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Discernment of high Trafficking: Consitency Regions (Hotspot)

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Abstract:- The law enforcement agencies reaction to trafficking human activities remains unsatisfactory as many cases of trafficking are still under investigation in as much as the information available to law enforcement agencies is unreliable. about the locations as well as prevalence rate of such crime. This research centers on the development of an agglomerative clustering model using hierarchical clustering algorithm of unsupervised learning method to improve this process and identify hot spot(s) of trafficking in Nigeria. Data needed for the model formulation will be secondary data; dataset on human trafficking in the form of .csv file will be utilized. The approach of visualizing trafficking statistics and similarity measurements aid in the detection of trafficking hotspots. The results of an agglomerative clustering technique are dendrograms which are tree-like structure that is easy to visualize compared with clusters of points presented by K-means clustering technique.

Keywords:- *Hotspot, Trafficking, Human trafficking, agglomerative, clustering model, dendrograms, k-means, law enforcement agency.*

I. INTRODUCTION

The exertion exploitation, slavery, or a person's profit-making service or advantage is referred to as human trafficking (Sigmon, 2008). Domestic slavery, labor, prostitution, or any mingling of these three are all possibilities. Human trafficking are major contravention of human rights and countenance of communal unfairness globally. Despite the difficulty in obtaining relevant data and trustworthy statistics, a new research estimates that there are approximately 24.9 million victims of vigor labor worldwide (ILO, 2017). These people are exploited in a variety of economic sectors, including agriculture, fishing, household work, construction, manufacturing, and the commercial sex industry. In spite of the fact that most victims are trafficked across international borders, 42% of victims are found to be victims of human trafficking within their own countries. Of these discovered victims, 71% are female and 28% are children (UNODC, 2016). There are many reasons why human trafficking has become so prevalent in Nigeria. Poverty, a lack of educational options, and a lack of jobs are the most common. Other contributing factors include family and child ignorance of the dangers of human trafficking, the high demand for inexpensive and submissive child labor in the informal economy, the desire of youth for manumit through migration, and institutional intermission such as insufficient political commitment, lack of national law- making contra human trafficking, and the absence of a judicial anatomy allowing for the perpetrators and accommodators to be brought to justice. Despite the fact that many nations around the globe, particularly in Nigeria, have raised their priority for combating human trafficking, little is known about the extent of the issue. Many organizations involved in combating human trafficking do not regularly gather and assess data that would enable them to determine whether their programs are effectively preventing, reducing the rate of trafficking, protecting victims, and prosecuting offenders as intended, despite the fact that there is a growing body of research on the subject ("ASEAN and Trafficking in Persons", IOM 2007). The study of unsupervised learning examines how computers could come to represent particular input patterns in a way that accurately captures the statistical makeup of the complete dataset. Unsupervised learning uses prior knowledge to determine which aspects of the input structure should be included in the output, in contrast to supervised or reinforcement learning, which clear goal outputs and ecological evaluations have linked to each input. According to the agency's study aim, efforts to assess and elucidate the habitual of either traffickers or sufferer of human trafficking come to be limited toward qualitative reports of certain forms of trafficking enslavement. In Nigeria, the anti-trafficking campaign has focused mostly on avoiding sexual enslavement of women or children; however, little attention has been paid to determine the scope of labor trafficking or comprehending its nature (UNODC, 2006). Any estimate based on data derived from these methods faces significant methodological challenges due to the lack of consistent systems to record and report information about cases of officially recognized human trafficking as well as the paucity of trustworthy research about the traits of victims and offenders.

Despite these obstacles, monitoring human trafficking has become more crucial in recent years, and many nations have increased their efforts to combat the problem. However, there are still flaws in anti-trafficking efforts. There is a dearth of political will, operational capability, and understanding about human trafficking as well as lack of effective counter-strategies. As a result, human trafficking continues to thrive. Currently, there is a lack of reliable information on the prevalence of human trafficking as well as accurate assessments of the responses of law enforcement and non-governmental organizations to the issue. There are concentrations of human trafficking in some locations and none at all in others, which is not a uniform distribution across maps. With this knowledge, people make decisions about where to go and where to stay in their daily activities. Their decisions about where they live, the school go, business activities, travelling and play are influenced in part by the knowledge that their risks of becoming a victim are higher in some locations than in others. On certain streets, individuals walk quickly and look suspiciously at

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approaching strangers, while on others, they stroll leisurely and look forward to meeting the next intriguing person they may encounter, and they witness others making similar decisions in the same regions. Law enforcement agencies utilized this grasp day to day. Conclusions regarding how to deploy deficient resources are depends on the location where the largest and lowest requests for human trafficking exist. Officers are taught to pay special attention to certain behaviors in some regions, but they are given no instructions in other places where same behavior is rare. A problem-oriented scenario forces law enforcement authorities to identify trafficking activity hotspots, figure out what's causing them, and then devise strategies to eliminate the hotspots.

This research is devoted to discernment of high trafficking – consistency regions known as (hot spot). Hot spot survey assist law enforcement agent(s) to point out high-trafficking regions, nature of trafficking actually committed, and the wisest course of action.

