The Socio-Economic Impacts of Predictive Policing on Minority Communities and Potential Solutions

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Abstract

Black defendants are 77% more likely to be labeled high-risk for violent recidivism than white defendants, even when accounting for prior offenses, age, gender, and other factors. This significant disparity highlights the urgency of addressing racial bias in predictive policing algorithms in the criminal justice system. While technologies of predictive policing were designed to enhance efficiency in law enforcement, they have quietly embedded systemic racial biases that are devastating for minority communities. This paper examines how predictive policing models contribute to cycles of over-policing and socio-economic inequality by relying on historically biased data. My analysis presents the devastating consequences of wrongful arrests, economic hardship, and psychological trauma, calling for urgent reforms. It outlines a way forward in the quest for fairer and more ethical use of predictive technologies. This paper aims to ensure policing technologies serve all communities equitably by improving data quality, integrating restorative justice practices, and establishing robust oversight policies.

Introduction

Robert Williams, a Black man from Farmington Hills, Michigan, was arrested on January 9th, 2020 for allegedly stealing watches from a Detroit store. He had been working when his wife called him telling him that the police were at his door, insisting he turn himself in. He drove back home, where the Detroit police were waiting for him. They told him he was under arrest and took him handcuffed into the car. Due to biased facial recognition software, the AI model used by the police department was faulty, leading Williams to be arrested for a crime he didn’t commit. Policing algorithms have become increasingly popular as law enforcement across the United States and other parts of the world adopt advanced technologies to enhance their technologies. With this comes numerous wrongful convictions, ruining the lives of many, especially those of African descent. According to a study by ProPublica, the COMPAS algorithm created by Northpointe (now known as Equivant), a widely used risk assessment tool, was found to falsely flag Black defendants as future offenders twice as much compared to white defendants. It also incorrectly predicted recidivism for Black defendants 44.9% of the time and only 23.5% for White defendants (ProPublica, 2016). COMPAS uses many data points to predict the chance someone will re-offend. The model uses things such as criminal history, age, and employment status. These prediction scores are useful for judges when deciding how long to sentence a criminal. Even though these models are helpful, they are often wrong, ruining lives economically, socially, and psychologically. How exactly do predictive policing algorithms contribute to racial bias in the judicial system, and how might we reduce the socioeconomic harm inflicted on the innocent?

First, I will introduce the paper's central theme, addressing racial bias in different types of predictive policing algorithms. I will outline the main objectives of this paper, including the reasons for racial bias in these algorithms and propose possible solutions to alleviate the socioeconomic harms done on communities. The next section will provide a detailed examination of how and why these models work. I will explore the reasons and motivations for using these predictive policing algorithms as well as how they work. The section will also address sources of bias, including data quality and the training process taken. Following this, I will analyze the downstream effects of racially biased policing. This segment will focus on the consequences of biased policing in minority groups, such as the wrongful incrimination of innocent defendants, the psychological impacts incrimination has on people, and the challenges faced when re-entering the labor market. Then, I will focus on the solutions to mitigate these racial bias issues, including changing datasets, enhancing accuracy, and establishing policies to regulate the use of these technologies. Finally, I will conclude the paper by summarizing the findings and emphasizing the importance of implementing said solutions in the real world.

Background

Predictive policing algorithms are progressively being used by police departments around the United States to forecast crime and better allocate their resources. With the adoption of these models, many states have become safer. Models like PredPol and HunchLab are used to reduce crime and improve relations between police and the community. But why are police departments worldwide adopting these models? Is it because they guarantee crime reduction? Or that they ensure fairer policing practices? Law enforcement uses these models to ensure more safety and reduce crime (Meijer & Wessels, 2019), yet these models still harm minority communities.

