by criminals having similar traits or skills required for the task execution.

Criminal network is a social cohort; [6] thus, members of such network possess unique traits, behaviours, skill sets, personality etc., which tends to bring about some sort of communities that can be identified within the network. A criminal network will usually have few leaders and a lot of followers being loyal to their leaders. However, some follower's loyalty is strongly tied to a particular leader within the gang and weak for others, thus leads to creation of clusters of communities [7]. Aside from loyalty, the personality or skill set of a criminal is liable to create a form of communities within the network, as the common skill set of a community within the network may determine the type of activities they handle within the network [8]. All these factors, among many others that are peculiar to a social network brings us to the study of community detection with a criminal network.

As it is established that a criminal network may be static or dynamic – usually dynamic in most cases, the death of criminal network members does affect the evolution of the network [9]. It is also a known fact criminal gangs do recruit new members as well as cut off members. This result into increase or decrease in the size of the network and its (sub)communities as the case maybe [10-11]. The analysis of criminal network, a branch of social network analysis (SNA), through the application of graph theory to enable graph analysis, and techniques rooted in social science which majorly investigates the relationship among entities whether structural or topological, is of great essence. Particularly, the identification of communities or subcommunities within a criminal network will help law enforcement agent to target or apprehend some set of criminals that are responsible or liable to wreck a particular form of havoc before the actual activities is being carried out.

In light of the essence of community detection and its pragmatic positive impact in our society in ameliorating the menace caused by criminal perpetrators, there exist several researches that had developed, implemented and evaluated various (sub) community detection algorithms using techniques, methods, tools, and technologies based on graph analysis, machine learning, mathematical modelling, social sciences and many others [12-17]. Thus, the comprehensive review of these works is the main contribution of this paper and to highlight the strength and limitation of these algorithms, as well as identify major researcher gap that are available and also, to see if major advancement can be made on existing method of community detection algorithm, particularly for criminal networks.

2. Community Detection

Complex system possesses constituents that interrelate between themselves which is able represented as nodes (the composing elements of the system) and links (the known interconnection between nodes [18-19]. The structure of these systems holds topological information that contains viable information which are processed into solutions to inherent problems of the complex system being represented as a graphical network.
In a network, communities are also referred to clusters, [20] though with no quantitative definition, is described as nodes with denser intra-group connections than inter-group connections [21-22]. Communities, also known as sub-graph in graph analysis, are inherent and usually hidden, and thus establishing the need of methods, algorithms or schemes to adequately detect them. More so, the definitions of communities vary from discipline to discipline, ranging from extracting most available number of subgraphs having high enough density within a graph, to creating partitions of a given network in order to minimize interconnections between parts [23-24]. This characteristic of real networks is called community structure or community clustering [25-26].

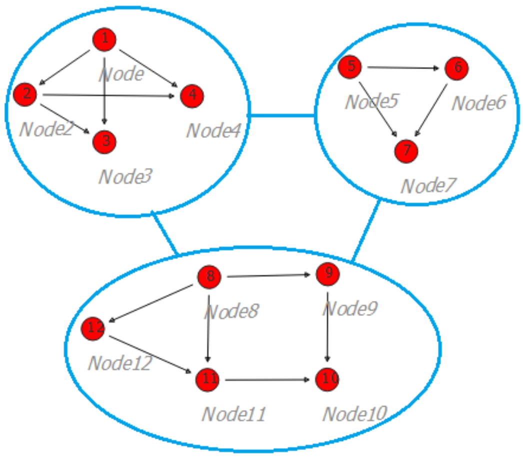

Figure 1. A simple graph with three communities, enclosed by the circles.

The goal of community detection is to partition the nodes of a given network with respect to the relationships among them, that is to create group of nodes within a given network that represent strongly linked sub-network from the entire network [20]. For the purpose of getting meaningful, usable, valuable and actionable information from complex networks, the community structure of the given network possess important information which is being mined through community detection mechanisms as is it now a dominant research areas due to the fact that many real-world problems can be depicted, formulated, and solved through graph and its analyses [25-26] and through community detection, the internal network organization of a given network is being uncovered and also, it foster proper understanding of the characteristics inherent to the dynamic processes peculiar to the network [3].