II. LITERATURE REVIEWS

Human trafficking is a complicated problem that has ramifications for societal issues and the world economy. It involves the business trade and exploitation of individuals in exchange for benefits or financial gain. It transcends national boundaries, appears in both underdeveloped and developed nations, and endangers fundamental human rights as well as a broader sense of world order (Winterdyk, Perrin, & Reichel, 2011). In addition to being a violation of human rights and a global public health issue, human trafficking is a modern form of enslavement (Gajic-Veljanoski & Stewart, 2007). Estimates of the number of people affected by human trafficking worldwide range from 27 million to 35.8 million. It is one of the offenses with the fastest-growing victim populations. The trade of human slavery is very profitable. According to Office (2012), forced labor and sexual exploitation generate an estimated $150 billion in illegal profits annually, ranking third in the world behind illicit drug and arms trade as the primary sources of income for organized crime (Haken, 2011). Although the scope of the problem is unknown, one thing is certain: it is a massive worldwide issue that is steadily worsening. While the practice of exploiting people for financial gain has a long and infamous history, until recently it was primarily associated with enslavement and was supported and tolerated by some influential groups and political parties. Sheath of this framework, such violations of human rights have grown considerably more covert in recent years and are now primarily called "human tracffiking". In general, academic research on this contemporary and covert phenomenon only recently began to be published, in the late 1990s (Winterdyk, Perrin, & Reichel, 2011), and has been examined in the contexts of criminology (Farrell, 2009; Kenyon & Schanz, 2014), sociological research (Capous Desyllas, 2007; Jordan, Patel, & Rapp, 2013; Kenyon & Schanz, 2014), and international studies (A (Logan, Walker, & Hunt, 2009; C. L. Miller, 2013). Data mining, artificial intelligence and machine learning are a few examples of analytical methods that could be used to resolve complex problems like predicting future trends and behaviors, finding more efficient ways to distribute limited resources and spotting patterns in data that may be of interest. These techniques can be used to evaluate trade-offs and various scenarios in addition to proposing the best course of action. Although authors are only aware of a handful of isolated studies in which these potent techniques have been used to stop human trafficking, despite the fact that it is clear that they are ready for implementation in combating the problemMore specifically, analytics-based methods have been employed to locate captives and trafficking networks (Kennedy, 2012; Latonero, 2011; Lesniewski, 2014). (Kennedy, 2012; Latonero, 2011; Lesniewski, 2014), (Ibanez & Suthers, 2014). Despite the fact that many governments around the globe are giving fighting human trafficking a higher priority, information on the extent of the issue is still lacking. Despite the fact that there is a growing body of study on trafficking, many organizations working to stop it don't regularly collect and analyze data that would let them determine whether their initiatives are successfully preventing, reducing trafficking, protecting victims, and prosecuting offenders. ("ASEAN and Trafficking in Persons", IOM, 2007).

A. Human Trafficking?

The term "human trafficking" is defined differently by different agencies and researchers. ("Protocol to prevent, suppress and punish trafficking in persons, especially women and children, supplementing the United Nations convention against transnational organized crime," 2002). It is defined as the practice of maintaining a person in an involuntary form of enslavement, such as household, labor, or sexual servitude, through the use of force, compulsion, or debt bondage. (Sigmon, 2008; Skinner, 2008). There are many victims all over the world, including juvenile soldiers, child brides, housekeepers, nannies, agricultural workers, prostitutes, and beggars. (Feingold, 2005; Logan et al., 2009). The term human trafficking is sometimes used interchangeably with the term "sex trafficking" (Crime, 2014). Despite the importance of sex trafficking, more than 68 percent of kidnapped people worldwide are believed to be victims of domestic and labor trafficking. (Farrell & Fahy, 2009; Office, 2012). Human trafficking is classified by Logan et al., (2009) into four categories: being born into slavery or debt bondage (when children acquire their parents' debts); being kidnapped, sold, or subjected to physical coercion; and being tricked into slavery. (Coercion and debt bondage). Examples of exploitation include prostitution, sex labor, pornography, exotic dancing, household work, factory work, the food service business, begging, and commercial fishing. (Logan et al., 2009).

B. What Causes Human Trafficking?

Although it has existed for a long time in a variety of forms, government discourse and media coverage suggest that human trafficking has only recently come to be seen as a significant social issue. (Cwikel & Hoban, 2005; Gulati, 2011). It is challenging and complex to determine the prevalence of human trafficking because it is a largely concealed activity (Farrell, McDevitt, & Fahy, 2010; Kangaspunta, 2007; State, 2013). The estimated number of victims of human trafficking in the United States and around the globe is shown in Table 1 using data from a variety of sources. Despite variations in statistics from year to year, it is clear that a sizeable portion of the people in contemporary society is vulnerable to and prone to human trafficking, and this group is not shrinking. Alarmingly, less than 1% of the entire projected number of individuals trafficked has been detected (State, 2013). The estimated number of trafficked people, the number of victims who have been identified, and the number of people who have been apprehended for human trafficking are all very distinct. (Clawson, Dutch, Solomon, & Grace, 2009).

Table 1: Estimation of the number of victims of human trafficking (Jayson, 2013)

Estimated Source	**Human Trafficking Estimation**	**Geographical Level**
Index of Slavery Around the World (2013).	28,310,000 – 31,310,000	Globally
United States of America Department of State, (2006), United States of America Department of State, (2013).		
Organization for International Labor, (2012). Organization for International Labor, (2012).	26,000,000	Globally
Health and Human Services Department U.S. (2009 report based on 2001 data).	4,000,000	Globally
Wilson, Walsh and Kleuber (2006).	20,900,000	Globally
Clawson, Layne and Small (2004).		
Wyler and Siskin (2011).	12,300,000	Globally
	199,000 (Minors only)	Within the U.S. smuggled into the United States smuggled into the United smuggled into the United States
	50,000	
	14,500-17,500	
	17,000	

Human Trafficking Estimation

By examining the use of mobile network equipment and demographic information of people residing in various parts of London, a group of academics was able to predict whether certain areas of the city will become a crime hotspot. (Bogomolov, Lepri, Staiano, Oliver, Pianesi & Pentland, 2014). They have proposed that mobile network anonymous data can be used to predict crime rates.

Using two datasets, 1990 US LEMAS and crime data 1995 FBI UCR, and classification techniques like Decision Tree and Naive Bayesian algorithm, 83.95% accuracy was achieved when attempting to predict a crime category for various states in the United States. (Iqbal, Murad, Mustapha, Panahy & Khanahmadliravi, 2013). If there were any unbalanced crime categories, the research did not identify them. Using the same databases and a range of machine learning techniques, (Shojaee et al., 2013) found that the k-Nearest Neighbor algorithm outperformed the others with an accuracy of 89.50%. They also improved the feature selection by using the Chi-square function. The Series Finder was a machine learning agent introduced by (Wang, Gerber, & Brown, 2012) that looked for patterns in crimes committed by the same or similar offenders or groups of offenders. Additionally, clustering has been used to look into regional patterns in criminal activity and criminal history (Freeman, 1999). (Redmond & Baveja, 2002) examined the data noise issue as well as how specific police reports or cases are distinct and don't have enough indicative matrices. They were able to forecast more accurately using their system, which they called Case-Based Reasoning (CBR), which they recommended as a technique to filter out these examples.

