From Peril to Promise: Harnessing Machine Learning and Natural Language Processing for Combating Privately Manufactured Firearms in the United States

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Abstract

This paper will serve as a review of current literature about using artificial intelligence, including but not limited to deep neural networks, machine-learning, and computer vision, in detection of privately manufactured firearms. This paper will review detection of privately manufactured firearms in the digital environment (e.g. the Web) and in the physical world (e.g. surveillance images and videos). Further, the hopes to illuminate how current forensic and crime analysis applied to traditional firearms are not transferable to privately manufactured firearms (PMFs), thus necessitating application of artificial intelligence methods that are currently used in traditional crime analysis and firearms regulation. Though there are few publications about using machine learning methods for identification of privately manufactured firearms, this literature hopes to change that by offering recommendations on how to apply machine learning techniques to the issue of PMFs. This paper advocates for the application of machine learning and computer vision techniques to identify and classify privately manufactured firearms, addressing a critical gap in current forensic methods. By leveraging advanced AI technologies, we aim to enhance surveillance and intervention strategies to combat the evolving challenges of gun violence.
Keywords: Artificial intelligence, machine learning, neural networks, privately manufactured firearms

Introduction

Historical Prevalence of Gun Violence in the United States

The United States faces a unique gun violence epidemic. It is estimated that 316 people are shot in the United States every day, which totals to 111,551 people shot every year (Corti, 2022). Gun violence is a principal public health issue where upwards of 40,000 deaths are reported by the U.S. Center for Disease Control and Prevention (CDC, 2023). Comparison of mortality from firearms in the United States compared to other countries dates back to 2010 with the comparison of violent death rates in the U.S. in 2010 to other high-income countries identified by the Organization for Economic Cooperation and Development (OECD) (JAMA, 2018). The study reviewed high-income countries such as the United Kingdom, Portugal, New Zealand, Italy, and Canada. Compared to any other high income country, firearm related deaths are 10 times likely for those in the U.S (Grinshteyn, 2010). Further, a study in 2016 reported that the United States was one of six total countries (Brazil, United States, Mexico, Colombia, Venezuela, and Guatemala) accounting for 50.5% of global deaths that resulted from firearm related injuries (JAMA, 2018). Also in 2016, the American Medical Association formally declared firearm violence as “a public health crisis that requires a comprehensive public health response and solution” (American Medical Association, 2016). Another study from 2019 reporting a global study on homicide revealed that “the rate of firearm-related homicides in the Americas rose to approximately 75%, which is higher than anywhere else in the world” (Cardoza, 2022).

Though literature shows the U.S. has had a long history of gun violence, with the example of the first school shooting in the U.S. dating back to 1853, the U.S. experienced a severe increase in gun violence after the arrival of the COVID-19 pandemic (Ricca, 2022; Braga 2022). Firearm related violence is a multidimensional problem that results from a number of factors, including contributors such as “poverty, social inequalities or rapid social change, alcohol and drug use, and young population age structure” (JAMA, 2018). The COVID-19 pandemic can fall under the category of rapid social change as every civilian was forced to change various aspects of their lifestyle. The pandemic is only one crisis linked to firearm violence in the U.S. Studies have show that a combination of ease of access, high levels of gun ownership, and lax gun laws contribute to higher rates of gun violence in the U.S., which is supported by studies that show "firearm availability increases the risk of suicide"(Johnson, 2021; Betz, 2022). The *Gun Violence Archive* emphasizes that the U.S. has witnessed the most troubling statistics in the past decade, with 647 mass shootings documented in 2022 and 197 school shootings documented in the same year (Gun Violence Archive, 2023). Though frequencies of mass shootings, school shootings, and firearm related deaths vary spatially and temporally, the consensus within the literature states that "firearm violence adversely affects any community, regardless of race, geography, or socioeconomic status" (Bailey, 2020).

