CHALLENGES OF CONTEMPORARY PREDICTIVE POLICING

Igor Vuković[1]
Ministry of the Interior of the Republic of Serbia
Petar Čisar, PhD
University of Criminal Investigation and Police Studies, Belgrade, Serbia
Kristijan Kuk, PhD
University of Criminal Investigation and Police Studies, Belgrade, Serbia
Brankica Popović, PhD
University of Criminal Investigation and Police Studies, Belgrade, Serbia

Abstract: Big data algorithms developed for predictive policing are increasingly present in the everyday work of law enforcement. There are various applications of such technologies to predict crimes, potential crime scenes, profiles of perpetrators, and more. In this way, police officers are provided with appropriate assistance in their work, increasing their efficiency or entirely replacing them in specific tasks. Although technologically advanced, police use force and arrest, so prediction algorithms can have significantly different, more drastic consequences as compared to those that similar technologies would produce in agriculture, industry, or health. For further development of predictive policing, it is necessary to have a clear picture of the problems it can cause. This paper discusses modern predictive policing from the perspective of challenges that negatively affect its application.

Keywords: predictive policing, crime forecasting, ethics, biases, artificial intelligence.

INTRODUCTION

The pressure on law enforcement agencies (LEA) to reduce crime rates is constantly growing. Social networks give particular impetus by providing unlimited resources for the exchange and distribution of information generated by crowdsourcing, mostly for criticizing the work of the police and demon-

1 igor.vukovic@mup.gov.rs

strating their omissions. Also, given the police powers, one could interpret police surveillance as "incredible discretion" (Selbst, 2017), is especially interesting for the non-governmental sector, various organizations, and the media.

Under such pressure, law enforcement is turning to modern technologies to improve police resource management, increase efficiency in crime prevention and reduce unnecessary contact with citizens. One such technology is predictive policing.

Meijer and Wessels defined predictive policing as "the collection and analysis of data on previous crimes for identification and statistical prediction of individuals or geospatial areas with an increased likelihood of criminal activity to help to develop policing intervention and prevention strategies and tactics" (Meijer, 2019). Predictive policing combines information technology, criminology, and predictive algorithms and represents a logical extension of existing methods due to the new reality that brings significantly more data and processing power (Selbst, 2017).

In addition to the optimal use of resources for prevention, the purpose of predictive policing is also deterring crime (Vogiatzoglou, 2019), i.e. pre-emptive policing, which essentially represents the reaction of the police before the criminal activity occurs (Meijer & Wessels, 2019).

Predictive policing does not replace conventional methods such as problem-oriented policing, intelligence-led policing, or hotspot policing but improves them by applying advanced statistical models and algorithms (Meijer & Wessels, 2019). Moreover, the "intelligence-led policing" paradigm has empowered the police to introduce more invasive, secret-service type technologies, which have become more sophisticated than ever before, and which include predictive policing (Vogiatzoglou, 2019). Predictive policing processes a large amount of data, just as conventional methods, yet it does not rely only on criminal data, as for this method, all data are relevant (Meijer & Wessels, 2019).

LEA uses predictive policing tools because their application achieves better results from the perspective of public safety, legal, and cost/resources (Oswald, Grace, Urwin & Barnes, 2018). However, the relationship between claims and proven benefits of crime reduction when it comes to spatial-temporal predictions is that positive and negative results are mixed, while for profiling, they are ambiguous (Meijer & Wessels, 2019). Despite this, more and more tools are being developed and used for this purpose, but there are also a growing number of challenges that predictive policing technologies face.

Crime prevention by applying predictive policing is opposed by the controversy of prejudice and "precrime[2]", which are further strengthened by more general concerns over the implicit biases contained in the historical data set and apparent implications for racial, gendered, ethnic, religious, class, age, disability, and other forms of discriminatory policing (Asaro, 2019).

LEA uses increasingly more and more data to prevent crime and it is not surprising given the nature of information-oriented policing (Gstrein, Bunnik, & Zwitter, 2019). However, this is where most of the problems lie, in the historical crime data used for forecasting in predictive policing technologies. In addition, there are problems of fairness of algorithm, transparency of technologies, various legal and ethical issues, and the perception of the usefulness of predictive policing systems. Also, turning to artificial intelligence that significantly expands the potential pool of people and activities under police surveillance raises different concerns (Joh, 2020).

2 Precrime is a science fiction concept that first appeared in the writings of Philip K. Dick in the novel *The Minority Report*, 1956. The term represents interventions undertaken to punish, disrupt, incapacitate or restrict those deemed to embody future crime threats.

In this paper, we have reviewed current research and its focus on various technology issues and identified what challenges modern predictive policing solutions must overcome during their development and implementation. We emphasize that although one of the main problems of predictive policing is transferring racial prejudice inherent to LEA's data to prediction, as demonstrated in many different studies (Brantingham, Valasik & Mohler, 2018), it will not be in the focus of this paper. Instead, we wanted to show that predictive policing technologies have challenges that need to be overcome beyond the current discourse on the struggle for racial equality.