III. METHODOLOGY

This chapter presents the hierarchical clustering algorithm to develop a model for detecting trafficking hot spot(s) in Nigeria. To test the algorithm, a data set on human trafficking in the form of .csv file will be utilized. The findings aid in determining how the strategy improves trafficking patterns comprehension. The five data sets are from the reports projected by research and programmed development department, NAPTIP for period 2014 through 2018. This chapter comprises tests that were created and run to assist analysts in identifying hotspots in representative samples of 3,846 records from trafficking data sets.

A. Algorithm of Hierarchical Clustering

Regular clustering is similar to hierarchical clustering, except that the goal is to create a hierarchy of clusters. This is important when you want to be able to choose how many clusters you want at the end. In this approach, the algorithm produce a hierarchical structure of clusters from a trafficking data set so that at the top level the hot spots of trafficking instance divides into just a few clusters, each of which divides into its own sub clusters at the next level down, and so on. For example, imagine grouping hot spots of trafficking dataset in Nigeria. You want a few broad categories of trafficking hot places for states at the top, but as you get further into the categories, you'll want greater granularity, i.e. more discrete clusters of trafficking hot spots for states. In terms of algorithm outputs, you get an enchanting tree that shows you the hierarchies between the clusters in addition to cluster allocations. From this tree, you may select the amount of trafficking hot point clusters you desire.

➢ *How Hierarchical (Agglomerative) Clustering Algorithms Work*

According to S.C. Johnson's 1967 definition, the fundamental procedure for hierarchical clustering is shown below, Given a set of N objects that need to be grouped and N*N distance (or similarity) matrix, the fundamental process is as follows:

- Start by assigning each object to a cluster so that, if you have N items, you now have N clusters, each containing one item. The distances (similarities) between the objects in the clusters should match those between the clusters.
- Find the clusters that are nearest to each other, then combine them into one cluster to reduce the number of clusters.
- Compare each of the previous clusters to the new one and calculate the distances (similarities) between them.
- Repeat steps 2 and 3 as necessary to cluster all of the objects into a single N-size cluster.

➢ *Application of Hierarchical (Agglomerative) Clustering Algorithm on Trafficking Data set*

Given a trafficking data set of 6 states as shown in table 2 below shows the fundamental procedures of hierarchical (agglomerative) clustering, as delineate by S.C. Johnson in 1967:

Table 2: Extract from Trafficking Dataset for the year 2018

Year Of Registration	State	Distribution of Trafficking	State-id
2018	Abia	19	1
2018	Adamawa	6	2
2018	Akwa Ibom	36	3
2018	Anambra	12	4
2018	Bauchi	13	5
2018	Bayelsa	0	6

Extract from Trafficking dataset

- **Step 1:** Assign each state to a cluster, so that you now have six (6) clusters, each containing just one state.
- **Step 2:** Generate distance matrix by computing Euclidean distances between each state and every other adjacent state.

Using equation 1 below, the distances are calculated as follows:

$$Distance[(x,y),(a,b)] = \sqrt{(x-a)^2+(y-b)^2} \qquad (1)$$

$$Distance(Abia, Adamawa) = \sqrt{(19-6)^2+(1-2)^2}$$

$$= \sqrt{(13)^2+(-1)^2}$$

$$= \sqrt{170}$$

$$=13.0384$$

$$Distance(Abia, Akwa\ Ibom) = \sqrt{(19-36)^2+(1-3)^2}$$

$$= \sqrt{(-17)^2+(-2)^2}$$

$$= \sqrt{293}$$

$$=17.1172$$

$$Distance(Abia, Anambra) = \sqrt{(19-12)^2+(1-4)^2}$$

$$= \sqrt{(7)^2+(-3)^2}$$

$$= \sqrt{58}$$

$$= 7.6157$$

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$$Distance(Abia, Bauchi) = \sqrt{(19-13)^2 + (1-5)^2}$$
$$= \sqrt{(6)^2 + (-4)^2}$$
$$= \sqrt{52}$$
$$= 7.2111$$

$$Distance(Abia, Bayelsa) = \sqrt{(19-0)^2 + (1-6)^2}$$
$$= \sqrt{(19)^2 + (-5)^2}$$
$$= \sqrt{386}$$
$$= 19.6468$$

$$Distance(Adamawa, Akwa\ Ibom) = \sqrt{(6-36)^2 + (2-3)^2}$$
$$= \sqrt{(-30)^2 + (-1)^2}$$
$$= \sqrt{901}$$
$$= 30.0166$$

$$Distance(Adamawa, Anambra) = \sqrt{(6-12)^2 + (2-4)^2}$$
$$= \sqrt{(-6)^2 + (-2)^2}$$
$$= \sqrt{40}$$
$$= 6.3245$$

$$Distance(Adamawa, Bauchi) = \sqrt{(6-13)^2 + (2-5)^2}$$
$$= \sqrt{(-7)^2 + (-3)^2}$$
$$= \sqrt{58}$$
$$= 7.6157$$

$$Distance(Adamawa, Bayelsa) = \sqrt{(6-0)^2 + (2-6)^2}$$
$$= \sqrt{(6)^2 + (-4)^2}$$
$$= \sqrt{52}$$
$$= 7.2111$$

$$Distance(Akwa\ Ibom, Anambra) = \sqrt{(36-12-6)^2 + (3-4)^2}$$
$$= \sqrt{(24)^2 + (-1)^2}$$
$$= \sqrt{577}$$
$$= 24.0208$$

$$Distance(Akwa\ Ibom, Bauchi) = \sqrt{(36-13)^2 + (3-5)^2}$$
$$= \sqrt{(23)^2 + (-2)^2}$$
$$= \sqrt{533}$$
$$= 23.0867$$