Firearm Ownership and Gun Culture in the United States

According to a survey published in 2017, the U.S. accounts for approximately 45.89% of firearms around the world that are privately owned, and in this context, that means in civilian hands. When adjusting the number of firearms, registered or unregistered to account for population, the number of firearms per 100 persons is calculated to be 120.5 firearms (Small Arms Survey, 2020). Though another comparable survey concerning international civilian-owned firearms has not been conducted, the United States Department of Justice Bureau of Alcohol, Tobacco, Firearms, and Explosives (ATF) has published data dating back to 2017. This comprehensive report includes statistics concentrating on the dynamics of commerce in firearms in the United States. The report identifies trends in firearm manufacturing in the U.S. GCA firearm manufacturing dominates the licensed domestic firearm manufacturing industry. Between 2000 and 2020, there was an 187% increase in the number of domestically manufactured GCA firearms (ATF, 2022). Between 2000 and 2020, there was a 4,281% increase in the production of miscellaneous firearms, with this growth accelerating within the past 10 years. Defined by the National Firearms Trafficking and Commerce Assessment, miscellaneous firearms are frames and receivers sold before being fully assembled in a finished firearm. A finished firearm is at the end of the manufacturing process and can be classified by the ATF. Further, the report highlights the growth of privately manufactured firearms–PMFs–which are defined by the ATF as a firearm (frame or receiver) that has been completed, assembled or otherwise produced by a person other than a licensed manufacturer. PMFs are not serialized, which introduced a number of challenges in forensic identification, reporting, tracing, and tracking of such firearms (ATF, 2023). Together, the heightened manufacturing of miscellaneous firearms and PMFs points toward a growing trend in consumer demand for customized firearms.

Gun regulations are a highly debated area of policy because of the variety of research that has difficulty discerning the effect of policy on deterring crime (Tannenbaum, 2019). However, there is research that provided data that showed an "excess" of firearm purchases was associated with a statistically significant increase in firearm violence. Though much research focuses on firearm ownership, purchasing, and policy in general, there is little convergence of all three topics on miscellaneous firearms and PMFs.

Rise and Popularity of Privately Manufactured Firearms

The term PMF includes a number of different firearms that can be produced. A selection of these names includes 80%-kit, 80%-gun, 80%-receiver, lower 80, unfinished frame, kit gun, jig gun, casting, receiver blank, receiver body, printed gun, wiki-gun, 3D gun, downloaded gun, homemade gun, flat, and ghost gun (Braga et al, 2022). One police department chief in Oakland, California remarked that the number of ghost guns that are plaguing the community is "unbelievable." However, one limitation is that there is not a standardized definition of a PMF that is used by all police departments. Further, the organization of police departments can impact accurate reporting and accountability. For example, the Oakland Police Department does not train all officers on recognizing PMFs (Braga et al, 2022).

Regarding the classification of PMFs, the Armament Research Services (ARES) establishes three categories for classification: (1) fully 3D-printed (F3DP) firearms, (2) hybrid 3D-printed firearms, and (3) parts kit completions/conversions (PKC). F3DP firearms are, as stated, fully 3D-printed. Hybrid 3D-printed firearms have “non-regulated” or “non-restricted” parts in their design (e.g. springs, screws, nails, metal tubing). PKC is made of parts that are “commercially available” and can be derived from “conventional firearms” (e.g. unfinished firearm frames, miscellaneous firearms). Currently, there are few publications analyzing PMFs with a forensic lens. The majority of publications that have begun addressing this forensic challenge focus on chemical analysis of the polymer comprising the firearm as a means of tracing the firearm back to a specific 3D printer (Szwed et al, 2023).

Regulating Privately Manufactured Firearms

The power of the internet means the common person can produce 3D-printed firearms from the comforts of the home in a fast manner, without much difficulty, even if they have no knowledge about the danger of PMFs (Tan, 2023). Additive manufacturing–3D printing–is known to have a large influence in engineering fields such as automotive and aerospace industries (Yampolskiy et al, 2016). The 21st century has witnessed the rise of plastics (also referred to as polymers) as the largest group of additive manufacturing and also witnessed the beginning of weaponization of 3D printers (Yampolskiy et al, 2016). Anybody with access to a 3D printer now has the ability to pull any computer-aided design (CAD) file from the internet and create a lethal firearm, essentially bypassing any form of gun control regulations (Tan, 2023).

The boom of 3D printed firearms can be traced back to the 2013 “hysteria” when two Daily Mail journalists used a 3D printer to create a plastic firearm, and transported it from London to St. Pancras aboard a train service. In the same year, Israeli journalists smuggled 3D firearms into the Israeli Parliament (Tan, 2023). The issue is that there is debate over whether the government has a constitutional right to regulate the release of CAD files containing 3D gun blueprints (Putrich, 2013). Though the presence of 3D printed firearms is not a “novel” issue, the ease of access to all the internet resources necessary to create a lethal firearm exacerbates the threat of these firearms (Karen, 2022). The unique safety issues caused by 3D printed firearms is rooted in challenges faced by crime scene investigators. Traditional analysis of a crime scene where a gun was involved "(1) striations on a fired bullet that can be matched to a gun because of barrel rifling; (2) patterns of GSR that vary depending on proximity of the weapon to the target; ... [and (3)] fingerprints on the weapon and casing ," and these pieces of evidence become nearly impossible to collect when the gun is 3D printed (Cizdziel, 2019).

