Human Trafficking: Analysis of Trafficked Locations

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Introduction

In today's world, human trafficking silently thrives, evading proper documentation and perpetuating exploitation on a global scale. The Harvard Journal of Law defines human trafficking as "a crime to compel another person to provide labor, services, or commercial sex through prohibited means of coercion and to exploit a minor for commercial sex" (Williams, 2018). It is a business that profits from the theft of freedom, akin to modern-day slavery. The financial implications are staggering, with studies revealing that it generates over $150 billion in illegal profits annually, rivaling major corporations like IBM and Disney (Road, 2023).

In order to effectively combat this issue, it's necessary to have accurate reporting that indicates where victims are being trafficked from and to. This information can only be found through self-reports and filed police reports (Hewson, 2022). Hence, our research will focus on utilizing reports to successfully predict when and where trafficking is likely to occur. Through this comprehensive approach, we strive to strengthen the fight against human trafficking and its devastating impact on individuals and societies worldwide.

Despite its global impact, human trafficking (HT) has been and continues to be hard to predict with machine learning due to the lack of available and accurate data surrounding it. The shortage of data can be attributed to multiple factors, including the secretive nature of the crime as well as the low frequency of reported cases by its victims. Due to this, research on victim exploitation locales remains underdeveloped compared to other aspects of the problem despite its plentiful variables like exploitation type and citizenship. Per the Counter Trafficking Data Collaborative (CTDC) dataset used in our analysis, approximately 60% of confirmed cases since 2001 involve external trafficking – the smuggling of HT victims across international borders. Understanding these movement patterns is crucial to prompt action in cases of missing persons and suspected trafficking incidents.

We believe that a data science approach would be the best way to combat this issue. One significant thing that we are looking for in our research are patterns that we can identify. Using machine learning models does just that, with the ability to find patterns that may be invisible at a glance. The data science approach also allows us to quantify our results with accuracy and measures such as f1 score. This is very important for our research specifically because we understand the ethical implications of human trafficking and will not put our intended tool out to the public unless we are confident that it is accurate. Lastly, the data available through the CTDC, which is large, allows us to perform machine learning models and be confident that it is representative of the true statistics of human trafficking worldwide. For these reasons, we conclude that the data science approach would be the most appropriate for our topic of human trafficking.

Assuming the representativeness of our data, we aim to forecast victim locations (destinations, not origins) and exploitation motives, considering factors such as age, gender, forms of exploitation, and governmental policies within countries that may contribute to higher trafficking rates. Our goal is to create a tool for government and policing officials to aid in the locating of human trafficking victims. By utilizing victims' demographic factors along with countries' policies, we aim to identify where victims will be trafficked. In order to implement our tool, we will strive for a high true positive rate – the more victims correctly located by our model, the greater the impact.

Literature Review / Background Section

Human trafficking is an umbrella term encompassing several primary forms, including forced labor, domestic servitude, child labor, and sexual exploitation. Beyond these well-recognized categories exist lesser-known forms that shed light on the intricate nature of this crime. For instance, bonded labor involves individuals becoming trapped in a cycle of debt bondage. Victims are forced to work to repay debts with exorbitant interest rates and/or deceptive lending practices. Child sex tourism is another uncommon form of trafficking that involves the exploitation of children in the commercial sex industry. This practice is especially prevalent in countries where HT policing is less strict. These under-the-radar forms of exploitation underscore the diverse and deceptive ways in which traffickers prey on vulnerable individuals.