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$$Distance(Akwa\,Ibom, Bayelsa) = \sqrt{(36-0)^2+(3-6)^2}$$
$$= \sqrt{(36)^2+(-3)^2}$$
$$= \sqrt{1305}$$
$$= 36.1247$$

$$Distance(Anambra, Bauchi) = \sqrt{(12-13)^2+(4-5)^2}$$
$$= \sqrt{(-1)^2+(-1)^2}$$
$$= \sqrt{2}$$
$$= 1.4142$$

$$Distance(Anambra, Bayelsa) = \sqrt{(12-0)^2+(4-6)^2}$$
$$= \sqrt{(12)^2+(-2)^2}$$
$$= \sqrt{148}$$
$$= 12.1655$$

$$Distance(Bauchi, Bayelsa) = \sqrt{(13-0)^2+(5-6)^2}$$
$$= \sqrt{(13)^2+(-1)^2}$$
$$= \sqrt{170}$$
$$= 13.0384$$

Using the result of the above computation, equation (1) yields the distance matrix represented in table 3 below:

Table 3: Distance Matrix of 6 States

	Abia	Adamawa	Akwa Ibom	Anambra	Bauchi	Bayelsa
Abia	0					
Adamawa	13.0384	0				
Akwa Ibom	17.1172	30.0166	0			
Anambra	7.6157	6.3245	24.0208	0		
Bauchi	7.2111	7.6157	23.0867	1.4142	0	
Bayelsa	19.6468	7.2111	36.1247	12.1655	13.0384	0

Distance Matrix

- **Step 3:** We need to find the cluster

Look for the minimum element in the distance matrix above which is 1.4142 at point (Anambra,Bauchi), then a dendrogram will be formed at the point.

- **Step 4:** Update the distance matrix

Compute distances between the new cluster at point (Anambra,Bauchi) and each of the old clusters.

❖ **At point Abia**

$$= MIN[dist((Anambra, Bauchi), Abia)]$$
$$= MIN[dist((Anambra, Abia), (Bauchi, Abia))]$$
$$= min[(7.6157, 7.211)]$$
$$= 7.2111$$

- **At point Adamawa**

$= MIN[dist((Anambra, Bauchi), Adamawa)]$

$= MIN[dist((Anambra, Adamawa), (Bauchi, Adamawa))]$

$= min[(6.3245, 7.6157)]$

$= 6.3245$

- **At point Akwa Ibom**

$= MIN[dist((Anambra, Bauchi), Akwa\ Ibom)]$

$= MIN[dist((Anambra, Akwa\ Ibom), (Bauchi, Akwa\ Ibom))]$

$= min[(24.0208, 23.0867)]$

$= 23.0867$

- **At point Bayelsa**

$= MIN[dist((Anambra, Bauchi), Bayelsa)]$

$= MIN[dist((Anambra, Bayelsa), (Bauchi, Bayelsa))]$

$= min[(12.1655, 13.0384)]$

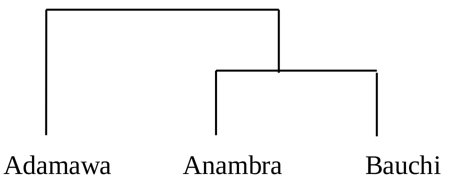
$= 12.1655$

Table 4: The updated distance matrix for cluster (Anambra, Bauchi)

Distance Matrix					
	Abia	Adamawa	Akwa Ibom	Anambra ,Bauchi	Bayelsa
Abia	0				
Adamawa	13.0384	0			
Akwa Ibom	17.1172	30.0166	0		
Anambra,Bauchi	7.2111	6.3245	23.0867	0	
Bayelsa	19.6468	7.2111	36.1247	12.1655	0

Updated distance matrix for cluster

- **Repeat step 3:**
The minimum element is 6.3245 at point ((Anambra, Bauchi), Adamawa), then form a dendrogram at the point.



- **Step 4:**
Compute distances between the new cluster at point ((Anambra, Bauchi), Adamawa) and each of the old clusters.

- **At point Abia**

$= MIN[dist(((Anambra, Bauchi), Adamawa), Abia)]$

$= MIN[dist(((Anambra, Bauchi), Abia), (Adamawa, Abia))]$

= min [(7.2111,13.0384)]

- **At point Akwa Ibom**

$$= MIN[dist(((Anambra, Bauchi), Adamawa), Akwa\ Ibom)]$$

$$= MIN[dist(((Anambra, Bauchi), Akwa\ Ibom), (Adamawa, Akwa\ Ibom))]$$

$$= min[(23.0867, 30.0166)]$$

$$= 23.0867$$

- **At point Bayelsa**

$$= MIN[dist(((Anambra, Bauchi), Adamawa), Bayelsa)]$$

$$= MIN[dist(((Anambra, Bauchi), Bayelsa), (Adamawa, Bayelsa))]$$

$$= min[(12.1655, 7.2111)]$$

$$= 7.2111$$

Table 5: The updated distance matrix for cluster (Anambra, Bauchi, Adamawa)

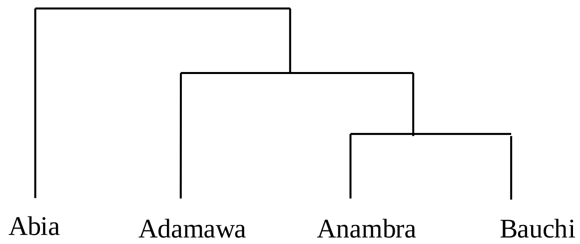
	Abia	Anambra, Bauchi, Adamawa	Akwa Ibom	Bayelsa
Abia	0			
Anambra, Bauchi, Adamawa	7.2111	0		
Akwa Ibom	17.1172	23.0867	0	
Bayelsa	19.6468	7.2111	36.1247	0