Using Artificial Intelligence for Classification of Firearms

A number of studies have a similar approach to using artificial intelligence to develop solutions to the issue of gun violence. In one study, Ineji et al. had a model identifying objects as belonging to one of two classes: knife or gun (Ineneji, 2019). Another model also with the aim of model classification used a pre-trained VGG-16 model in three classes: knife, pistol, or non-weapon (Grega, 2016). Further, one model by Lai et al. detected pistols and rifles in a real-time object detection study (Lira, n.d.). To date, there is no image classification model that seeks to distinguish privately manufactured firearms from firearms manufactured by licensed individuals who are authorized by the government to do so. This gap highlights the substantial potential for machine learning and natural language processing to enhance surveillance and preventative measures. These technologies can empower data scientists to develop sophisticated detection systems capable of identifying privately manufactured firearms in live video feeds, while also utilizing data to track and analyze trends over time. Moreover, advanced machine learning techniques can significantly improve firearm classification, differentiating between legally manufactured and privately manufactured firearms, thereby aiding law enforcement in the digital age. By harnessing these technologies, we can make strides toward more effective monitoring and intervention strategies to combat the evolving challenges of gun violence. This paper bridges the gap between traditional forensic methods and emerging challenges in firearm regulation by exploring the potential of artificial intelligence, particularly machine learning and computer vision, in detecting and classifying privately manufactured firearms.

Discussion of the Literature

Machine Learning as a Tool in Crime Prediction

Predicting crime using machine learning and deep learning techniques has garnered significant attention from researchers, who aim to identify patterns and trends in crime occurrences. Machine learning, a subset of artificial intelligence, utilizes statistical models and algorithms to analyze data and make predictions, while deep learning, a more advanced subset, employs artificial neural networks with multiple layers to model complex relationships between inputs and outputs. Both methodologies have shown potential in various aspects of crime prediction. For instance, deep learning algorithms, such as convolutional and recurrent neural networks, have been trained on spatial and temporal crime data to predict patterns in specific cities. These algorithms analyze crime data, including the time, location, and types of incidents. Additionally, computer vision and video analysis, a significant application of deep learning, has been used to scrutinize surveillance footage, detecting and classifying criminal activities like vandalism, theft, and assault. Despite these advancements, several challenges persist. High-quality crime data is often difficult to obtain and can be incomplete or unreliable, posing a significant hurdle. Moreover, the collection and use of crime data raise privacy and ethical concerns that need to be addressed. Another critical issue is the interpretability of machine learning and deep learning models, which can be complex and obscure, limiting their effectiveness in decision-making processes. In crime-related classification, convolutional neural networks (CNNs) are employed for image-based tasks, such as detecting weapons in crime scenes, while recurrent neural networks (RNNs) are utilized to study temporal data patterns. Addressing these challenges is crucial to fully harness the potential of machine learning and deep learning in crime prediction (Mandalapu, 2023) .

Computer Vision as a Tool to Monitor Firearms Trafficking

The internet has allowed access to a large set of images stored in the World Wide Web, whether that be on social media platforms or websites that are part of the dark Web. Computer vision can be used to classify RGB images and serve as a critical component of efforts to leverage the Web to track criminal firearms trafficking networks. One reference emphasizes this, saying that "forums, social media posts, Dark Web marketplaces, and even commercial=eshops can be utilized as image sources." Deep Neural Networks (DNNs) have been identified to be useful in firearms classification; however, they are limited in the sense they require large amounts of labeled training data. This presents a challenge to sourcing images from the Web and means DNNs are limited to small datasets that are taxing to collect. This challenge can be overcome using self-supervised learning (SSL) methods, specificallySimCLR, Deep-ClusterV2, DINO, and MAE. One study used these SSL methods and compared them to “traditional” supervised pre-training methods using the ImageNet-100 and ImageNet-1k datasets. The results indicated that SSL methods have potential in achieving the accuracy achieved by traditional methods and bypassing the requirement for a large amount of training data (Konstantakos, 2024).

Computer vision is a subset of artificial intelligence that allows computers to understand the visual world, which is applicable in crime analysis and surveillance. The limitation of computer vision in crime analysis is that the quality of surveillance systems can hinder the ability to gather forensic evidence (Shah, 2021). One study on facial recognition from proof quality videos made determined this limitation of computer vision through analysis of security surveillance (Burton, 1999).