Enhanced crime pattern analysis and resource allocation is one of the standout advantages of predictive policing. Models like PredPol (now Geolitica), utilized by the LAPD, use historical crime data to predict when and where crimes will likely occur. Then the model releases maps giving cops a certain radius on where to patrol (Lapowsky, 2018). This allows the police department to allocate resources more strategically, reducing crime (Sankin & Mattu, 2023). Though most predictive policing algorithms are trained on crime data, HunchLab, another policing algorithm, uses weather data, temporal cycle/event data, demographic data, and routine activity modeling data. They believe that by using non-criminal data, the model can limit bias and prevent the data from veering (Azavea, 2014). These models also improve community security using historical data to prevent crime before it happens. Using algorithms to find patterns, these models forecast potential criminals, allowing police officers to allocate their resources effectively. The ShotSpotter model aids in the immediate response to gun violence incidents and helps law enforcement detect and locate high-risk areas through real-time gunshot detection (Meijer & Wessels, 2019). Additionally, these models can help when identifying potential repeat offenders, allowing for lower recidivism rates. By using these models on those who are statistically likely to reoffend, law enforcement can implement preventative measures for those people, reducing crime and promoting rehabilitation.

Predictive policing algorithms have revolutionized the way modern police forces function, changing the way police departments operate, enhancing their ability to ensure public safety, and increasing clearance rates (i.e. percentage of cases solved). Before using predictive policing algorithms in the early 2000s, crime clearance rates were significantly lower. For instance, from 1999-2002, the average clearance rate for all 4 years was 20.25%. The average clearance rate from 2020-2022 was higher at 33.14%. With the implementation of policing algorithms by the 2020s, multiple cities have seen improvements nationwide (FBI: UCR, n.d.).

Given these improvements, the question arises: how are these models biased? Why are they considered “unethical”? There are multiple reasons why these models are biased. Most predictive policing algorithms rely on historical crime data, which can be inherently biased due to previous policing methods. If certain minority communities around the United States were over-policed in the past due to human bias, then the models will reflect higher crime rates in those specific areas. This results in continued over-policing in those areas, resulting in an endless cycle of bias. This cycle is called a feedback loop, where the biased input leads to biased predictions, resulting in biased output, and so on (Ensign & Friedler, 2018).

Furthermore, the design and implementation of predictive policing algorithms may unintentionally be embedded with racial biases. For example, the COMPAS model, used to assess the risks of recidivism, is racially biased towards African Americans, predicting higher chances of recidivism compared to white defendants. Larson et al. (2016) concluded that compared to white defendants, Black defendants were predicted to have a higher recidivism risk and a higher risk score overall. Even when controlling data for prior crimes, age, gender, and future recidivism, Black defendants were still 45% more likely to have a higher risk score (Larson et al. 2016). These biases not only show the systemic inequalities of the data themselves but also affect judicial decisions and help promote unequal treatment in the criminal justice system. Therefore, the racial bias within predictive algorithms underlines the need for thorough evaluation and accountability play in the development and use of such technologies in order not to avoid further systemic discrimination.

Effects of Racial Bias in Policing

Given the biased nature of racial policing, the consequences of their deployment are profound and extremely far-reaching. Not only do these biases distort data, they impact people’s lives in many ways. Racial bias in policing algorithms often leads to wrongful incrimination of innocent individuals, especially those from minority communities. Understanding AI policing algorithms’ impact calls for recognizing how biases programmed into these algorithms drive particular harms. The big difference here is that, while policing algorithms use traditional techniques, AI policing algorithms use biased, historical data, targeting minority communities to a greater degree and more frequently, due to flawed data input. Since these algorithms are trained on years of biased data, minority neighborhoods are targeted, resulting in more surveillance and unjust arrests. These findings become cycles of targeting, with minority communities being continuously flagged for surveillance and intervention, due to biases from the past. The nature of these algorithms also ensures that members of the communities in question are prioritized as plausible threats, regardless of their actual behavior. This leads to a cycle in which the biased algorithm predictions cause increased police presence and intervention, further reinforcing the data leading to their deployment. Like the COMPAS algorithm, unfair monitoring is also seen in the use of the PredPol (now Geolitica) algorithm in African American neighborhoods located in Oakland, California based on biased crime data (Lum & Isaac, 2016). These wrongful incriminations caused by these machines have immediate and long-term effects. Their impacts range from psychological stress and effects on familial relationships to economic hardships and the inability to enter the job market.