Human trafficking as a whole is a widespread issue that spans across the world. Human trafficking has been tracked to nearly every country in the world, with an estimated 20 to 30 million slaves across the globe (Punam, 2018). With the world-wide effects of human trafficking, the causes are often a combination of numerous variables. Some of these key variables include poverty, unemployment, corruption, and weak policies enforcing the crackdown on human trafficking. These factors create vulnerabilities in the system that traffickers exploit, leading to forced labor, sex trafficking, and the exploitation of men, women, and children. The majority of human trafficking cases involve the sexual exploitation of women and young girls as the primary victims (79%). The second most prevalent form of human trafficking is forced labor, accounting for 18% of cases. Forced labor is less commonly identified and reported compared to sexual exploitation (UNODC, 2009). With this issue being so widespread, it is important to know where it is happening. A breakdown of the victims of forced labor reveals that the most dense area is the Asia and the Pacific region, which accounts for 56% of forced labor. Other areas include Latin America and the Caribbean (10%), the Middle East along with North Africa (9.2%), and US and Western Europe (10.8%). Also, countries in transition or those weakened by internal or external conflicts contribute to about 8% of people. In total, at least 161 countries are involved in human trafficking, serving as points of origin, transit, or destination (Rahman, 2011). The wide involvement of multiple countries in trafficking is shaped by a diverse range of policies and conditions, ultimately influencing their respective rates of human trafficking in multifaceted ways.

It is important to take in the country's factors when looking at the trafficking that goes into the country as well as coming out of it. A country's policies along with their economy contribute to how trafficking occurs within it (Kabbash, 2021). Throughout the world, varying governments affect their likelihood of human trafficking occuring. There has been a shown linkage between human trafficking and prostitution legislation (Gerasi, 2018). This shows that when a country has policies that make prostitution legal or decriminalized it, they have lower trafficking rates. This phenomena can also be credited by prostitution being considered trafficking in countries that prostitution is illegal in. Along with prostitution legislation, criminal justice laws also play a larger role in trafficking numbers in individual countries (Gerasi, 2018). Government and police corruption also have a strong relationship to human trafficking (Bale, 2007). We must take this into account when looking at the countries with lower recorded cases of human trafficking, as the data could be skewed due to corruption within the government and policing systems. Lastly, the economy has a large impact on the trafficking rate for countries. Though gross domestic product (GDP) itself does not have a direct impact on human trafficking, it does relate to social cohesion within a country (Goubin, 2018). With little desire to communicate within a community, reporting becomes more difficult which then makes human trafficking easier to facilitate. Overall, a country's economy and policy can have a large effect on their rates of human trafficking.

Nearly every country around the world have varying internal policies. With this knowledge, human trafficking and international justice systems have a complicated, non-linear relationship with one another. With new forms of HT becoming more commonplace, such as criminal exploitation, we must continue to put victim support at the forefront (Villacampa, 2018). Villacampa et al. introduce a victim-centered approach to HT that emphasizes protecting victims' rights. For this to flourish, victims must be treated as such in their passage through the criminal justice system. Villacampa conducted a qualitative analysis in Spain, organizing 37 interviews with practicing criminal justice and victim assistance services professionals to allow for an

in-depth exploration of the topic. Both sets of interviewees receive domain-specific and common questions from all participants. The common section attempts to “determine the degree of knowledge of the trafficking phenomenon and the applicable regulations.”
Conversely, the domain-specific section seeks to evaluate how professionals act in cases involving trafficking victims of criminal exploitation. Because interviewees worked in either criminal justice or victim assistance, this section of the questionnaire was tailored to participants based on their fields. Villacampa finds that when Spanish police (the police force in Spain) fail to identify victims of criminal exploitation, other professionals falsely believe that victims should be treated as genuine offenders in the justice system. The study also indicates the significance of trafficking type(s) that victims face as it pertains to experiences within the justice system: “(When) victims are exploited in multiple ways, (such as) when sexually exploited women are forced to commit crimes, the case for victim status is built on the sexual exploitation – rather than the criminal exploitation – suffered. As a result, when criminal exploitation is the only form… suffered, it is much harder… for criminal justice professionals to build a case for victim status.” (Villacampa, 2018). Due to this dilemma, properly classifying victims becomes difficult, which then clouds the data.