In the first part, we explain the concept of predictive policing and give examples of practical applications. In the second part, we discuss the problems in developing and applying predictive policing in detail. Finally, in the third part of the paper, we discuss the severity of the challenges based on the relationship between the problem and current solutions.

PREDICTIVE POLICING

Ultimately, the goal of predictive policing is to prevent crimes before they occur, which would eliminate the need for other vital elements of criminal justice - retribution and reformation (Asaro, 2019). Predictive policing is an umbrella term that encompasses the application of analytical techniques to identify the most likely targets for police intervention and prevent crime or solve a past crime based on statistical prediction (Griffard, 2019). Prediction in the use of the police is not a new concept. Crime mapping determines hot spots that have been present for many years, whereas offender profiling is used to predict criminal behavior based on psychological and environmental factors. The new thing that predictive policing brings as a concept is incorporating data mining (Selbst, 2017).

Predictive policing refers to a three-part process consisting of entering one or more types of data, processing data by an appropriate algorithm where the result is the prediction of crime in some domain of interest, and applying prediction results when making strategic and tactical decisions in the field (Kutnowski, 2017). Currently, there are three broad categories of data-driven technologies: predictive technologies, surveillance, and data mining technologies (Ferguson, 2018). Although data mining technologies are also used for predictive policing purposes, we have singled them out to highlight their other broad application in forensic recognition by DNA, faces, or fingerprints biometrics.

The use of predictive technologies by law enforcement is part of a longer historical transition from reactive to proactive policing enabled by the temporal density of big data (Karppi, 2018). Big Data analytics involves working with large and complex data sets whose processing become possible by a recent significant increase in available computing resources and trend forecasting (Kutnowski, 2017). Data sets in predictive policing solutions primarily represent historical crime data over which different algorithms are applied. The task of the algorithms is to identify individuals or geographical areas with elevated risks for future crimes based on which one could better allocate valuable resources towards fulfilling a police mission or goal (Karppi, 2018; Asaro, 2019).

In previous predictive policing solutions, the application of algorithms relied on a "blended theory" according to which both criminals and victims follow common life patterns, while overlaps in these patterns indicate an increased likelihood of crime (Vogiatzoglou, 2019). Using patterns extracted from historical data of previously registered criminal offenses allows predicting time slots and places for certain crimes to be precise (Vogiatzoglou, 2019).

The phenomenon is referred to as the "near repeat effect", as in "repeat victimization" where houses or similar properties in the neighborhood that have already been burgled could become the target of attack again in a short period of time.

We can divide predictive policing technology into three generations, one that predicted locations of property crimes, one that evolved to predict the locations of violent crimes, and the latest that predicts the participation of certain persons in the commission of crimes, whether they are perpetrators or victims (Griffard, 2019). Place-based predictions are focused on hot-spot detection and are used primarily for resource management. Person-based predictive policing, but not investigation-driven, and suspect-based predictive policing, which is a continuation of offender profiling, is related to the latest predictive policing solutions (Selbst, 2017).

The use of data analysis and statistical methods to predict the probability of crime has quickly become popular with LEAs in the US and then across Europe (Gstrein et al., 2019). The reason is in the advantages of big data policing: more innovative policing, faster investigation, predictive deterrence, and the ability to visualize various crime problems (Ferguson, 2018). What additionally contributed to this were initial successes such as those by Richmond police department, which adjusted its surveillance routes based on a forecast of where gun firing would occur on New Year's Eve in 2003, resulting in a 47% reduction in gunfire, and 246% more weapons that were seized (Meijer & Wessels, 2019).

Currently, there are many predictive policing solutions based on different concepts of application of algorithms that process a large number of diverse data.

PREDICTIVE POLICING APPLICATION

The Harm Assessment Risk Tool (HART) was developed by University of Cambridge statistical experts in collaboration with the Durham Constabulary to assist decision-making by custody officers when assessing the risk of future offending (Oswald et al., 2018). HART divides offenders into three different groups: those who are likely to commit a more serious crime in the next two years (murder, attempted murder, grievous bodily harm, robbery, sexual crimes, and firearm offenses), i.e. those who represent a high-risk group; those who will commit non-serious crimes in the same period are designated by the system as a moderate-risk group; those who are unlikely to commit crimes in the next two years, a low-risk group. HART uses a random decision tree algorithm during the classification, an ensemble learning method for classification, regression, and other tasks. The model was built on 104,000 custody events between 2008 and 2012 using 34 predictor variables, of which 29 were directly from the suspect's offending history.