The economic impacts of racial bias in policing algorithms extend far beyond those who are wrongfully targeted; they have a lasting effect throughout entire communities, intensifying the economic disparities. Individuals who face wrongful arrests and charges often go through financial burdens, including costly legal fees and lost income due to the time spent dealing with the justice system. Studies indicate that employment discrimination is predominantly found in African American and Hispanic applicants (Quillian et al., 2017). According to a study by Amanda Agan and Sonja Starr, employers are less likely to hire individuals with a criminal record, regardless of their circumstances. They also say that callback rates for applicants with and without convictions were 8.5% and 13.6%, respectively (Agan & Starr, 2017). These economic hardships are not restricted to individual misfortune: they have wider implications for minority communities that are targeted by policing algorithms. For example, Sharkey and Torrats-Espinosa (2017) found that increased police presence and aggressive law enforcement tactics correlate with a decline in economic activity and investments in those neighborhoods. This reveals the broader impact of racial bias in policing algorithms, showing how biased algorithms can contribute to the economic decline of entire communities, causing cycles of poverty. Furthermore, the broader implications for economic stability are profound, as those unable to find jobs are more likely to experience economic hardships and have higher risks of recidivism (Looney & Turner, 2018). This creates another type of feedback loop, where individuals are wrongfully charged, which then lowers their chances of another job, and then increases the chances for them to commit a crime. In a 2018 study by Evan Rose, those who lose their job are about 30% more likely to have committed a crime three years after a layoff than their former coworkers who were not laid off (Rose, 2018).

The economic hardships faced by biased policing algorithms are only one side of the broader harm inflicted upon individuals and communities. Beyond financial strain, these algorithms cause psychological and social impacts, exacerbating the challenges faced by those who are wrongfully arrested. Compared to White people, Black people are 3.23 times more likely to be killed in a police encounter (Schwartz & Jahn, 2020). The psychological effects of such encounters, especially those involving the killing of unarmed Black individuals, are profound, extending far beyond just the immediate victims. Research suggests that these incidents contribute to significant mental health obstacles within Black communities, with police killings of unarmed Black Americans causing an estimated 55 million excess poor mental health days per year among Black adults in the U.S. (Bor et al., 2018). The study suggests these numbers may underestimate the actual impact, as the data excludes potential spillover effects on Black Americans in other states that could also affect their mental health. Furthermore, police killings are often underreported, and some cases may have been missed in the data collection process. These incidents increase feelings of threat, lack of fairness, and low self-worth, which negatively affect mental health (Bor et al., 2018).

Racial bias in policing algorithms has profound, multi-dimensional effects on marginalized communities, including incrimination of the innocent, economic problems, and psychological distress. The use of biased historical data in the AI algorithms used in policing, such as COMPAS and PredPol, triggers a vicious cycle of discrimination against minority neighborhoods, further leading to over-policing and wrongful arrests. It distorts crime statistics and generally amplifies economic inequality by burdening the victims with legal expenses, lost wages, and diminished prospects. It also has ripple effects, punishing not merely individual misfortune but suppressing economic activity and investment in whole communities as well as reinforcing cycles of poverty. Moreover, the cost of increased surveillance and violence, especially those fatal encounters with the police, tears at the social fabric of those communities and erodes mental health. If anything, these kinds of harm only demonstrate how biased algorithms in policing help exacerbate systemic inequities and underline the strong need for these reforms to at least mitigate the far-reaching and damaging consequences.