With the difficult task of reporting human trafficking correctly, research results have varied. The reason for this is due to the differences in approach throughout research in terms of identified vs. presumed cases of human trafficking (Allum, 2021). Human trafficking is inherently difficult to track due to the fluctuation in reporting policies by country. The United Nations General Assembly adopted a resolution titled “Transforming our world: the 2030 Agenda for Sustainable Development” (Saner, 2018). Of the goals, human trafficking was highlighted as a major point of change. Through analysis of these goals, it was concluded that the current measures in place were inadequate for measuring human trafficking and need to be improved on. With this knowledge, there have been methods used to fill this gap in data availability and accuracy. One form that has been used is to implicitly estimate the total scope of human trafficking based on the “true” cases that have been recorded (Jahik, 2005). The issue here comes with the accuracy of the predictions and no true way of determining whether this data is reliable when doing analysis or making claims. Another aspect in this issue is dismissing cases of human trafficking, or not classifying them properly which can skew the data. There are growing concerns that labor exploitation is being overlooked as a result of people not understanding that this is human trafficking as well (Gregoriou, 2018). With concerns of both over-representation along with under-representation, our goal is to find the most accurate data without having to predict any instances.

Crime Statistics on trafficking are only as reliable as the crime data informing them (NIJ, 2020). Labor and Sex Trafficking data appearing within the FBI’s National Uniform Crime Reporting Program significantly undermines the extent of trafficking crimes in the U.S. Previously, there had been no research on the validity of UCR data on trafficking within the objective of the article to “accurately report trafficking crimes reflects the true incidence of crime in a community” (NIJ, 2020). Through the work of the National Institute of Justice, it has been discovered that the inability of a wide majority of law enforcement officers to identify local trafficking offenses, including a vast amount of underreporting of these incidents. After taking the information to a national scale, the research team led by Amy Farrell concluded, “The UCR Program undercounts both human trafficking offenses that exist in local communities and human trafficking offenses that are identified by local law enforcement.” The crux of the problem identified within the study is to make estimations of human trafficking from collected data accurately. Law enforcement investigators and even Victim Service Providers need to be able to identify victims, and It’s been found that there is inadequate victim identification on both levels. As a result, the data collections available are limited and underrepresented victim populations. To connect this back to our current research, this represents the gaps and limitations within trafficking data as a whole, making our data only representative of a fraction of trafficking victims.

In terms of action based on previous analysis, it has shown to be difficult to determine how effective the preventative measures have been. Evaluations of anti-trafficking policies have been scarce and not publicly available, so it is unknown if or how they are being considered (Davy, 2016). Along with this, the evaluations that are available are not proficient to make conclusions of the effectiveness of the action, which then harm the credibility of them (Bryant, 2020). Without proper evaluation in place to hold the actions accountable there is not a clear view in this field of what actions have worked and what have not. With this knowledge, we intend to address the evaluation aspect by creating a tool that can be assessed in a way that makes it clear regarding the effectiveness of the tool. With the data that we possess, we believe that we can accurately predict where a victim of human trafficking will be trafficked to.

Theory and Hypothesis

Human trafficking manifests through a variety of discernible variables that exhibit correlations with victims' geographical locations and the specific forms of trafficking to which they are subjected. An in-depth analysis of these predictive factors provides a pathway to identify likely destination countries for trafficking victims and the nuanced motivations of their exploitation. Implicit in our approach is the assumption that our trafficking data, spanning 82 countries, accurately reflects the global landscape. Additionally, we rely on the assumption that the human trafficking indicators dataset, merged with the trafficking data, represents the indicators within those countries. On the premise of these assumptions, we endeavor to predict both the location and nature of exploitation for potential victims.

Testing our theory with these variables yields results that hold the potential to incentivize government entities to undertake similar analyses with more granular and detailed data. The revelation that machine learning can uncover patterns in location and trafficking motivations may encourage governmental bodies to further invest in this technology, ultimately enhancing their ability to safeguard the well-being of their citizens. However, it is crucial to acknowledge a notable risk associated with our theory—the reliance on a singular data source. This limitation not only constrains the scope and reach of our predictions but also curtails the output capabilities of our models. Addressing this limitation through broader data acquisition remains a critical consideration for the robustness and reliability of our findings.