New York Police Department uses the Patternizr system (Griffard, 2019). The purpose of Patternizr is to assist investigators in identifying crime patterns of robberies, burglaries, and grand larcenies that may have been committed by the same individuals or groups of people based on past crime data. During the development of the system, 39 distinct attributes were identified (date and time of the event, whether weapons were used, how many suspects there were), based on which three models were trained, one for each type of crime, using data collected in the period from 2006 to 2015 and complex decision-tree based classification algorithm.

The Illinois Institute of Technology develops the Strategic Subject List (SSL) algorithm used by the Chicago Police Department. The system considers 48 factors, such as the number of arrests, convictions, drug arrests, gang affiliations, and uses them in determining an individual's social network - which is arrested together with an individual (Asaro, 2019).

The Dutch Crime Anticipation System (CAS) was internally developed in 2013. The tool made predictions about locations, and in some cases it also sought to identify individuals at risk of victimization (Gstrein et al., 2019). CAS uses a "heat-map" for prediction visualization where a specific territory is divided into networks of 125 x 125 m regions. If the chance of crime is high, then regions are highlighted. Furthermore, it uses a near-repeat concept, such as "repeat victimization" (Strikwerda, 2020). The input used by the system includes data such as crime rates and less obvious information such as the distance of the highway from the crime scene, assuming that the features of the urban environment affecting the accessibility of places shape patterns of offending. The intensive application of the CAS tool for predicting crime locations makes the Netherlands the first country in the world to deploy predictive policing on a national scale (Strikwerda, 2020).

The Hunchlab solution developed by Azavea applies the near-repeat concept and other approaches such as Risk Terrain Modeling that considers only exogenous factors, such as specific landmarks' position to improve the results (Degeling & Berendt, 2018). HunchLab system is theoretically agnostic and starts without a hypothesis than applied machine learning technique combines variables that most accurately predict the locations and times of the crime (Shapiro, 2017). HunchLab uses public crime reports, requests for police assistance, weather patterns and Moon phases, geographical features such as bars or transports hubs, and schedules of significant events and school cycles as inputs.

The Lower Saxony project "PreMap" 2016 is a system intended for predictions related to domestic burglary based on "repeat victimization theory" (Gstrein et al., 2019).

CHALLENGES OF PREDICTIVE POLICING SOLUTIONS

There have been conflicting views on predictive policing. It helps police units with limited resources to achieve better results and drastically increase public security, but also provides deceptive and undeserved legitimacy of impartiality to law enforcement (Griffard, 2019). Thus predictive policing is praised for its effectiveness, while being criticized for its unethical behavior (Karppi, 2018).

There are examples in practice due to which the problems of development and application of predictive policing solutions must be paid special attention. The most extreme example is the SyRI (System Risk Indication) system, which is no longer in use due to the decision of the Dutch Court. The system used employment data, civic integration data, debt data, health insurance data, and personal data (name, address, date of birth) as input, without taking into account the previously used indicators or the model. The court ruled that because of all the above, it was not possible to determine whether or not interference with the right to privacy was necessary in relation to achieving the legitimate aim (Strikwerda, 2020).

However, there are examples where further implementation has been abandoned due to system inefficiencies. For example, authorities of the German city of Nuremberg did not continue to use their near-repeat Precobs system for burglaries because, after six months, there were many burglaries that the system did not anticipate, although some were committed by serial offenders (Degeling & Berendt, 2018).

We divided the problems of predictive policing technology into groups related to input data, prediction errors and biases, ethical and legal issues, and transparency. Problems within one group affect problems within other groups, often in a causal relationship, so the classification is made based on the problem's key feature.

INPUT DATA

Input data has been highlighted in most studies as the cause of the problems that technology has. Although there are different technical solutions for predictive policing systems, one thing is for sure - historical police data is the primary data source. Different categories of specific data can be used, such as information on past crimes (type of crime, time, and location), arrests, and calls for service (Richardson, Schultz & Crawford, 2019). The problem with input data, which is limited to reports by victims and police observations, is that there are a large number of unreported and unseen crimes, especially in the area of domestic violence, which is why the system will not have enough data to predict (Strikwerda, 2020). If there is not enough data, if irrelevant, inaccurate, and outdated data are used, it will directly reflect on the accuracy of the prediction (Gstrein et al., 2019).

The prediction is also affected by the erroneous assumption that historical crime data are objective. Those data are deeply related to the practice and priorities of police organizations (embedded with political, social, and other biases). They can hardly be treated as data resulting from consistent scientific measurements because there are no standardized procedures for their collection and evaluation (Richardson et al., 2019). The result is that arbitrarily selected data is entered into the reports at the police officers' discretion.