In order to mention but not overemphasize the importance of community detection and its mechanisms, in context of this paper, since community detection enable the detection of some group of nodes that possess highly dense intra-group connection, that implies that it functions by identifying the groups of criminals that highly interact with each other. In real-time investigation, the identification of communities will help to crack down influential criminals and their peculiar subordinates. This is among the reasons why community detection algorithms are being formulated, implemented, evaluated, and improved with respect to various participating disciplines such as computer science [3], sociology, statistical physic and even biology to mention a few [27-28].

In this paper, thorough and comprehensive review of community detection algorithms which are fundamental to graph analytics is being carried out. More so, more importance is being given to community detection algorithms that are being used for criminal network analysis as reviewed in the next section.

3. Community Detection Algorithms

The essence of detecting communities within a network had being discussed in previous section, thus, this section will provide an overview of community detection algorithms and their general categories More so, recently existing community detection algorithm is being reviewed in sub-section below.

Community detection algorithms exhibits some common characteristics such as being an iterative process that terminates based on one or two conditions, hierarchical partitioning of the network into modules which are usually depicted as dendrogram containing nested hierarchical modules, and also the output of any community detection algorithms is being accepted based on reasonable criteria (e.g. "optimal), although each community detection algorithms is formulated based on diverse definition, understanding and interpretation of what communities are with respect to various participating disciplines, and as such resulting into different computational method for detecting community through graph analysis [29].

With respect to the hierarchical nature of all community detection algorithm, the method of used in detecting community can either be agglomerative or divisive as revealed by [30]. Agglomerative method of clustering, also known as "bottom up" approach, initiate the partitioning of a network from a singleton (i.e. one single node) moving up the structural hierarchy present in the network and then merges other nodes causing, at each step, the merging of larger size of the graph until the whole graph or its components are being merging together. On the other hand, divisive clustering process – a "top down" approach, initiate the partitioning of a network by considering the complete network as a single module, and then recursively splits the root nodes as it moved down through the hierarchical structure present in the given network., i.e. it disassemble a complete network down to a single node [31-32].

3.1 Community Detection Methodologies Classification

This section, we present a classification of existing community detection and graph clustering methods based on their methodological principles. We have thoroughly reviewed popular community detection papers. Furthermore, in Section 4, we provide a review and discussion the algorithms particularly pertinent to their application on a social media and criminal network, depending on the underlying methodological principle as well as the adopted definition of community. We consider four broad classes of community detection and graph clustering methods: 4.1) Modular Based Algorithms, 4.2) Traditional Algorithms, 4.3) Dynamic Algorithms, 4.4) Random Walk Algorithm. Also, a useful listing of a popular community detection methods appears in Table 1.

According to [3], most community detection methodologies are broadly categorized as:
1) Local- community based method: an agglomerative approach for detecting communities based on the notion of k-cliques. 2) Betweenness-Centrality based method: it uses the divisive clustering process for finding communities, and lastly 3) Modularity method: an optimized method which was formulated based on quality function. In general, all develop community detection algorithms are formulated, implemented and even improved based on these highlighted methodologies.

In a broader view, as presented by [20], community detection algorithm can be -I- Division algorithms in hierarchy clustering methods, which separate into local parts, through eigenvalue of modularity matrix or edge clustering coefficient, a complete network. -ii-Direct Partitioning, whose functions by detecting disjoint communities from an entire network using a bottom-up approach. -iii- Label Propagation that make use of synchronous update strategy, in which nodes belongs to a group based on neighbours' choice i.e. local neighbourhood of a node is considered to recognize communities. -iv-Leadership expansion is the method of detecting communities based on local leader group as it is known that members are densely connected to some core nodes. -v-clique percolation which is based on the assumption that communities are formed by multiple adjacent cliques. -vi-Agglomeration hierarchical clustering, which builds hierarchical tree starting from small clusters to large clusters. -vii- Matrix Blocking methods construct ordered hierarchy tree and then extract subgraphs with much density as communities. And lastly, -viii- Skeleton clustering method simply find communities by using the skeleton of the given network when selecting densely connected clusters.