Methodology

Data

Our research draws on two key datasets to examine human trafficking comprehensively. The Counter Trafficking Data Collaborative (CTDC) provides a global repository, offering detailed insights into individual cases since 2001, including victims' citizenship, exploitation locations, control methods, and demographics. The second dataset, the Human Trafficking Indicators (HTI) by Dr. Richard Frank, focuses on country-level indicators such as tier assessments, internal trafficking, and enforcement measures.

It is important to acknowledge the international data limitations inherent in our study. Variability in countries' perspectives on human trafficking, enforcement priorities, and political policies results in a heterogeneous landscape. Not all nations perceive human trafficking with equal urgency, contributing to a nuanced and complex information landscape. Despite this challenge, we strive to maximize information retrieval globally, primarily relying on the extensive dataset from CTDC, supplemented by contributions from Dr. Richard W. Frank at the Australian

National University. This dual-source approach enhances the robustness of our research findings.

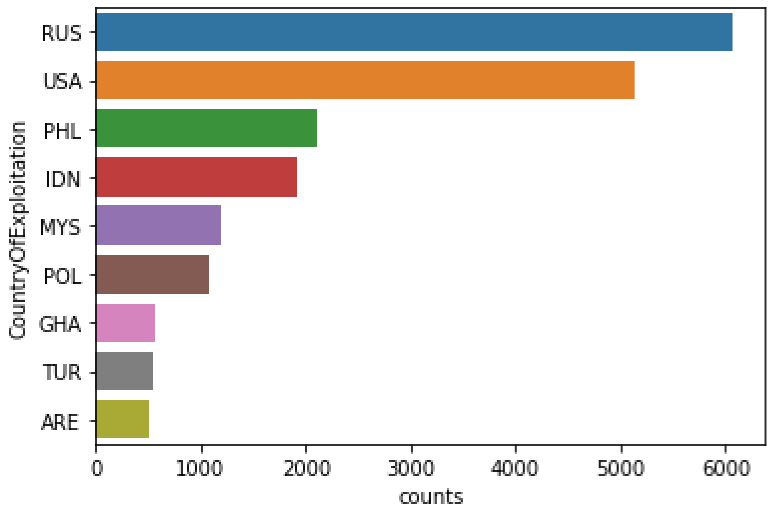
Data Cleaning

Cleaning the data required a variety of assumptions to make it viable. The HTI dataset used had a limitation in years, starting in 2001 and ending in 2017, while the CTDC victim dataset expanded to 2024. When merging these datasets, we decided it would be safer to stop the merge in 2017 with the HTI dataset rather than infer 2017 HTI data for future years. Since laws and country enforcement evolve, we cannot safely assume that the HTI dataset is representative of the victims. Having to filter our data to the years 2001-2017 only minorly decreased the volume of data.

The dataset contains observations with several empty cells, suggesting that little is known about the corresponding victims. We opt to remove these observations from the dataset because they provide minimal value for training and insufficient data for testing, lacking descriptions of age, gender, and other key demographic values. Removing these data points was the only liable option other than synthetically making the data. A total of 70% of the data had a missing value, although a lot of these were victims that were yet to be found.

The dataset exhibits a substantial imbalance in the frequency of observations across countries of exploitation, with a notable prevalence in Russia and the U.S, which take up a combined 30%. In the predictive model, we employed rebalancing to prevent bias towards these countries. This involved increasing observations for every other country while maintaining the overall distribution, as seen in Figure 1.