The problem with data related to machine learning is the use of training algorithms for data essentially labeled by the police close to their contact with criminals, most often after arrest, and which are not updated later during criminal proceedings and evidence. This is also one of the reasons why most crime labels may be incorrect, whether they describe the type of crime or the existence of one, which will reflect in a model training and prediction ability (Selbst, 2017). For example, suppose crime is downgraded or not reported at all. In that case, the level of risk that can be assigned to the place and time must be downgraded, as in the situations when hate crimes are wrongly downgraded from constituting criminal offenses to incidents (Kutnowski, 2017). The consequences of downgraded or upgraded crime are under-policing or over-policing, respectively. The example of the Los Angeles Police Department (LAPD) shows the seriousness of the problem. They misrecorded 14,000 serious assaults as minor offenses from 2005 to 2012, which was discovered only in 2015 when LAPD already started using predictive policing solution company PredPol (Richardson, 2019).

There is also the minimum amount of data needed for prediction when it comes to model training, making it harder for smaller cities to spot the system's positive effects (Degeling & Berendt, 2018).

Problems with the data used to train the model and the prediction itself reduce the process of crime prognosis, that is, the positive effect of the system on pure dice rolling. This was confirmed by the Memphis Police which, after three years of using the IBM Blue CRUSH (Criminal Reduction Utilizing Statistical History) system, had a thirty percent reduction in crime rate in the metropolitan area. However, later, the audit analysis determined that a large amount of data was not entered into the system, making a precise prediction of where the crime would take place impossible (Bakke, 2018).

No matter how precise and no matter how more objective than the police they may be, classifying algorithms depends on previous data. The problem of making decisions based on historical offender data can be influenced by past arrest history, force targeting decisions, social trends, and prioritization of certain offenses, such as child sexual abuse offenses, domestic violence, and hate crime (Oswald, 2018; Gstrein, 2019).

In addition to the data itself, the choice of features used during training is crucial, which is a particularly demanding job for person-based prediction (Selbst, 2017). It is impossible to collect all the attributes about the subject or consider all the environmental factors with a model. Features that inadequately capture the relevant distinction between people or locations will make the prediction less accurate (Selbst, 2017).

When the use-value of the input data is in question, it is linked to the specific subject of the investigation. So the probability of near-repeat events of armed robberies increases in the first seven days but does not exist after that (Meijer & Wessels, 2019). If robberies do not occur in a certain period, historical data lose their significance, and the system based on them will not be able to make predictions for specific crimes.

Most errors in police data occur in everyday work, and the more complex the data, the greater the chance for bias to be embedded in subtle and difficult-to-detect ways (Kutnowski, 2017).

BIASES AND THE INFLUENCE OF ERRORS IN CLASSIFICATION

Training data must represent a sample of the entire population concerning the ultimate goal of the algorithms, which is pattern matching and generalization, otherwise, sampling bias occurs. For example, police data can be biased because it reflects police practices and policies that can lead to a specific group of people or regions being overrepresented in the police data used for training and model work. In addition, important information such as white-collar crime data can be omitted from the input data because priority is traditionally given to violent, street, and quality of life crimes (Richardson et al., 2019). One of the problems is also unbalanced data sets like, for example, the police have significantly more information about people who are injured than about those who are not (Selbst, 2017).

Unbalanced gatherings lead to an increased presence of the police in low-income and minority neighborhoods, which citizens do not perceive as a form of protection, prevention but a source of harm (Shapiro, 2019). So instead of one of the goals of predictive policing, which is to reduce contact with citizens, i.e. to minimize the optimal organization of resources, it achieves the opposite prediction based on crime history data that direct the police to such regions where most of the data is collected. Data mining techniques can reproduce existing patterns of discrimination, inherited prejudices of previous decision-makers, or reflect the widespread biases in society (Selbst, 2017; Bakke, 2018). Thus technological solutions have been criticized for focusing on low-level “nuisance” crime or areas with high crime levels and therefore poor neighborhoods (Oswald & Babuta, 2019). In the same context, the appearance of the feedback loop caused by the bias of crime statistics is also interesting. The police pay attention to the neighborhood with many immigrants. Although the area has an average crime rate, the number of detected crimes in that area becomes greater than in other areas, which in turn causes even more police to be sent to such locations (Zuiderveen, 2020).

The problem with generalization is that each learning algorithm has an inductive bias to favor simpler hypotheses and conditional independence and the assumption that factors work independently to contribute to their effect (Degeling & Berendt, 2018). Examples include placing a campus zone on an increased risk map for the crime of rape, which is supported by the fact that many females have opportunities to interact frequently with members of the opposite sex, like within fraternities. However, in this case, the risk is more of a social feature than a geographical one.

In research related to predictive policing, automation biases have also been identified, representing a tendency to over-rely on automated outputs while ignoring other correct and relevant information (Oswald & Babuta, 2019). Similarly, confirmation bias is present, where the algorithm's decision is not checked, but more efforts are made to prove the accuracy of the prediction (Griffard, 2019).