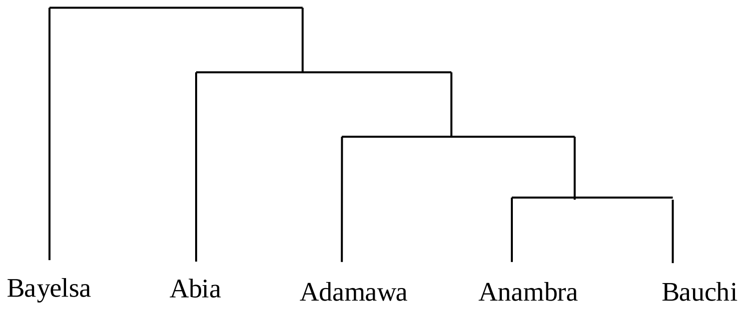
Updated distance matrix for cluster

[

- **Repeat step 3**

The minimum element is 7.2111 at point (((Anambra, Bauchi), Adamawa), Abia), then form a dendrogram at the point.





- **Repeat step 4**

Compute distances between the new cluster at point (((Anambra, Bauchi), Adamawa), Abia) and each of the old clusters.

At point Akwa Ibom

$$= MIN[dist((((Anambra, Bauchi), Adamawa), Abia), Akwa\ Ibom)]$$

$$= MIN[dist((((Anambra, Bauchi), Adamawa), Akwa\ Ibom), (Abia, Akwa\ Ibom))]$$

$$= min[(23.0867, 17.1172)]$$

$$= 17.1172$$

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At point Bayelsa

$$= MIN[dist((((Anambra, Bauchi), Adamawa), Abia), Bayelsa)]$$

$$= MIN[dist\big((((Anambra, Bauchi), Adamawa), Bayelsa), (Abia, Bayelsa)\big)]$$

$$= min[(7.2111, 19.6468)]$$

$$= 7.2111$$

Table 6: The updated distance matrix for cluster (Anambra, Bauchi, Adamawa, Abia)

Distance Matrix			
	Anambra, Bauchi, Adamawa, Abia	Akwa Ibom	Bayelsa
Anambra, Bauchi, Adamawa, Abia	0		
Akwa Ibom	17.1172	0	
Bayelsa	7.2111	36.1247	0

Updated distance matrix for cluster

- **Repeat step 3**

The minimum element is 7.2111 at point ((((Anambra, Bauchi), Adamawa), Abia), Bayelsa), then form a dendrogram at the point.

- **Repeat step 4**

Compute distances between the new cluster at point ((((Anambra, Bauchi), Adamawa), Abia), Bayelsa) and each of the old clusters.

❖ **At point Akwa Ibom**

$$= MIN[dist(((((Anambra, Bauchi), Adamawa), Abia), Bayelsa), Akwa\ Ibom)]$$

$$= MIN[dist\Big(\Big(\big(((Anambra, Bauchi), Adamawa), Abia\big), Akwa\ Ibom\Big), (Bayelsa, Akwa\ Ibom)\Big)]$$

$$= min[(17.1172, 36.1247)]$$

$$= 17.1172$$

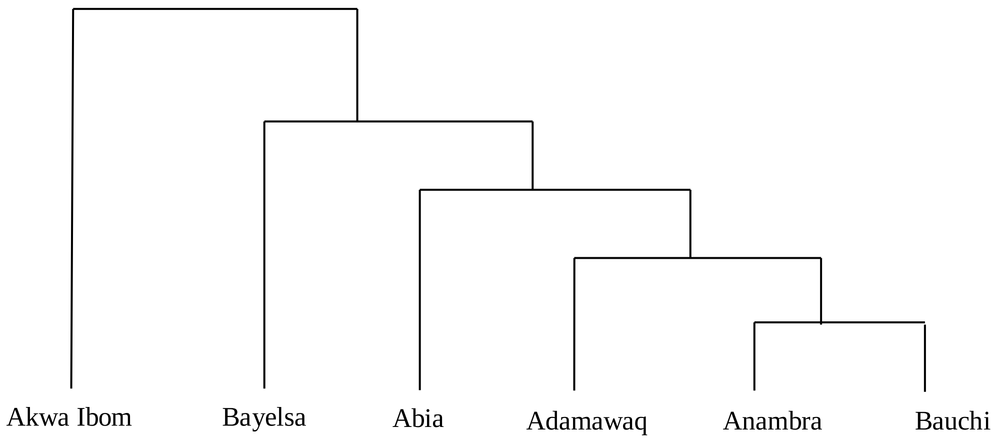
Table 7: The updated distance matrix for cluster (Anambra, Bauchi, Adamawa, Abia, Bayelsa)

	Anambra, Bauchi, Adamawa, Abia, Bayelsa	Akwa Ibom
Anambra, Bauchi, Adamawa, Abia, Bayelsa	0	
Akwa Ibom	17.1172	0

Updated distance matrix for cluster

- **Repeat step 3**

The minimum element is 17.1172 at point (((((Anambra, Bauchi), Adamawa), Abia), Bayelsa), Akwa Ibom), then form a dendrogram at the point.



IV. RESULT AND DISCUSSIONS

- The suggested trafficking clustering approach is implemented in Python 3.7. The nature of the datasets, experimental set-up, experiment assessment, and ultimately experimental findings and discussions are all covered in this chapter.

- Dataset Descriptions

The experiment in this study included data from different years of human trafficking (2014 - 2018). Tables 8, 9, 10, 11, and 12 show a list of the trafficking datasets for the time period under consideration.