Solutions

To counter the harmful effects of racial bias in policing algorithms, a different approach is necessary. Biased data, mistaken predictions, and over-surveillance continue to harm minority communities through wrongful arrests, economic devastation, and psycho-emotional trauma. Addressing these challenges requires dealing with the root of the bias, correcting the systems that perpetuate biases, and instituting mechanisms that could help avoid similar future incidents. These three critical levers include: improving data quality, mitigating downstream harm with social services, and creating clear policies on the use of these technologies. Implementing these measures will take small but meaningful steps toward healing the effects of prejudiced algorithms in building a fairer system.

Improving Data Quality

Armed with the task of overcoming machine bias, it is necessary to remember that machine biases often stem from biased data. Currently, predictive policing algorithms are based on historical arrest data and thus reinforce societal biases, such as the disproportionate number of racial minorities arrested today. One way to reduce machine bias is through more diverse, accurate, and complete data. Generally, AI algorithms are provided with diverse data on aspects that are relevant to the purposes of a model. This is constituted mostly by structured data, which results from electronic records on various information, including but not limited to demographics and socioeconomic status, which could potentially affect algorithm output. Diversifying data is a well-regarded response to bias across various fields. For example, to minimize bias in healthcare, providers may diversify data from patient medical claims records, surveys, wearable devices, and many more health-related activities. In the stock market, models could be used to analyze trends and make predictions. Predictive policing algorithms could follow an approach similar to that of diversifying data in healthcare and the stock market. However, at this step, sampling bias is extremely problematic because datasets may not represent the demographics they are supposed to describe. For instance, a model that has been mostly trained on data from older, non-Black males may generalize poorly for other demographic categories (Nazer et al., 2023). Moreover, through incomplete data, misclassification, and measurement biases, prevalence creates further inaccurate predictions and worsens disparities in underrepresented populations (Nazer et al., 2023).

Overall, the scientists consider several lines for making datasets fairer. First, is the serious pressure to include far more broad and varied sources of information. Researchers propose not relying just on arrest records and crime statistics-which, with historic over-policing of marginalized communities, are themselves also too often biased-including non-criminal data. For example, methods such as that used by HunchLab draw on weather, community events, and socioeconomic factors to lessen reliance on prejudiced criminal data. The resulting analysis will then use non-criminal-based data, which gives a more comprehensive outline of that area without the bias of prior cases of over-policing (Azavea, 2014). In addition, AI developers and data scientists should not depend on a single source of data but rather pool data sets from numerous institutions to guarantee the representation of important variables such as race, ethnicity, and socioeconomic status (Nazer et al., 2023). This way, diversifying lowers the risk of bias associated with the fallacies of generalization across different population subgroups. Methods such as re-weighting and the imputation of missing data help in building more fair and neutral models, at least where sensitive variables are unevenly distributed in a data sample. It requires cooperation from researchers, authorities, and organizations to develop public datasets that are fully inclusive and very comprehensive (Nazer et al., 2023). One more significant improvement is data curation for balanced data, which is certainly a key step in preventing the model from learning biased associations. This can sometimes require over-representing specific groups in data or adding extra weight to certain variables. For example, algorithms developed using historical crime data should balance inputs so the system cannot continually identify areas with over-represented minority populations as high-risk zones, entering a self-perpetuating cycle of biased predictions (Ensign & Friedler, 2018).

Likewise, data scientists are pushing collection processes further and getting finer grains of information on variable factors such as income, education, and the context of neighborhoods to give them insight into people and communities. Ethical frameworks on data collection, anchored within community-based participatory research, ensure that processes for collecting data—whenever possible—occur with and alongside communities, rather than to communities, so resultant datasets better reflect lived experience. Many researchers are aggressively researching techniques to improve the fairness of algorithms on datasets and are placing more emphasis on pipeline debiasing strategies from data collection to model training. In this, adversarial debiasing frameworks with methodologies for fair representation learning aim to remove the bias in the training phase so that the model becomes non-discriminatory concerning given variables such as race or gender (Bellamy et al., 2019).