The impact of false positives and false negatives varies with the purpose of the prediction system. For example, when it comes to prediction errors related to terrorism, false negatives can be more expensive as they can lead to attacks and casualties that could have been avoided as compared to false positives, which may lead to the search of an innocent person (Degeling & Berendt, 2018). However, the stakes in false positives certainly increase if the system helps decide on incarceration or intense psychotherapy.

TRANSPARENCY

One of the problems of predictive policing is opaque, lacking transparency because everything happens due to the "black box" of proprietary solutions and mathematically complex algorithms (Ferguson, 2018). It is not acceptable for predictive policing systems to be a black box. A combination of approaches to combat opacity, such as end-user-facing components, independent audits, a context-specific regulatory framework, and the use of open-source code is needed (Oswald et al., 2018). When it comes to transparency of predictive policing, LEAs have institutions in charge of supervising this kind of work. However, there are also problems such as a code of silence, conflict of interests, and a perceived lack of objectivity (Bakke, 2018).

The European Union GDPR and Directive 2016/680 for automated data processing in the LEA context contain a right to human review of automated individual decisions and an obligation for states to adopt appropriate protection of the rights and freedoms of a data subject (Gstrein et al., 2019). Therefore, in addition to data privacy issues, Lower Saxony gave up cooperation with IBM to avoid the situation that due to proprietary solutions, it cannot explain decisions made based on the suggestion of an externally developed system (Gstrein et al., 2019). Furthermore, due to the lack of transparency and the limited ability to explain predictions, it is difficult to measure the severity of crime risks to be prevented and the risks of proper crime prevention, which can lead to disproportionate invasion of privacy, but also discrimination, stereotypes, and stigmatization (Strikwerda, 2020).

The non-transparency of predictive policing systems also leads to incorrect use of their forecasts and making wrong decisions. For example, many officers reported that they were not fully informed of how the SSL list was compiled, so they assumed or were led to believe that all were perpetrators of violent crimes and would most likely use even more violence. In contrast, the SSL list combined potential victims and perpetrators in a single metric of "being involved in violence" (Asaro, 2019). It is interesting for SSL that one-third of the individuals on the list are individuals who have never been arrested or victims of crime, and seventy percent of that group received a high-risk score, which is a result that certainly requires explanation (Richardson et al., 2019).

Some of the arguments for insisting on transparency are (Bakke, 2018): transparency aids accountability, preventing police misconduct, transparency helps provide a remedy to the aggrieved party, allows a more significant number of parties, with a greater variety of interests, to review predictive policing, and transparency also builds community trust.

On the other hand, there is a need for restrictions on access to data that the police work with due to the secrecy of the data and the interest of ongoing investigation.

There is an interest in the data used in decision-making and the mechanisms by which those decisions are made regarding transparency. For the former, personal data protection laws support transparency. Nevertheless, even in such laws there are frequently some exceptions that restrict access to data or to general information that someone's data is being processed. In addition, there are intellectual properties, which protect the manufacturer from disclosing how the systems work or what algorithms they use, based on which amounts of data they make decisions. Thus, while complete transparency may not be feasible, complete darkness is not in the interest of either side.

ETHICAL AND LEGAL ISSUES

Police organizations suffer tremendous pressure to produce annual crime reductions, leading to manipulation of criminal statistics and provoking other inappropriate behaviors to artificially reduce serious crime statistics (Richardson et al., 2019). Therefore, one cannot look at people, and therefore police officers, as perfect decision-makers, and compare the system's predictions with the mystical perfect human decision-maker (Oswald et al., 2018). Given that predictive policing has become a profitable industry today, manufacturers are trying to emphasize the efficiency and fairness of their products as a tactic in the fight for contracts with police organizations (Griffard, 2019). Thus, the goal of predictive policing technologies is not only to identify hidden patterns but also to create a "neutral" data-driven tool by preventing unconscious biases from being involved in the operation of the algorithm (Selbst, 2017). However, there are examples where the tools have not reached the required standards of neutrality. For example, the UK Information Commissioner's Office has found that the manner of operation of a Gangs Matrix predictive policing tool by the Metropolitan Police in London was a breach of UK data protection law and possibly the Equality Act 2010, which is why the Mayor's Office for Police and Crime conducted a review (Grace, 2019). Among other things, the review found that 82.3% of people on the Matrix were racial or ethnic minorities, and 55.6% of them were under 18 years of age.

If we look at current data analysis techniques in predictive policing from a position of effectivity, we can accept that we are in a situation where computers are becoming increasingly necessary, and humans are becoming increasingly random (Karppi, 2018). So one of the ethical issues with predictive policing is whether we are moving to a time when we might do something just because the computer said so. For example, when a predictive policing system generates a chart in different colors to visualize the threat level without explaining how the threat is conceived, are the police then under the control of technique from the perspective of epistemology (Karppi, 2018)? A different but also ethical problem that builds on the previous one is "judgmental atrophy" where, consciously or not, police officers distance themselves from risky decisions and leave them to the system. On the other hand, police officers may resist applying the artificial tool. Although big data crime prediction can eliminate humans' inclination to utilizing stereotypes regarding class or race when they encounter incomplete information about suspects, algorithms have the same problem because crime data is often incomplete (Karppi, 2018). This issue further raises ethical concerns because predictive policing tools become part of a chain for which inclusive evidence leads to unjustified actions (Oswald et al., 2018).