Table 8: Trafficking Dataset for the year 2014

Year Of Registration	State	Distribution of Trafficking	S/No
2014	Abia	12	1
2014	Adamawa	0	2
2014	Akwa Ibom	26	3
2014	Anambra	45	4
2014	Bauchi	22	5
2014	Bayelsa	1	6
2014	Benue	63	7
2014	Borno	10	8
2014	Cross River	25	9
2014	Delta	40	10
2014	Ebonyi	12	11
2014	Edo	155	12
2014	Ekiiti	4	13
2014	Enugu	18	14
2014	FCT	1	15
2014	Gombe	2	16
2014	Imo	19	17
2014	Jigawa	10	18
2014	Kaduna	113	19
2014	Kano	68	20
2014	Katsina	35	21
2014	Kebbi	0	22
2014	Kogi	6	23
2014	Kwara	7	24
2014	Lagos	3	25
2014	Nassarawa	3	26
2014	Niger	3	27
2014	Ogun	10	28
2014	Ondo	8	29
2014	Osun	10	30
2014	Oyo	7	31
2014	Plateau	8	32
2014	Rivers	3	33
2014	Sokoto	139	34
2014	Taraba	15	35
2014	Yobe	0	36
2014	Zamfara	66	37

Trafficking Dataset for the year 2014

Source:https://www.naptip.gov.ng/wp-content/uploads/2017/05/2014-Data Analysis-Final-1.pdf.

Table 9: Trafficking Dataset for the year 2015

Year Of Registration	State	Distribution of Trafficking	S/No
2015	Abia	22	1
2015	Adamawa	2	2
2015	Akwa Ibom	39	3
2015	Anambra	31	4
2015	Bauchi	0	5
2015	Bayelsa	1	6
2015	Benue	59	7
2015	Borno	10	8
2015	Cross River	19	9
2015	Delta	59	10

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2015	Ebonyi	8	11
2015	Edo	166	12
2015	Ekiiti	2	13
2015	Enugu	26	14
2015	FCT	0	15
2015	Gombe	3	16
2015	Imo	23	17
2015	Jigawa	1	18
2015	Kaduna	11	19
2015	Kano	55	20
2015	Katsina	0	21
2015	Kebbi	77	22
2015	Kogi	26	23
2015	Kwara	25	24
2015	Lagos	14	25
2015	Nassarawa	2	26
2015	Niger	11	27
2015	Ogun	15	28
2015	Ondo	7	29
2015	Osun	7	30
2015	Oyo	31	31
2015	Plateau	17	32
2015	Rivers	14	33
2015	Sokoto	9	34
2015	Taraba	0	35
2015	Yobe	0	36
2015	Zamfara	2	37

Trafficking Dataset for the year 2015

Source:https://www.naptip.gov.ng/wp-content/uploads/2017/05/2015-Data-Analysis-1.pdf

Table 10: Trafficking Dataset for the year 2016

yearOfRegistration	State	Distribution of Trafficking	S/No
2016	Abia	35	1
2016	Adamawa	1	2
2016	Akwa Ibom	50	3
2016	Anambra	19	4
2016	Bauchi	1	5
2016	Bayelsa	11	6
2016	Benue	38	7
2016	Borno	12	8
2016	Cross River	13	9
2016	Delta	73	10
2016	Ebonyi	15	11
2016	Edo	233	12
2016	Ekiiti	7	13
2016	Enugu	33	14
2016	FCT	1	15
2016	Gombe	0	16
2016	Imo	60	17
2016	Jigawa	1	18
2016	Kaduna	5	19
2016	Kano	10	20
2016	Katsina	4	21
2016	Kebbi	12	22

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2016	Kogi	10	23
2016	Kwara	12	24
2016	Lagos	9	25
2016	Nassarawa	8	26
2016	Niger	0	27
2016	Ogun	50	28
2016	Ondo	20	29
2016	Osun	16	30
2016	Oyo	27	31
2016	Plateau	10	32
2016	Rivers	4	33
2016	Sokoto	12	34
2016	Taraba	5	35
2016	Yobe	0	36
2016	Zamfara	3	37

Trafficking Dataset for the year 2016

Source:https://www.naptip.gov.ng/wp-content/uploads/2017/05/2016-DataAnalysis1-1.pdf

Table 11: Trafficking Dataset for the year 2017

Year Of Registration	State	Distribution of Trafficking	S/No
2017	Abia	33	1
2017	Adamawa	6	2
2017	Akwa Ibom	40	3
2017	Anambra	37	4
2017	Bauchi	52	5
2017	Bayelsa	5	6
2017	Benue	79	7
2017	Borno	12	8
2017	Cross River	14	9
2017	Delta	128	10
2017	Ebonyi	19	11
2017	Edo	246	12
2017	Ekiiti	8	13
2017	Enugu	33	14
2017	FCT	0	15
2017	Gombe	0	16
2017	Imo	39	17
2017	Jigawa	39	18
2017	Kaduna	5	19
2017	Kano	79	20
2017	Katsina	5	21
2017	Kebbi	1	22
2017	Kogi	12	23
2017	Kwara	11	24
2017	Lagos	6	25
2017	Nassarawa	10	26
2017	Niger	1	27
2017	Ogun	36	28

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2017	Ondo	32	29
2017	Osun	19	30
2017	Oyo	49	31
2017	Plateau	8	32
2017	Rivers	6	33
2017	Sokoto	17	34
2017	Taraba	2	35
2017	Yobe	55	36
2017	Zamfara	2	37

Trafficking Dataset for the year 2017

Source:https://www.naptip.gov.ng/wp-content/uploads/2017/05/2017-April-September-data-analysis.pdf

Table 12: Trafficking Dataset for the year 2018

Year Of Registration	State	Distribution of Trafficking	S/No
2018	Abia	19	1
2018	Adamawa	6	2
2018	Akwa Ibom	36	3
2018	Anambra	12	4
2018	Bauchi	13	5
2018	Bayelsa	0	6
2018	Benue	38	7
2018	Borno	1	8
2018	Cross River	17	9
2018	Delta	18	10
2018	Ebonyi	8	11
2018	Edo	94	12
2018	Ekiiti	0	13
2018	Enugu	13	14
2018	FCT	1	15
2018	Gombe	0	16
2018	Imo	25	17
2018	Jigawa	5	18
2018	Kaduna	1	19
2018	Kano	36	20
2018	Katsina	13	21
2018	Kebbi	0	22
2018	Kogi	0	23
2018	Kwara	8	24
2018	Lagos	2	25
2018	Nassarawa	1	26
2018	Niger	0	27
2018	Ogun	10	28
2018	Ondo	7	29
2018	Osun	8	30
2018	Oyo	12	31
2018	Plateau	7	32
2018	Rivers	4	33
2018	Sokoto	10	34

2018	Taraba	1	35
2018	Yobe	0	36
2018	Zamfara	0	37

Trafficking Dataset for the year 2018

Source:https://www.naptip.gov.ng/wp-content/uploads/2019/07/4th-Quarter-2018-Analysis.pdf.