Before



After

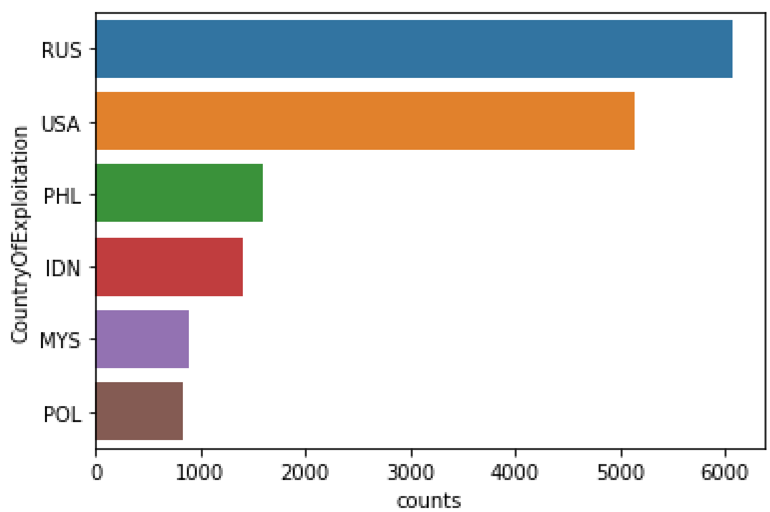


Figure 1

Prediction Methods

To make the predictions, we utilized various methods to see which realm of classification models would best recognize the patterns in human trafficking destinations. Our prediction methods include Neural Network classification and Decision Trees. We wanted to focus on the neural network for classification since neural networks thrive in recognizing unseen patterns.

The decision trees will act as an explanatory factor for the neural network. Decision Trees allow us to see the factor’s importance, allowing us to analyze which factors are being used by the models to predict the destination accurately.

The Neural Network we are utilizing is the SKlearn MLPclassifier. This neural network provides an easy implementation with no initial parameters required while allowing for great model customization. The MLP classifier which utilizes a multilayer perceptron neural network, which is a neural network that is great for measuring non linear relationships. Due to its ability to measure relationships in non linear data such as ours it became a great fit for our research. Sklearn also has helpful resources for parameter tuning for the model. Using cross-validation allowed for expansive tuning of the model, helping us obtain the optimal model for our neural network. Cross validation provided us with the insight of using 40 hidden layers, tanh activation function, and an adaptive learning rate.

Decision Trees, chosen for their explainability, act as interpretable components complementing the Neural Network. They reveal the factor's importance, aiding in understanding which factors contribute to accurate destination predictions. The transparent nature of decision trees provides insights into the neural network's operations and offers a potential alternative solution due to its step-by-step branching nature.

Results

Analysis

Our models have shown us informative insights to the patterns of human trafficking and provided promising results for tracking trafficking victims. Through our analysis we have found that our two most accurate models are our decision tree and our neural network. We concluded that these were the most accurate through a combination of accuracy of our models along with f1 score, which is a measure of predictive performance typically used in machine learning models ranging from 0 to 1, and Area Under Curve (AUC) which also ranges from 0 to 1, which works with Receiver Operating Characteristic charts to show how well our model predicts.

The decision tree provides us with great insight on what factors lead to a person being trafficked from one country to another with its feature importances. As seen in Figure 2, our features are sorted by importance from greatest to least. It is important to note that in order to focus on the feature importance of our variables in this decision tree, we have to omit the citizenships within the decision tree feature importance output.