Predictive policing techniques that determine the profile of individuals use a wide range of personal information in addition to historical data from crime records (Vogiatzoglou, 2019). The data that individuals produce through social media play a significant role in determining the potential future of the individual, that is, in increasing accuracy in the prediction of crime (Karppi, 2018). The wide range of private data used in prediction poses a potential risk of excessive privacy breaches, which do not significantly benefit. The Dutch government has stopped using SyRI, a solution intended to predict fraudsters, due to a court decision indicating a breach of privacy concerning Article 8 of the European Convention on Human Rights (Strikwerda, 2020). In addition, there is the problem of sharing private data with manufacturers. Lower Saxony started the "PreMap" project in 2016 after previously collaborating with IBM and abandoned that collaboration for fear of sharing data with a private company (Gstrein et al., 2019).

Specific solutions such as CAS had an ethical and legal problem due to the development of the system in providing support to the multi-agency approach, i.e. shared information between intelligence agencies and the police (Gstrein et al., 2019). Moreover, this information exchange was further influenced by the rise of new threats to national and public security, mainly terrorism, and its spread beyond national borders, leading to overlapping law enforcement and intelligence services (Vogiatzoglou, 2019).

The epistemological and ontological problem is related to drawing boundaries between different areas and those living in them, for example, division into areas in which the law prevails and those in which it does not (Karppi, 2018). However, if the border is drawn, a new ethical question arises: whether the citizens of the zones marked as high-risk should be informed by the police about their endangerment, even if there are chances of false positives. What the algorithm certainly does not do is that when anticipating possible criminal activities in a particular area, it cannot inform the police about the underlying conditions that contribute to crime in that area, aggravating the preventive role of predictive policing (Karppi, 2018). The reason for this can be found in the fact that social variables are codependent and are in constant flux (Kutnowski, 2017).

PERCEPTION OF USEFULNESS

The question for LEA is also a measure of the usefulness of such systems from the perspective of citizens. Do citizens see that such systems are profitable? For example, murder is severe in impact but does not happen frequently, so it is difficult to predict, unlike vehicle theft and robbery, which have a moderate impact but are more predictable and readily addressed (Shapiro, 2017). Efforts to thwart more easily predictable crimes, such as burglary or larceny, may have higher success rates, but the "payoff" of deterring less predictable and more harmful crimes such as murder and assault may be more significant in citizens' perceptions (Shapiro, 2019).

DISCUSSION

When data is used for model training and prediction, the problems are related to wrongly qualified crimes and thus erroneously labeled, then to irrelevant, inaccurate, and outdated data. In addition, the input data used, primarily historical crime data, convey the subjectivity of police officers, primarily their prejudices, and specific aspects of the moments in which they arose, such as LEA priorities or community and media focus on a particular type of crime or event. Thus, when developing the appropriate tools, the problem is also choosing the appropriate features that affect the accuracy of the crime forecast.

PredPol, a company that develops solutions based on place-based predictive policing, collects and analyzes the time, place of crime, and type of crime from reports. Drug-related offenses data are excluded (as well-documented for racial disparities), and also traffic citation data (often subject of corruption), from its prediction to remove police officer bias (Richardson et al., 2019). However, it cannot be said that such a choice solves all potential problems, i.e. that reports related to other crimes do not contain officer discretion which should be excluded as a prediction factor. In addition, a call for service that is perceived as objective enough may contain irregularities if something is reported that is not essentially a criminal activity but is based on the suspicion or discomfort of those who report (Richardson et al., 2019).

Also, when it comes to input data, it is necessary for analysts to at least try to eliminate errors from existing data sets before models are trained on them or prediction is performed (Oswald et al., 2018). Eliminating errors from a large amount of historical crime data is a particular challenge. It requires significant human resources, with potentially all the problems that initially led to the data problems.

During the application of predictive policing solutions, it was noticed that historical data transmit widespread biases that exist in society. In addition, there are also sampling biases, feedback loop, inductive bias, automation bias, and confirmation bias. The solution applied by Patternizr when it comes to minimizing bias is based on depriving the model of sensitive information related to suspects such as gender and race, while other information used, such as location, is taken very roughly (Griffard, 2019). The example of the Patternization solution shows an attempt to find a compromise. However, the problem of choosing the appropriate indicators for prediction remains whether there is enough left to profile the perpetrator and determine whether it is the same or different group of perpetrators.