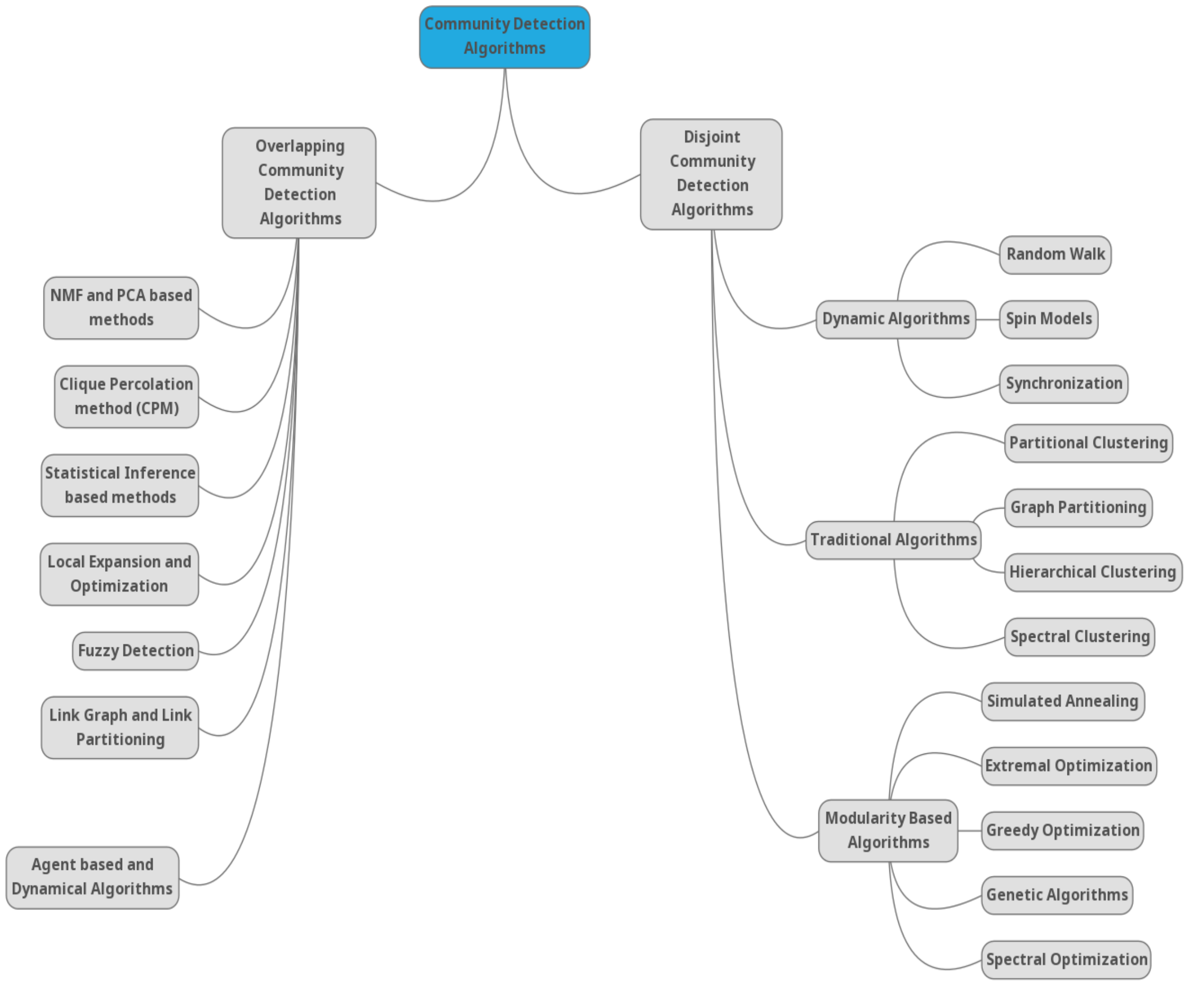

Figure 2. Taxonomy of Community Detection Algorithms adopted from [14].

4. Review of Community Detection Algorithms

As presented in Figure 2 above, a comprehensive taxonomy of community detection algorithm was adapted from [33-34] work which broadly categorized all community detection algorithms into two and later into sub-groups as depicted in the Figure 2.