Overall, improving data and the process of gathering it, if done correctly, can alleviate a lot of bias made by machines. Progressively, people are trying to collect more representative data, including non-criminal data, and balance datasets so that biased predictions are not made. This is especially important in predictive policing. Such a multi-faceted approach to dataset improvement is one crucial step toward bringing fairness and justice to AI systems.

Promoting Social Services

While mitigating algorithmic bias is important, it's equally crucial to deal with the greater social issues predictive policing serves to magnify. Algorithms that target the most marginalized communities cause harm by exacerbating social inequalities and further stigmatizing those populations. Social services and rehabilitation programs can balance and reduce harms by addressing the root causes of the crimes committed, such as poverty, lack of education, and mental health problems.

Social services are to be designed to further the principles of restorative justice in policing, such as giving voice to the victims and addressing harms caused. This will mean services that support an increased number of victims and offenders who will benefit from facilitating collaboration by the police and external restorative justice providers, embedding restorative justice into the police organization culture and decision-making processes. This could disrupt cycles of harm and criminality, especially if this were delivered within a victim-sensitive framework, supported by trained officers within a range of policing roles (Burn et. al, 2018). For example, job training programs, housing assistance, and mental health services all work to minimize the need for punitive responses and create community resilience against the systemic biases baked into predictive policing models. Similarly, rehabilitative programs need expansion and reform with an emphasis on restorative justice that supports healing from harm rather than punishment. These practices encourage offenders to take responsibility for their actions while simultaneously offering victims the opportunity for closure and rehabilitation. If it is the case that the “offender” is the police department responsible for the AI algorithm and the “victim” is the person wrongly incriminated, the use of restorative justice can be very beneficial. For example, if a man was wrongly incriminated by an algorithm used by the police department, restorative justice could be helpful in resolving the issue, on both ends. A representative from the police department, the wrongly incriminated man, and a mediator could have a meeting where both sides could lead to mutual understanding. The incriminated man could share with the police how he was affected economically, psychologically, and mentally. The representative from the police department could take responsibility for their actions through means of compensation or a public apology, understand the harm they have caused, and even have an opportunity to redeem themselves by participating in community outreach programs. If this is not the case, (where the incriminated person is the offender) restorative justice could help decrease recidivism, lowering further adverse impacts from biased policing since the emphasis shifts toward reconciliation within communities instead of further criminalization (Lanni, 2022). More importantly, this is an investment in community cohesion that, over time, has a diffusing effect on the negative impact of biased predictive policing algorithms on society. Community engagement is also crucial in driving effectiveness within social services and rehabilitation programs. Interventions based on lived experiences of marginalized populations contribute to the application of broadened insights to interventions that could be more effective against what are often very complex challenges and start to counteract negative influences from biased algorithms.

The fight against the inequalities perpetuated by predictive policing algorithms necessarily involves addressing harms downstream through increased social services and rehabilitation programs. Indeed, it is in the application of supportive frameworks focusing on rehabilitation, community engagement, and restorative justice whereby one can hope for a more fair judiciary, one that will minimize the negative consequences of machine bias and foster a truly fair and just world for all.

Governing Policing Algorithms

Predictive policing algorithms raise a number of ethical and legal issues regarding their application. Regarding the fairness, efficacy, and ethics of deploying these algorithms, clear policies should be developed respective to when they are applied. The policy's context must take into consideration geographic and situational parameters, type of crime forecasted, and the role of human judgment in preventing uncritical application of forecasts (Lum & Isaac, 2016). If the usage of these algorithms is not controlled or limited, people will still be wrongly incriminated and the problem will worsen.