A. *Experimental Setup*

Python 3.7 has been used to execute the experiment for this study. We had to import the datasets from the Python root directory prior to starting the experiment. The clustering algorithm will choose the best k (number of clusters) figure that is appropriate and yields the best results based on our dataset. Distance metric and linkage parameter that will offer the best way of visualizing the experimental results in the form of a dendrogram will be chosen. Therefore, the distance metric and linkage parameter used in this research are "Euclidean" and "ward" respectively.

B. *Evaluation of Experiments*

In this research, an experiment was conducted to examine the performance of the model based on accuracy of both distance metrics and linkage parameters of the model across all the five datasets. Though the performance of this approach is evaluated without taking time or throughput into account, the major goal is to improve the accuracy of the suggested technique regardless of execution duration. The results of experiments are recorded in Table 13 below. In Table 13, the results showed that the experiment was carried out five (5) times out of which accuracy of 0.21621621621621623 was achieved as the best accuracy. The accuracy of 0.21621621621621623 implies that the model performed best for the analysis of 2018 trafficking dataset.

Table 13: Accuracy of the Model

No. of Experiment	Distance Metric	Linkage Parameter	Accuracy
2014	Euclidean	Ward	0.05405405405405406
2015	Euclidean	Ward	0.05405405405405406
2016	Euclidean	Ward	0.08108108108108109
2017	Euclidean	Ward	0.05405405405405406
2018	Euclidean	Ward	0.21621621621621623

Accuracy of the Model

C. *Experimental Results and Discussions*

The results of the experiment conducted on Tables 8, 9, 10, 11 and 12 are shown in the Figures 4, 5, 6, 7 and 8 respectively.

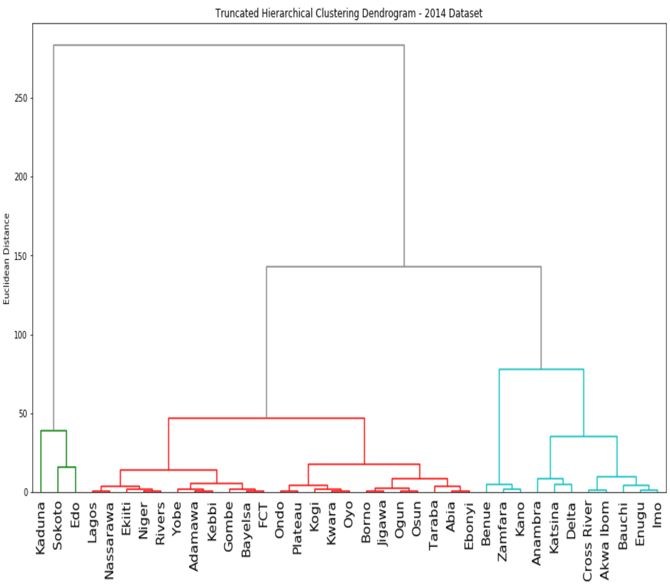

Fig. 4: Dendrogram of trafficking data for the year 2014

Figure 4 shows a dendrogram of trafficking hot spots of all states in Nigeria for the 2014 trafficking dataset, which shows Edo as the leading hot spot state followed by Sokoto, Kaduna and so on.

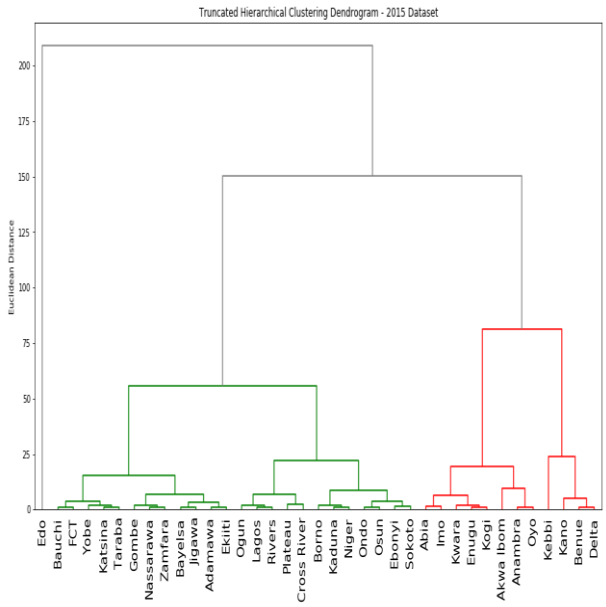

Fig. 5: Dendrogram of trafficking data for the year 2015

Figure 5 shows a dendrogram of trafficking hot spots of all states in Nigeria for the 2015 trafficking dataset, which shows Edo as the leading hot spot state followed by Kebbi, Benue and Delta with same occurrences.