In the subsections below, various community detection algorithms are being reviewed:

4.1 Modular Based Algorithms

A recent work carried out by [26] presented the detection of community through the usage of differential evolution algorithm (CDDEA) and considering modularity density as an optimization function. The performance of the developed algorithm was compared against traditional modularity-based algorithms having used the normalized mutual information (NMI) metric and was tested on both real world and synthetic network. On real world network, CDDEA had NMI value of 1 which indicated that the communities detected by this method are same as the real communities. This CDDEA performance was also replicated on synthetic network thus highlighted the strong prowess of this method in detecting communities within a network. In the study conducted by [30], the statistically significance of usable community detection algorithm which is based on modularity is been presented. Riding on the modularity function, in other to solve the problem of overfitting that plagues most methods based on modularity, the paper formulated an enhanced modularity function by adopting approach from statistical physics thereby treating modularity as the Hamiltonian of a spin system and thus, focused on its Gibbs distribution for discovering many high-modularity partitions rather than maximizing the modularity which discover just a single partition. Having developed and implemented this improved modularity function, its performance was evaluated against known methods (Louvain and OSLOM) and it outperformed both as it detected, more efficiently, hierarchical structures in real-world networks having recursively applied the algorithm until no statistically significantly subcommunities are found as seen in the paper's table of result. The study of [33] presented the implementation of variations of tractable fully Bayesian methods as used for a stochastic block model. The developed tractable method was able to solve cluster assignment problem and also best select the number of clusters. [35]. A full Bayesian method, that deals with model parameters and cluster assignment uncertainty, and Belief Propagation method, a method for posterior inference with retained correlation information among cluster assignments, were combined to develop the models in the study and was both implemented and evaluation on both dense and sparse graphs. After the experimentation of six methods as used in the study, on both real network and synthetic data, two algorithms, namely FIC+BP and F2AB, significantly outperformed the other four algorithms namely, cICL, VB, IRM, and FAB. Also, the method selected the smallest K value for all real dataset used except for "usaport" dataset. The major contribution of the study was improving FAB through the combinational usage of BP and this contribution resulted in a significant difference as the FIC+BP outperform the FAB algorithm on seven datasets out of eight used in the study. The best algorithm in the study had as major limitation of being inconsistent.

4.2 Traditional Algorithms

Another study carried out by [35], presented the usage of spectral clustering algorithm for finding communities within a sparse network. It was established that the standard usage of spectral algorithms for clustering and tentatively detection of communities within a network usually produced a suboptimal solution and it sometimes performed woefully by failing to detect communities when other methods detected communities for the given network. Thus, the research work presented an enhanced spectral clustering algorithm that performed excellently by detecting communities even down to known theoretical limit, thereby performed as good as other statistical inference method such as belief propagation methods, and outperformed traditional spectral clustering algorithm, even on sparse network. The key to the performance of this enhanced spectral method is the usage of nonbacktracking matrix (a matrix representing the walk on directed edges of a network having prohibited backtracking) of the network that maintained a strong separation between the bulk eigenvalues and the eigenvalues that hold strong information about the community structure of a network even if its sparse. The developed algorithm was implemented and evaluated, and also its performance was compared against classical operator such as normalized Laplacian and belief propagation method, and it resulted in performance as good as BP method and much more outstanding than traditional spectral clustering method. A parsimonious method for detecting communities in a typically large networks was presented by the research study carried out by [36]. The paper identified the common problem of stochastic block model solutions as the assumption of knowing the number of communities in advance which is quite opposite in practical sense. Thus, the paper presented a method of obtaining the previous unknown number of communities and also detecting communities accordingly, all from the data without any assumption The study thus implemented the minimum description length (MDL) principle to best-select the optimal model that fitted optimally on the given data (i.e. the model that produce a result containing the minimum information required to completely describe the data). The result obtained through MDL usage was then supplied to the implementation of Monte Carlo algorithm to enable safe detection of arbitrary communities that are available in a large network. This hybridized implementation resulted in to development of fully nonparametric analysis, as well as simple, efficient and unbiased analysis of large-scale properties present in a large network for which no assumptions are made (i.e. no a priori information) and also, the detection of communities from large network. Another community detection algorithm was presented by [37] demonstrated that there exists an exact equivalence between the method of modularity maximization (with an incorporated resolution parameter) and the method of maximum likelihood as being used on planted partition model. Among the contribution of this work is the exposure of the weakness inherent in modularity method in which it assumes all communities within a network have similar characteristics which often not the case in real-world networks, and the resolution parameter used in conjunction with the modularity maximization often takes the value of one (1) which is also not correct in most cases.