Predictive policing should be used only in very specific high-level instances and never involve wholesale surveillance across the municipality. Damilola Sholademi (2024) sets the context by saying that empirical research on predictive models in general reveals that results are greatly influenced by insights derived from historic data. Countering this, Céline Castets-Renard argues that it is important that policies clearly define geographic limits to predictive policing to make sure that it is only applied within areas with recurring high crime rates. Since most predictive algorithms depend on historical data, which are often indicative of discriminatory practices, oversight of such systems is necessary to offer an objective application of criminal justice assets and help mitigate biases made by the algorithm (Castets-Renard, 2021). Predictive policing algorithms should focus their target on serious offenses such as violent crimes, which clearly threaten public safety, rather than over surveilling minority communities that commit less severe crimes. Because the data driving these systems usually embodies biased practices from the past, using algorithms for lesser crimes could exacerbate existing inequities. Such restrictions work to prevent an excess of policing, and these limitations are placed on them so that human judgment and empathy are core to law enforcement decisions (Castets-Renard, 2021).

Additionally, effective human oversight is needed to mitigate these risks in predictive policing. To maintain oversight, human officers are responsible for reviewing algorithmic outputs before any decision is made. This practice is crucial in high-stakes situations, as AI systems—though helpful—can replicate existing biases and errors embedded in the data. These risks highlight the need for human judgment to complement automated recommendations, especially in areas requiring ethical and contextual awareness (Busuioc, 2022). The policy should be clearly spelled out to indicate when human officers may override any system forecast, so that the officers will be able to act at instances when suggestions proposed by algorithms may not be in conformation to community norms and real conditions. For instance, law enforcement personnel should receive training aimed at recognizing situations in which the algorithm may exhibit bias or when its recommendations fail to account for local social dynamics. In addition, it is essential to require ongoing evaluations of the system's accuracy and its effects on communities, implementing modifications to algorithmic results in response to the changing landscape of crime data and community input (Tréguer, 2021). Accountability mechanisms need to be imposed on policymakers to ensure that outputs from algorithms are reviewed periodically and any impacts they cause. When human judgments contradict the recommendations made by algorithms, decision-making needs to be documented to assess whether such decisions were appropriate and based on sound judgmental reason (Oluoch, 2024). Even if an algorithm makes a decision, the police officer in charge should use certain data points and knowledge they would use without these models to make a proper decision, before taking action. There should be accountability of officials for any decisions that lead to unfair outcomes to ensure human interventions make better decisions, not perpetuate algorithmic biases (Babuta & Oswald, 2020).

Overall, algorithm-based predictive policing should be used with well-set policies regarding geographical and situational limits, human reviews, and overrides while embedding ethics and efficiency. Otherwise, predictive policing has a high potential to make biased decisions that further increase social inequalities, rather than acting to reduce crimes effectively. Such policies would have to be designed in cooperation with multi-agency police agencies, policy thinkers, and also the community in order to balance public safety with protection against civil liberties.

Conclusion

This paper, through various examples, shows just how deeply predictive policing algorithms affect racial bias within the judicial system. While these technologies are in place for better law enforcement effectiveness, they ultimately create more harm to minority communities. This analysis underlines how biases within algorithms, which are inherently tied with flawed historical data, perpetuate a cycle of over-policing, economic inequality, and psychological harm.

Biased models result in unfair outcomes, such as wrongful arrests and social stigmatization, further worsening socio-economic disparities. Evidence of these consequences point to the need for reforms regarding data quality, the inclusion of social services, and strict regulatory oversight to temper these harms. This paper ultimately calls for a balanced approach to predictive policing — one that is focused on preventing further injustices. If policymakers, the police, and technology developers are to refine these systems to serve all communities better, they must prioritize fairness and justice as guiding principles. Only by confronting the flaws embedded within predictive policing can we begin to create a justice system upholding safety, fairness, and humanity. We must decide whether we will allow technology to further exacerbate the errors of the past or if we should innovate policing technology to truly represent the principles of justice we aim to uphold.

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