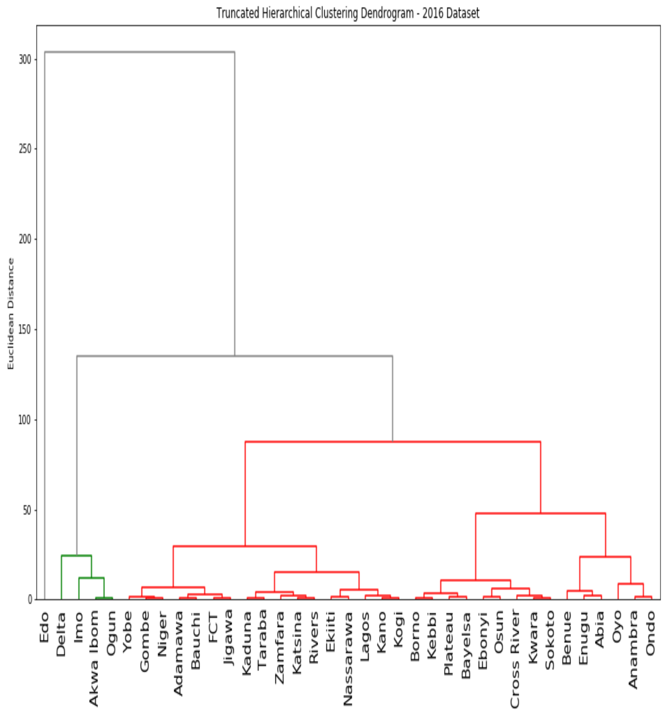

Fig. 6: Dendrogram of trafficking data for the year 2016

Figure 6 shows a dendrogram of trafficking hot spots of all states in Nigeria for the 2016 trafficking dataset, which shows Edo as the leading hot spot state followed by Delta and Imo respectively.

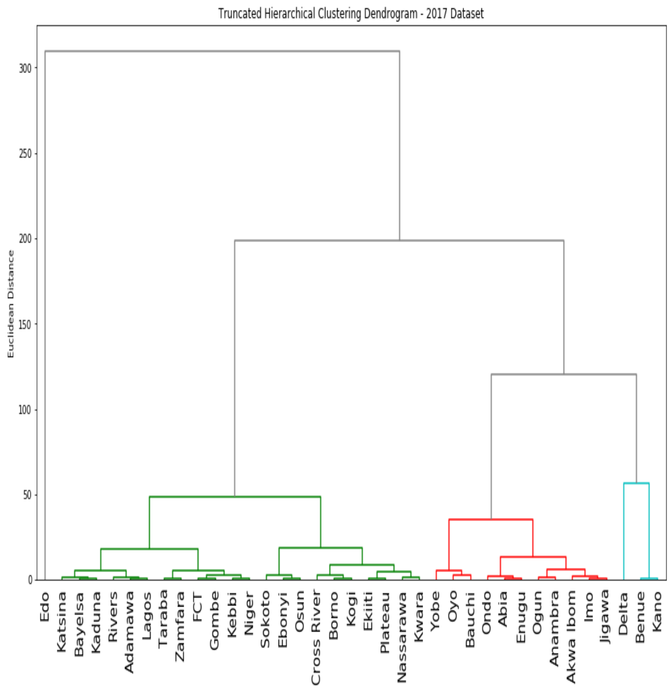

Fig. 7: Dendrogram of trafficking data for the year 2017

Figure 7 shows a dendrogram of trafficking hot spots of all states in Nigeria for the 2017 trafficking dataset, which shows Edo as the leading hot spot state followed by Delta, Benue and Kano with same occurrences.

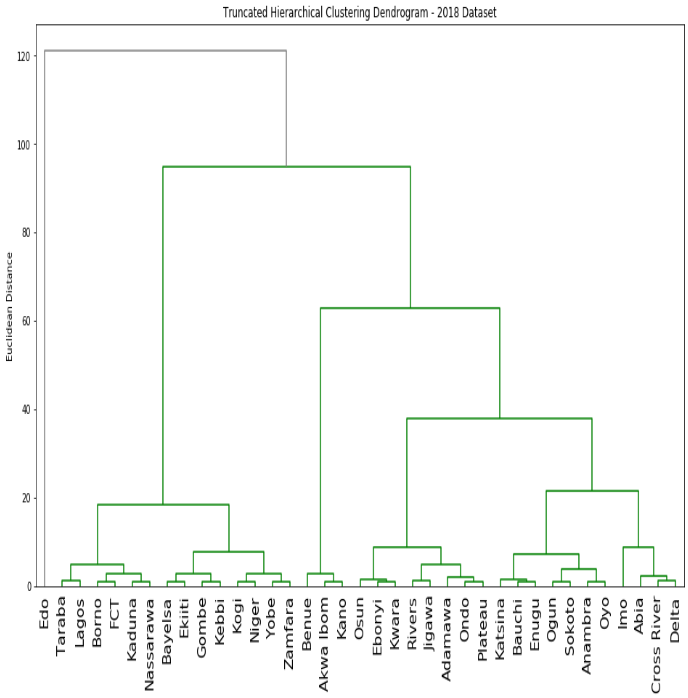

Fig. 8: Dendrogram of trafficking data for the year 2018

Figure 8 shows a dendrogram of trafficking hot spots of all states in Nigeria for the 2018 trafficking dataset, which shows Edo as the leading hot spot state followed by Benue, Kano and Akwa Ibom having same occurrences.

V. CONCLUSION

The goal of this study is to determine the significance of trafficking hot spots representation and similarity assessment in improving a clustering technique's accuracy when using a hierarchical clustering algorithm. Using the hierarchical clustering algorithm and various dendrograms to illustrate trafficking hotspots, numerous experiments were carried out on five datasets. Python 3.7 programming environment was used to carry out the experiment. The experiment showed that the suggested clustering method performed well on different datasets related to human trafficking. The following findings were drawn as a result of the analysis:

- On 2018 datasets, clustering algorithm had the best accuracy, with a value of 0.21621621621621623.
- The approach of visualizing trafficking statistics and similarity measurements aid in the detection of trafficking hotspots.

VI. RECOMMENDATION

The bottom-up or agglomerative clustering approach of visualizing trafficking hot regions is described in this study. In addition to the findings of this study, the following recommendations were made:

- This is a different method to K-means clustering that doesn't need us to commit to a specific number of clusters K. K-means clustering requires us to pre-specify the number of clusters K which can be a disadvantage.
- The results of an agglomerative clustering technique are dendrograms which are tree-like structure that is easy to

visualize compared with clusters of points presented by K-means clustering technique.

- Since clustering only indicates trafficking hot spots in high granularity of states, therefore it will be an interesting work to visualized trafficking hot spots in smaller granularity of Local Government and Communities.
- Implementation of the technique on different unsupervised machine learning algorithms in order to measure the accuracy and time.

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