4.3 Dynamic Algorithms

Another contribution of this work is the provisioning of a derivation of more rigorous and principled modularity method. Also, the exact equivalence of maximum-likelihood and modularity methods strengthens the prowess of the algorithm of being a constituent method for detecting available communities without known bias. The maximum-likelihood and modularity maximization equivalence method were implemented on eight (8) network datasets, and its performance was up to per for six (6) datasets based on consensus, while its performance on the remaining two (2) network data was undetermined as there is exist no consensus on the number of communities available therein. The identification and tentatively evaluation of community structure in a given network was also carried out by [38] using methods that often not used in this area of research. It is known that most community detection algorithms are based on hierarchical clustering technique, however, most implemented clustering technique are agglomerative based. The research focused on using the divisive clustering technique in conjunction with other methods to detect communities from wide range of network (both real-world and synthetic) [39] and thus evaluated the performances of the developed community detection methods. Adopting the divisive method for clustering, the research method sought for edges within a network that are most "between" other nodes, rather than looking for the most-weakly connected node pairs as primitive for divisive clustering methods. In order to find most "between" edges among nodes, the research work implemented these betweenness measures: shortest-path betweenness, random-walk betweenness, and current-flow betweenness (based on elementary circuit theory and calculated using Kirchhoff's law), these methods were implemented on the some datasets, including : Zachary's karate club, collaboration network, dolphins network, Victor Hugo's Les Miserable, a computer-generated network with 128 vertices having 4 communities, network of webpage hyperlinks among many others. Overall, this study revealed the excellent prowess of divisive clustering method in detecting communities in a network as used with other methods. Detecting communities in a network in a scenario that the number of communities for that network is previously unknown seems to be a quite tedious tasks, as one will be unsure of the result of detected communities after using some appropriate methods. It is to proffering solution to this form of problem that [40] carried out a study for estimating the number of communities for a given network. The study adopted a mathematically principled approach in order to estimate the ideal number of communities [41-43] that are present in a given network through the usage of maximum-likelihood method. To demonstrate this, various networks were selected consisting both computer-generated network and real-world network, all with known community structure in order to properly evaluate the performance of the study's algorithm [45-47]. Results showed that the implemented maximum-likelihood method correctly inferred the number of communities available for each network data, thereby revealing the strength of the method for making safe inference of the number of communities that can be present in a previously unknown number of communities [48-49].

4.4 Random Walk Algorithm

A very interesting research was conducted by [48], unlike previously already works that was based on the hierarchical structure of network and some method based on modularity and or maximum-likelihood function for detecting communities, this work is based on using the information flow within a network to detect communities within the network. This information theoretic approach for discovering community can be applied on weighted and directed networks as the information flow within the network is centrally the core basis of this method. The method used in the study made use of probability flow of random walks on, representing the information flow of, a network after which the network is being decompose into module through the compression of the description of the probability flow, resulting into a map that simple highlights the regularities within the structure and their connectivity. Concisely, the study implemented random walk method to obtain the network representation – information flow, Huffman coding to describe the random walk on the network thereby created unique names for important structures which represents communities available in the given network. Originally, traditional community detection methods lay waste of the directions and weights of the links, which were core in the work of [48-53]. The implemented method was compared against modularity-based method and it performed distinctly different in some cases. With respect to the type of network being analysed, the method developed is most suited for network when the links represents flow or patterns of movement among vertices. Chen & Saad's work [54], as they referred to it, is the extraction of dense subgraph with respect to community detection in a network. Having established the problem as very challenging but really essential in the analyses of graph structures and complex network, the work revealed community detection has being similar to the problem of re-ordering matrices in sparse matrix techniques and thus exploited the concept and resulted in the method of identifying matrix column similarities. Using matrix blocking technique – the permutation of rows and columns of a sparse matrix in the way that non-zeros cells are moved towards the diagonal, the resulting matrix reveals diagonal blocks that are dense and sporadic non-zeros areas. Contextually, the dense block corresponds to dense subgraph i.e. communities available in the given network. This matrix blocking technique was implemented on several network datasets which are either directed or undirected or bipartite in nature – a showcase of the robustness of the study.

Table 1 below, we have organized the collection of facts from various sources, done a critical analysis and provided our findings, such as pros and cons of each popular algorithm, where conclusions can be drawn about the popular community detection algorithm from Table Where as the following table, Table 2 shows a Graphical Comparison of Community Detection Algorithm, together with the Graph based theories and name of algorithms.