Continuous empirical control with careful policy development is needed to prevent biases in prediction using algorithms and ensure the fairness of their outputs. An experiment conducted in three divisions of the Los Angeles Police Department, in which they randomly changed the use of the results of place-based prediction performed by the algorithm and based on the best practice of analysts from the divisions for about 200 days, showed twice the drop in crime at mean patrol dosage using algorithms (Brantingham et al., 2018). It should be noted that the algorithm used reported crime data for a limited range of offenses, burglary, car theft, plus crime location and time data and that the prediction was performed in 150x150 meter boxes. The experiment set up in this way did not show biased arrests.

One of the main classification problems involves unbalanced sets, but a particular challenge is related to classification errors (false negatives and false positives) because they may produce conflicting effects depending on the crime.

When it comes to transparency problems, which include technical barriers (police are not able to answer the question of how the system came to a particular prediction), technological (solutions are most often proprietary) and tactical barriers (police prefer not to reveal their proactive investigative strategies to perceived tactical advantage) must be overcome in order for predictive policing to be successful and to gain the trust of citizens (Ferguson, 2018). This condition in practice produces a large number of different challenges and the need for numerous compromises.

If at all possible, finding the right compromise is a challenge in itself, given the complexity of the problems accompanying predictive policing. Thus, for example, the goal of all algorithmic decision-making technology should be to augment human legal intelligence, not to replace it, and it is necessary to strive for artificial intelligence to rule the Law in a stable and contestable way (Oswald et al., 2018).

Therefore, the result of the Patternizr system is the expression of confidence in the prediction, which is determined in the range from 0 to 1, so the final decision is up to the user of the system. Similarly, SSL evaluates prediction results in the range from 1 to 500, leave the decision to humans. The initial version of the HART system required police officers to make their predictions of arrests of each offender whenever the algorithm was used. The results showed that: police officers were generally uneasy with forecasting both high and low-risk predictions, that the majority (63.5%) predicted moderate risk behavior, and that police officers and the model agreed only in 56.2% of the time (Oswald et al., 2018). The challenge remains how to avoid the importance of prediction in the decision-making process by police officers, or on the other hand, to avoid "judgmental atrophy." Also, there was a problem with interpreting the prediction results on the example of SSL, i.e. understanding the way and meaning of visualizing predictions (Gstrein et al., 2019).

One of the positive examples of compromise is applying the randomization process in the HunchLab solution, where the police patrol is not always sent to the area marked as the riskiest but to those marked with a lower degree of risk. This randomization avoids over-policing specific communities while avoiding patrols being less predictable to potential offenders and avoiding crime displacement, noticing the focus of police criminals moving into new areas. (Shapiro, 2017, 2019).

In order to reach an ethically acceptable predictive policing solution from the aspect of human rights, it is necessary to perform detailed tests and checks such as a three-part test (Degeling & Berendt, 2018): a suitability test, whether the applied measure will achieve the goals, and a necessity test, whether there are less intrusive measures that can give the required results; and a proportionality test, where it is weighed whether the violation is more severe than the value of the goal to be achieved, and where the goal is crime prevention, the police must not go beyond the scope of their tasks. The lack of legal frameworks that would more precisely determine the area of operation of predictive policing tools, i.e. where the border with intelligence work is currently, hinders the development of tools that would enable wide application.

When it comes to ethical oversight of artificial intelligence, it is necessary to understand the computational techniques it deploys and essentially understands the data sets over which artificial intelligence operates, how data is collected and the biases that those datasets may represent (Asaro, 2019).

When it comes to algorithms for predictive policing, the idea is clear from an ethical point of view: the choice of the solution that least violates individual human rights, i.e. the adoption of the least intrusive means compared to other possibilities (Oswald et al., 2018). The challenge, with all these problems, even with all the extensive research in the field of predictive policing, is to find an appropriate solution that will not bring profit on the one hand and loss on the other. For example, one of the solutions that researchers are working on is the penalized likelihood approach, which seeks to include fairness into the Hawkes process[3], but has been shown at the cost of the algorithm's accuracy (Mohler, Raje, Carter, Valasik & Brantingham, 2018). In addition, the precision and fairness of artificial intelligence models do not guarantee that their use will provide fair, ethical, and socially desirable results; therefore, attention must be focused on the practice of those who use them (Asaro, 2019).

3 The Hawkes process is a mathematical model for these "self-exciting" processes, named after its creator Alan G. Hawkes, and It is a counting process that models a sequence of "arrivals" of some type of data over time, for example, gang violence. Each arrival excites the process in the sense that the chance of a subsequent arrival is increased for some time period after the initial arrival.

CONCLUSION

The choice of where to focus the work, when to arrest, where to use force is the right of the police only, with a particular role of the prosecution and the courts. Mistakes that occur in making these decisions have significant consequences for those to whom police measures are applied and can lead to stigmatization of entire communities. In addition, they negatively affect the sense of security and trust among the citizens of the community within which the police organization operates, due to the growing influence of various media, primarily social networks.

