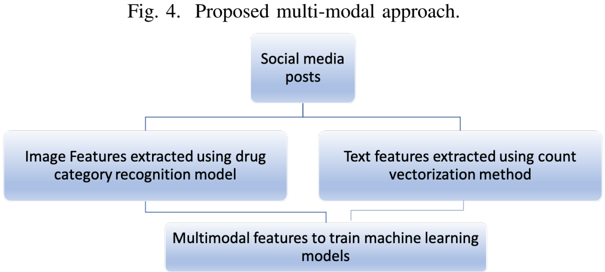
Drug Types	Precision
Cannabis	0.71
Cigar	0.45
Cocaine	0.79
Hookah	0.49
LSD	0.73
Mushrooms	0.64
Pills	0.66
Raw Cannabis	0.36
Syrup	0.61
Mean Average Precision	0.60

Fig. 3. Drug Category Detection from Images

C. Detection of drug-related posts from social media

Our second approach is to build a drug-related post detection model in order to identify different drug-related posts from social media. We describe this approach in this section using three different subsections below which are data collection, data processing and Model training and results.

Fig. 4. Proposed multi-modal approach.



1) Data Collection: In order to detect drug-related posts we have scrapped 8733 non-drug-related posts and 10004 drug-related posts from Instagram including both caption and images using Instaloader [26] scrapping API. Among them we have finally found 7791 drug-related and 4743 non-drug-related posts which have both image and caption. All the drug-related posts were collected from suspected drug dealer's accounts from Instagram.

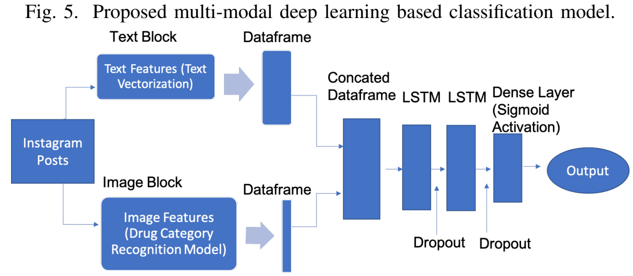
TABLE IV
RESULTS OF TEXT BASED CLASSIFIERS FOR DRUG-RELATED POSTS DETECTION

Model	Precision	recall	F1 score	accuracy
Logistic Regression	0.99	0.92	0.95	0.94
Random Forest Classifier	0.97	0.92	0.95	0.93
Decision Tree Classifier	0.96	0.9	0.93	0.91
KNeighbors Classifier	0.93	0.78	0.85	0.83
SVC SVM Classifier	0.99	0.82	0.9	0.88
Deep learning model	0.98	0.93	0.95	0.94

2) Data Processing: The drug type detection model helped us to identify the types of drugs found in each image which is used as an image feature to train the drug-related post classification model. In the drug type detection model, we have set the prediction probability threshold to 80 percent to avoid false positive predictions as much as possible. We also preprocessed the text by removing the punctuation and stop words. We converted the text into vectors using Sklearn CountVectorizer [32] and selected best 5000 features among them using SelectKBest [32].

3) Model training and Results: To train drug-related post detection model we have employed feature-level fusion technique to integrate both text and image features which is shown in figure 4. We have used different machine learning models such as logistic regression, random forest, decision tree, k-nearest neighbors(KNN) classifier, support vector machine and our deep learning model. In figure 5, we have presented the structure of our deep learning model. In table IV, we displayed results of text based classifiers for drug-related posts detection where we only used text features extracted from text vectorization method. We found that combining both image and text based features together using feature level fusion technique improves the performance of classification model and our deep learning based approach outperforms any other machine learning models which is shown in table V.

Fig. 5. Proposed multi-modal deep learning based classification model.



D. Automatically detect drug dealers profile from social media

This section describes drug dealer classification model which comprises 3 different subsections below.

1) Data Collection: We manually detected Instagram accounts of drug dealers and scrapped their Instagram profile including images, captions, profile images, comments using

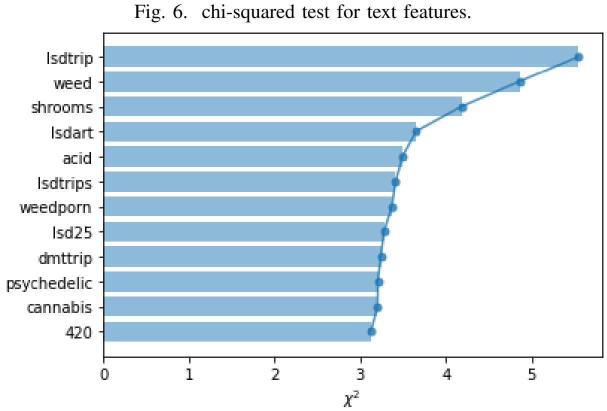
TABLE V
RESULTS OF MULTI-MODAL CLASSIFIERS FOR DRUG-RELATED POSTS DETECTION

Model	Precision	recall	F1 score	accuracy
Logistic Regression	0.97	0.94	0.96	0.95
Random Forest Classifier	0.96	0.94	0.95	0.94
Decision Tree Classifier	0.93	0.91	0.92	0.9
KNeighbors Classifier	0.94	0.79	0.86	0.84
SVC SVM Classifier	0.97	0.86	0.91	0.9
Deep learning model	0.98	0.96	0.97	0.96