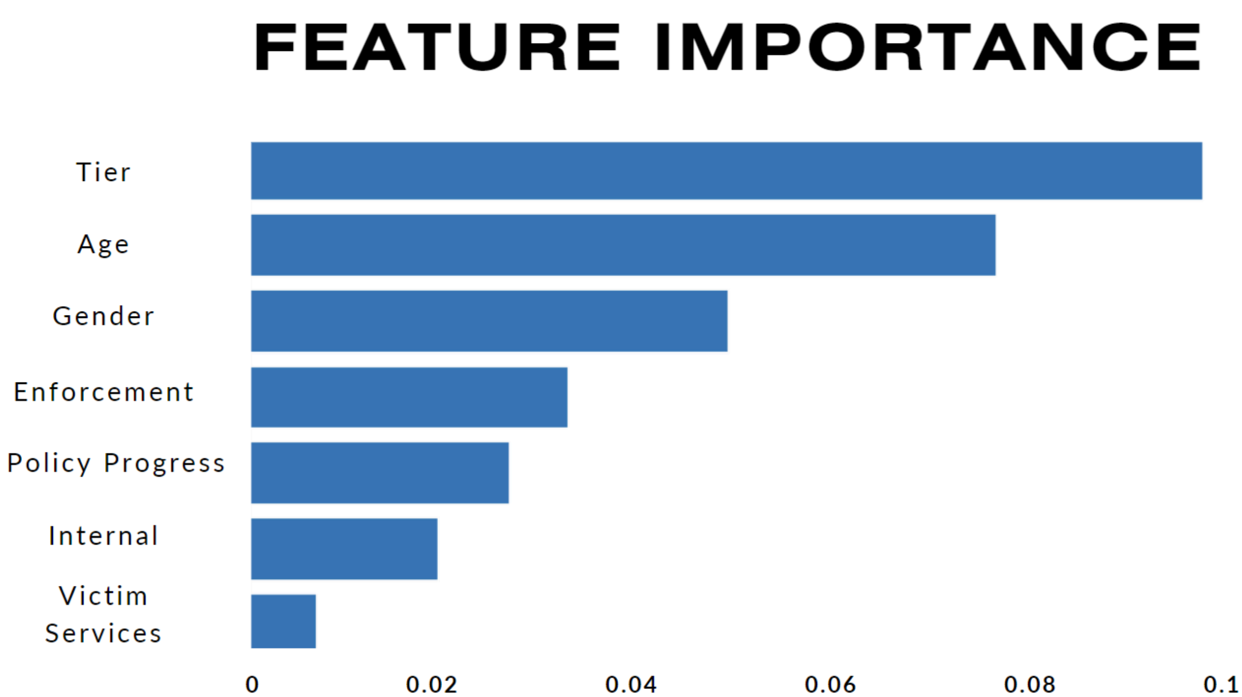


Figure 2

As seen above tier and age are huge indicators that provide insight as to where someone is being trafficked. Tier is a feature provided in the Human Trafficking Indicators dataset that marks a country's tier level respective to their level of justice and protection against human trafficking. With these features the decision tree was able to obtain an accuracy of 80% with an f1 score of .22. An f1 score of .22 indicates a low precision and recall, meaning that the model underperforms in predicting true positive and false positives consistently. To obtain an even better understanding of the model we decided to find the ROC and AUC using a one vs. all micro averaged measure. Figure 3 shows the ROC curve with an AUC of .997.