The challenges faced by developing and applying predictive policing systems make it unlikely to find a complete system that will perform all the necessary crime forecasts while meeting all technical, legal, and ethical requirements. Also, the problems that would subsequently arise, primarily legal and ethical, would nullify all the effort and resources invested in development and, in the first place, seemingly optimal resource management using predictive policing tools.

When developing a system for predictive policing, all challenges must be taken into account. It is important to create a system that can overcome these challenges rather than try to get ahead of the competition. First of all, LEAs must be aware of the challenges and strive to advance their work because they will suffer the most extensive consequences.

REFERENCES

1. Asaro, P. M. (2019). AI Ethics in Predictive Policing: From Models of Threat to an Ethics of Care. *IEEE Technology and Society Magazine*, 38(2), 40-53.
2. Bakke, E. (2018). Predictive Policing: The Argument for Public Transparency. *Annual Survey of American Law*, 74 (1), 131-171.
3. Brantingham, P. J., Valasik, M. & Mohler, G. O. (2018). Does Predictive Policing Lead to Biased Arrests? Results From a Randomized Controlled Trial, *Statistics and Public Policy*, 5(1), 1-6.
4. Degeling, M. & Berendt, B. (2018). What is wrong about Robocops as consultants? A technology-centric critique of predictive policing. *AI & Soc*, 33, 347–356.
5. Ferguson, A. G. (2018). Illuminating Black Data Policing. *Ohio State Journal of Criminal Law*, 15(2), 503-525.
6. Grace, J. (2019). 'Algorithmic impropriety' in UK policing? *Journal of Information Rights, Policy and Practice*.
7. Griffard, M. (2019). A Bias-Free Predictive Policing Tool?: An Evaluation of the NYPD's Patternizr. *Fordham Urban Law Journal*, 47(1), 44-83.
8. Gstrein, O. J., Bunnik, A. & Zwitter, A. (2019). Ethical, Legal and Social Challenges of Predictive Policing. *Católica Law Review*, 3(3), 77-98.
9. Joh, E. E. (2020). Increasing automation in policing. *Commun. ACM*, 63 (1), (January 2020), 20–22.
10. Karppi, T. (2018). "The Computer Said So": On the Ethics, Effectiveness, and Cultural Techniques of Predictive Policing. *Social Media + Society*, 1-9.
11. Kutnowski, M. (2017). The ethical dangers and merits of predictive policing. *Journal of CSWB*, 2(1), 13-17.

12. Meijer, A. & Wessels, M. (2019). Predictive Policing: Review of Benefits and Drawbacks. *International Journal of Public Administration*, 42(12), 1031-1039.

13. Mohler, G., Raje, R., Carter, J., Valasik, M., & Brantingham, J. (2018). A penalized likelihood method for balancing accuracy and fairness in predictive policing. *In 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2454-2459.

14. Nissan, A. (2017). Digital technologies and artificial intelligence's present and foreseeable impact on lawyering, judging, policing and law enforcement. *AI & Society*, 32, 441-464.

15. Oswald, M., Grace, J., Urwin, S. & Barnes, G. C. (2018). Algorithmic risk assessment policing models: lessons from the Durham HART model and Experimental proportionality. *Information & Communications Technology Law*, 27(2), 223-250.

16. Oswald, M. & Babuta, A. (2019). Data Analytics and Algorithmic Bias in Policing, Downloaded Jun 5, 2021 https://researchportal.northumbria.ac.uk/files/21729582/ Babuta_Oswald_ Data_Analytics_and_Algorithmic_Bias_in_Policing.pdf.

17. Richardson, R., Schultz, J. M. & Crawford, K. (2019). Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice. New York University Law Review, 94(Online 15), 15-55.

18. Selbst, A. D. (2017). Disparate Impact in Big Data Policing. *Georgia Law Review*, 52(1), 109-195.

19. Shapiro, A. (2017). Reform Predictive Policing. *Nature*, 541, 458–460.

20. Shapiro, A. (2019). Predictive Policing for Reform? Indeterminacy and Intervention in Big Data Policing. *Surveillance & Society*, 17(3/4), 456-472.

21. Strikwerda, L. (2020) Predictive policing: The risks associated with risk assessment. *The Police Journal: Theory, Practice and Principles*, Downloaded Jun 1, 2021 https://journals.sagepub.com/doi/10.1177/0032258X20947749, 1-15.

22. Vogiatzoglou, P. (2019). Mass Surveillance, Predictive Policing and the Implementation of the CJEU and ECtHR Requirement of Objectivity. *European Journal of Law and Technology*, 10(1), 1-18.

23. Zuiderveen Borgesius F., J.(2020) .Strengthening legal protection against discrimination by algorithms and artificial intelligence. *The International Journal of Human Rights*, 24(10), 1572-1593.