Instaloader [26]. In this project we have scraped 131 drug dealers profiles and 206 non-drug dealers profile. Among them we have finally used 105 drug dealer profile and 130 non drug dealers profile which have both captions and images. For each profile we manually labelled them as 'drug dealer' and 'non-drug dealer' based on their profile characteristics. Drug dealers normally show their intention of selling drugs by sharing contact information such as Wickr ID and Kik ID, Snapchat id, WhatsApp id, email etc.

2) Data Processing: In order to classify 105 drug dealer's profiles and 130 non-drug dealer's profiles, we have acquired image and text features using the same approach as drug-related post classification model . In Figure 6 we have displayed the top 12 hashtags drug dealers frequently used to sell drugs on social media which is determined using chi-squared test.

Fig. 6. chi-squared test for text features.



3) Model training and results: To train the drug dealer classification model, we have done feature-level fusion to integrate both text and image features and employed them into different machine learning and deep learning models. The results of text feature based classification models are displayed in table VI and the results of multi-modal classification models are shown in table VII.

IV. LIMITATIONS AND FUTURE WORK

Even though we have collected three different datasets and trained three different models in order to accurately detect illicit sales related posts and drug dealers from social media, we have few limitations to mention. We have scrapped limited

TABLE VI
RESULTS OF TEXT BASED CLASSIFIERS FOR DRUG DEALER DETECTION

Model	Precision	recall	F1 score	accuracy
LogisticRegression	1.0	0.81	0.9	0.94
Random Forest Classifier	1.0	0.88	0.93	0.96
Decision Tree Classifier	0.88	0.88	0.88	0.92
KNeighbors Classifier	1.0	0.25	0.4	0.76
SVC SVM Classifier	0.6	0.56	0.58	0.74
LSTM classifier	1.0	0.94	0.97	0.98

TABLE VII
RESULTS OF MULTI-MODAL CLASSIFIER FOR DRUG DEALER DETECTION

Model	Precision	recall	F1 score	accuracy
LogisticRegression	0.89	1.0	0.94	0.96
Random Forest Classifier	1.0	0.94	0.97	0.98
Decision Tree Classifier	1.0	0.94	0.97	0.98
KNeighbors Classifier	1.0	0.19	0.32	0.74
SVC SVM Classifier	0.7	0.88	0.78	0.84
LSTM classifier	0.94	1.0	0.97	0.98

number of profiles to train the drug dealer classification model which causes our deep learning based classifier performs closer to other machine learning models. For future work we will incorporate more training data as well as we have many other future plans which are described below.

A. Detecting human trafficking, money laundering and illegal gun sales from social media

Our approach is generalizable to detect human trafficking, money laundering, illegal gun sales from social media, and it can be a highly effective tool for law enforcement agencies. We will apply a similar approach to detect other illicit retail networks from social media.

B. Geo-locate illicit actors from Social Media

We propose to determine the geo-location information by combining multiple approaches. First, the distribution of drugs by geographic regions is available in the HIDTA databases. Second, the DEA maintains location information of various drug labs in the US along with the drug traces found in each of these locations. Third, we will build on existing research for geo-locating Social Media by label propagation models [4], [33]. Also, drug dealers normally share their Whatsapp number or phone number asking people to contact them to buy their drugs, which can be used to track their location. There are different ways to extract drug dealer's Geo-location from social media, such as: (a) Social media location tags, (b) Hashtags containing location information, (c) Social media posts with phone numbers, (d) Social media posts with WhatsApp ID, (e) Website links, (f) Other contact Information such as Wickr ID and Kik ID.

V. CONCLUSION

In this study, we have proposed a multi-modal fusion based deep learning technique with improved performance to detect illicit drug sales from social media. We have also trained a drug category detection model which can detect different types of drugs from images. Drug dealers mostly share images of drugs along with drug-related hashtags in social media. Also, they share their contact information such as Whatsapp number, phone number, email, website address, Wickr ID , Kik ID etc. which shows their intention to sell drugs. In this study, we propose to detect drug dealers profile, types of drugs being sold and contact information in order help law enforcement agencies to dismantle their illicit retail networks.

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