Artificial Intelligence as a Tool in Policing

Smart policing, which leverages advanced technologies such as artificial intelligence, aims to enhance crime prevention and reduction efforts. The increasing number of criminal incidents and the vast amount of crime data that are challenging to process manually have driven the adoption of smart policing tools. These tools include predictive policing techniques that utilize crime documentation, predictive crime maps, and AI algorithms to increase city safety. A systematic review of AI frameworks based on ML and NLP in smart policing reveals the effectiveness of methods like information extraction and named-entity recognition (NER). NER, for instance, detects entities such as people, places, and dates, significantly reducing analysis time and enabling police analysts to respond more efficiently. However, despite the promise of these technologies, several challenges persist. The implementation of ML and NLP in policing requires substantial technical expertise and raises ethical concerns, particularly regarding potential biases and unethical discrimination. Ensuring the ethical deployment of these technologies is crucial, as their success depends on accurate crime analysis and ethical considerations. Predictive policing and other AI technologies have shown potential to outperform traditional response-based policing by more effectively monitoring criminal activities and allocating safety resources. By easing the analytical burden on police, ML and NLP could facilitate the broader adoption of smart policing, ultimately reducing crime opportunities and minimizing harm from victimization and offending. However, addressing ethical challenges and resource-intensive data extraction remains vital for their successful implementation (Sarzaeim, 2023).

Conclusion

Crimes involving 3D-printed firearms have large potential to expand into a larger problem before the law can keep pace with these firearms, even if crimes involving 3D-printed firearms are not widespread now (Wenzinger et al, 2024). While the current body of literature on machine learning and natural language processing (NLP) predominantly addresses the detection and prevention of crimes involving traditional firearms, these technologies hold significant potential for application to privately manufactured firearms (PMFs) as well. Machine learning models, which have been successful in identifying weapons and predicting crime patterns, can be adapted to recognize the unique characteristics of PMFs. For instance, convolutional neural networks (CNNs), which have been trained to detect weapons in surveillance footage, could be refined to identify the specific features of PMFs. Similarly, natural language processing techniques, such as named-entity recognition (NER), which extract critical information from crime reports, can be tailored to identify mentions of PMFs. Despite the scarcity of publications specifically addressing PMFs, the foundational technologies and methodologies used in existing studies provide a robust framework that can be expanded upon. By leveraging these advanced tools, researchers and law enforcement agencies can develop more nuanced and targeted approaches to combat the emerging threat posed by PMFs. This highlights the necessity for future research to focus on the distinctive challenges posed by PMFs, ensuring that machine learning and NLP methods are equipped to handle the evolving landscape of firearm-related crime. In conclusion, this paper underscores the urgent need for further research and practical initiatives to harness the full potential of artificial intelligence in combating the proliferation of privately manufactured firearms. By adopting fine-grained classification techniques, leveraging transfer learning, and ensuring robustness to variability, AI can significantly enhance our ability to detect and mitigate the risks associated with PMFs.

Future Directions and Recommendations

The potential of applying a deep learning model for the classification of images of PMFs lies in its ability to distinguish subtle differences or characteristics that may not be readily apparent to human observers or traditional image recognition algorithms. While it is true that some PMFs may resemble conventional firearms, deep learning models are needed to detect distinct features or variations that can be identified with deep learning models.

(1) Fine-grained Classification: Deep learning models can be trained to perform fine-grained classification, which involves distinguishing between highly similar categories. By leveraging large datasets of images of both privately manufactured firearms and conventional firearms, deep learning models can learn to identify subtle differences in design, components, or manufacturing processes that may be indicative of a privately manufactured firearm.

(2) Transfer Learning: Transfer learning techniques can be employed to adapt pre-trained models to the task of classifying privately manufactured firearms. By fine-tuning models that have been trained on large-scale image datasets, such as ImageNet, researchers can leverage the knowledge encoded in these models to improve performance on the specific task of distinguishing PMFs from conventional firearms.

(3) Feature Extraction: Deep learning models are capable of automatically extracting high-level features from images, which can capture nuanced characteristics of firearms that may not be easily discernible to human observers. By analyzing these learned features, researchers can gain insights into the underlying factors contributing to the classification of privately manufactured firearms, potentially revealing novel patterns or attributes that differentiate them from conventional firearms.

(4) Robustness to Variability: Deep learning models are inherently robust to variations in lighting, orientation, and background clutter, which are common challenges in image classification tasks. This robustness enables them to effectively classify images of privately manufactured firearms across diverse environmental conditions and contexts, enhancing their applicability in real-world scenarios.

While it's true that some PMFs may closely resemble conventional firearms, the goal of employing deep learning models is not to identify broad categories of firearms but rather to discriminate between specific subclasses or types, such as PMFs versus commercially manufactured firearms. By focusing on the unique characteristics and attributes of PMFs, deep learning models can offer valuable insights and capabilities for addressing the challenges associated with their detection and classification.

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