Table 1 Popular Community Detection Algorithm

S/N	Reference	Community Detection Algorithm	Potential Implementation	Pros	Cons
1.	(Liu & Liu 2018) Reference [26]	Differential Evolution Algorithm based Modularity Density	X-ray reflectivity refinement Model selectiont and parameter estimation for protein-protein interaction Membrane Optimization	Outperformed traditional modularity algorithms in detecting better community partitions. It has a tunable parameter that determines the rate and quality of detecting communities.	It has a mixing parameter (μ) which if increased continually, detection of communities becomes more difficult for CDDEA.
2.	(Zhang & Moore 2014) Reference [30]	Improved Modularity algorithm by treating modularity as the Hamiltonian of a spin system (based on statistical physics).	Checking for completeness in community structure System-environment (thermodynamics) Subgraph identification problem	Sought consensus of many high-modularity partitions rather than maximizing modularity. Statistically significant and does not overfits. Provide method to determine number of hierarchies of (sub) communities or groups. It detects both top-level communities and subcommunities which are deeper in hierarchy	Based on our assumption, high-modularity partitions may not detect vastly different characteristics
3.	(Hayashi & Kawamoto 2015) Reference [33]	Factorized asymptotic Bayesian (FAB) inference with Belief Propagation (BP).	Detection of genetics polymorphism Asymptotic Marginal Likelihood	Consistent results over sparse and dense graph. Automatic selection of K-value, and it maintains equal prediction accuracy with more complex models. No hyperparameters	One of the implemented algorithms – (F^2AB) lack consistency due to use of Belief Propagation.
4.	(Krzakala et al. 2013) Reference [35]	Enhanced Spectral Clustering algorithm based on nonbacktracking walk	Evaluating overfit and underfit in models of network community structure Presence of errors in learning communities Social Recommendation System	Encoding of sparse data using a "nonbacktracking" matrix. Enhanced spectral algorithm for solving data clustering problem given a sparse network. Development of an asymptotically optimal method that can detect communities all the way down to the detectability transition	Based on our assumption, Enhanced Spectral Clustering algorithm might detect many false positive communities due to its asymptotically optimal method that can detect communities all the way down to the detectability transition
5.	(Peixoto 2013) Reference [36]	Minimum Description length (MDL) principle, multilevel Monte Carlo algorithm	Self-organizing kernel Information Fusion Face Identification Neural network prediction and decision policy	Ability to detect reasonable communities in a large network. Produced an unbiased, simple, efficient and fully nonparametric analysis of large-scale characteristics of large networks Provision of general bounds on the detectability of arbitrary block structure from empirical data	Based on our assumption, MDL principle may not perform as good as it does on a large dataset, compared on a small dataset due to the nonparametric analysis.
6.	(Newman 2016) Reference [37]	Modularity optimization and maximum likelihood equivalence	Kernel optimization Maximum likelihood in statistical estimation Estimation time of decomposition	Exposed some hidden assumptions and limitations of the modularity method. Modularity maximization is less nonlinear than maximum-likelihood method Modularity maximization is a consistent method for detecting communities	Modularity maximization method assumes all communities to have statistically similar characteristics The resolution parameter is undetermined, often takes the value 1, but it is not correct. This method is applicable only when the resolution parameter value is correct.

7.	(Newman & Girvan 2004) Reference [38]	Divisive clustering technique, shortest-part betweenness, random-walk betweenness, current-flow betweenness	Resistance distance Electrical, current flow betweenness Information flow analysis (protein)	Intrinsic “recalculation step” for edge betweenness after initial removal of high-scoring edges Ability to extract communities from both real-word and artificially generated networks. It can be also be used for analyzing complex network.	High computational cost
8.	(Newman & Reinert 2016) Reference [40]	Maximum-likelihood	Phylogenetic analysis for maximum likelihood Reconstruction for emission tomography Assessing the performance of PhyML 3.0 and newer versions Estimation of population growth rates based on the coalescent	Excellent strength in estimating the number of communities in a network Applied and evaluated on real-world network	Requires scaling up in order to analyze network data with thousands of vertices.
9	(Rosvall & Bergstrom 2008) Reference [48]	Probability flow of random walks, compression of information flow on network	Discovering the geographical borders Vertex centralities in input-output networks Distributed community detection	Detecting communities in a weighted and directed networks Flow-based approach to community detection	Can only be used on directed and weighted graph Best suited to analyze network where links represents a flow or pattern of movement
10	(Chen & Saad n.d.) Reference [51]	Matrix Blocking	Light blocking and cell spacing for liquid crystal matrix displays Blocking of anti-bodies Specific inhibitory protein blocking / pathway improvement	Does not require number of cluster specification Lower computation cost Does not require clustering of the whole nodes in a network – all nodes do not participate in its algorithmic computation. Can be implemented on directed, undirected, and or bipartite graph	To terminate recursions, the method set a minimum density threshold which in exceptional case may result in singletons