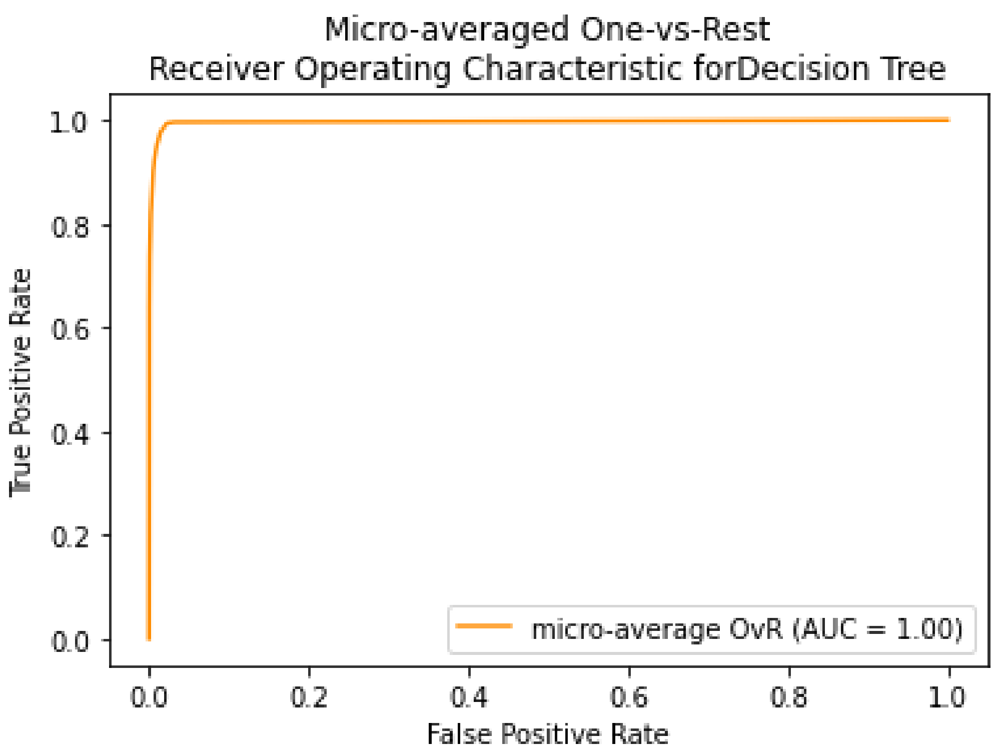


Figure 3

ROC and AUC describe how well the model does in distinguishing the different classes from one another. We want an AUC score of above 0.5 which would show that our prediction model is more accurate than a random guess. Based on the ROC and AUC of .997 we can determine that the decision tree does a great job in differentiating each country from another without much crossover.

Our neural network showed great promise in accurately predicting the country in which someone is being exploited to. The neural network out performed the decision tree in every metric, which we expected. The neural network was able to obtain an accuracy of 80% with an f1 score of .77. These measures showed us that our model can not only predict accurately but it has great precision and recall for those predictions. We also measured the ROC and AUC of the neural network using the one vs all micro average. The AUC of the model was .998 with the roc shown in figure 4.

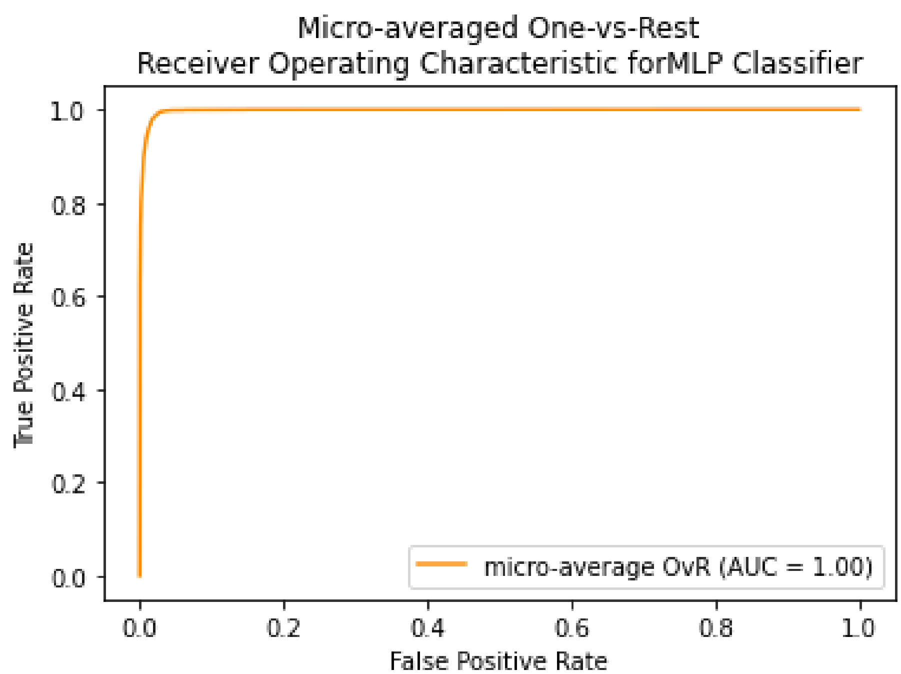


Figure 4

Looking at the ROC above it follows the same pattern as the decision tree with a high AUC showing that the model is able to differentiate between the different countries.

Results

Our models provide great promise and insight into which country is exploiting a person based on demographic and country-level factors. Decision trees helped us see which factors provide the greatest insight, but it had a weakness in precision and recall of its predictions. Our neural network provided us with accurate predictions with high precision, recall, accuracy and a very promising AUC. Table 1 shows a comparison of the metrics among all our models.

Models	Accuracy	F1 Score	AUC
Random Forest	81%	.78	
Decision Tree	80%	.22	.997
Neural Network	80%	.77	.998
SVM	78%	.73	
Gradient Boosting	58%	.54	

Table 1

As shown in Table 1, the real difference among the models lies in the f1 score. The f1 score provides us with a summary of the recall and precision of the models. This means our neural network had better recall and precision on the predictions than our decision tree, this was expected and the goal of our neural network since the main function of the decision tree was to provide us with insight on the feature importances.

Based on the results of our predictions and the feature importances discovered we found that the tier of a country, meaning the level of law and enforcement on these crimes is a leading factor in determining where a person may be trafficked. It seems that countries of origin with similar tiers will lead to a victim being exploited to similar countries. An example case of this is that the US has the highest possible tier there for the trafficking all stays within the US itself rather than being exported to another country. After tier we see age and gender also are major factors in the determinations which led us to conclude that these factors can help determine which country the person is being exploited to. This would be due to different countries trafficking for various reasons such as labor or sexual exploitation.

Application

With the insights that we have gained from our decision tree and neural network models, we can create a plan of action to properly address the issue of human trafficking. With accuracies of 80% on both our models, we deem that we can use them in our solution. By using our decision tree feature importance we can see that Tier is the most important variable when searching for where a human trafficking victim is being trafficked to. This means that when a country has less or weak policies that combat human trafficking, they are more susceptible to victims being trafficked into the country. With this knowledge, we can go back to the HTI data to determine which countries are the lowest in their policies and flag them.

The next steps to this application would be adding additional layers to our model, including but not limited to, specific location data and type of trafficking occurred. With this extra layer our tool would become more sophisticated, thus yielding higher accuracies and f1 scores. This expanded approach will enable us to pinpoint trafficking hotspots with greater precision and tailor interventions based on the type of trafficking prevalent in each location. Once our tool is refined we can then work with police forces around the world to put this into action in order to better locate lost persons who may be in the human trafficking system.

Conclusion

In conclusion, the pervasive nature of human trafficking presents a significant challenge to global efforts aimed at combating this modern-day form of slavery. Through our research, we have delved into the web of factors contributing to human trafficking and the complexities surrounding its detection and prediction.

Our approach focuses on leveraging data science techniques to predict and understand the patterns of human trafficking. Despite challenges such as data scarcity and underreporting, our analysis using machine learning models yielded promising results. Specifically, our decision tree and neural network models demonstrated high accuracy rates in predicting trafficking destinations, with insights collected from factors such as tier assessments, age, and gender playing pivotal roles.

One key takeaway from our findings is the critical role of governmental policies and enforcement in shaping trafficking dynamics, which information we gained through our decision tree. Countries with weaker anti-trafficking measures and lower tier assessments are more susceptible to becoming destinations for trafficking victims. This underlines the importance of strengthening international collaboration and implementing robust policies to combat human trafficking effectively.

Moving forward, our research provides a foundation for developing targeted interventions and tools to aid law enforcement and policymakers in identifying and addressing human trafficking hotspots. By harnessing the power of data science and predictive modeling, we aim to contribute to the ongoing efforts to eradicate this heinous crime and protect the rights and dignity of individuals worldwide.

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