Table 2. Graphical Comparison of Community Detection Algorithm

Name of algorithm / Features/Graph Based Theories	Differential Evolution Algorithm based Modularity Density	Improved Modularity algorithm by treating modularity as the Hamiltonian of a spin system (based on statistical physics).	Factorized asymptotic Bayesian (FAB) inference with Belief Propagation (BP).	Enhanced Spectral Clustering algorithm based on nonbacktracking walk	Minimum Description length (MDL) principle, multilevel Monte Carlo algorithm	Modularity optimization and maximum likelihood equivalence	Divisive clustering technique, shortest-part betweenness, random-walk betweenness, current-flow betweenness	Maximum-likelihood	Probability flow of random walks, compression of information flow on network	Matrix Blocking
High-modularity partitions	✓									
Maximizing modularity		✓	✓	✓		✓		✓		
Tuneable parameter	✓									
Able to determine number of (sub) communities	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
No hyperparameters							✓			
Has an unbiased, simple, efficient and fully nonparametric analysis	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Maintains equal prediction accuracy		✓	✓	✓	✓		✓			
Recalculation step						✓				
Lower computation cost	✓	✓	✓		✓			✓		

5. Community Detection in Criminal Network

In this section, a strict review of studies carried out to detect communities in a typical criminal network is being reviewed, having conducted a search of literatures within the range of 2010 – 2019, as depicted in Figure 2 below.

Detection of communities in a criminal network was carried out by [55], and focused was placed on analysis the network data of an organized criminal network that involve in the case of money laundering. As of the year of the study, the author reported that there is no existence of literature for detection of money laundering through the usage of graph-based detection methods. Having selected the “Enrol email database” as the dataset for the study, the author developed a novel method for community detection named shortest paths network search algorithm (SPNSA). SPNSA was used to detect communities among money launderers. In order to detect communities, the author validated SPNSA in three distinct scenario, the first being when the criminals are known by the investigator, the second scenario being when the investigator is unable to detect one of the criminals involved and lastly, the third scenario represent when the investigator have no prior knowledge about the criminal and he/she is at the beginning stage and adequately suspects that there is an ongoing occurrence of crime. At all scenarios highlighted in the study, SPNSA extracted communities are sparse and can be easily subjected to further investigation as reported by the study. More so, it was able to extract communities with at least four criminals in the scenario when no criminal is previously identified. Conclusively, the strength of this method for detecting criminal communities lies in the fact that detected communities are small and sparse unlike traditional community detection algorithms or k-Neighborhood approach that do result in the extract of communities that are quite dense and complex.

The study conducted by [56] focused on detecting communities in a drug trafficking network. It was established in their paper that identifying of communities within a criminal network enable disrupting operations within the network and to detect communities is more difficult in a criminal network than any other social network as criminal links are usually covert i.e. intentionally hidden by members to reduce exposure of law enforcement agents, and dense toward few nodes. Thus, the first approach implemented in the paper was to augment edge within the network before carrying out community detection activities. Through edge augmentation, the author reported the network was restored having tested the link augmentation method before its final implementation. The data used in the study were Caviar and Ndrangheta (Stupor Mundi and Chalonero), and both Louvain and SpeakEasy algorithms were used to detect communities. The experiment resulted in more stable detection of communities with SpeakEasy algorithm while the Louvain algorithm detected unstable communities. Network augmentation also help in the appropriate assignment of high degree nodes into communities. By and large, edge augmentation was carried out to restore the network before the actual detection of communities within the real-life criminal network.

Another study carried out by [57] revealed the importance of detecting criminal groups. It espoused on the availability of rich data sources which hold both unstructured and structured data form and the capacity of fussing these multiple heterogeneous datasets into one, as be done by intelligence and law enforcement agencies. It is to efficient usage of these rich data about criminal activities that the research was based on, mainly to extract minimal overlapping contextual communities purposefully for maximum disruption of crime or terrorism or criminal network. The research work developed “GraphExtract” – an intelligence and investigative process algorithm, which make use of sparse, variable, and low on details data to make proactive detection of atomic instances of crime. “GraphExtract” is a novel graph-mining solution takes uses multi-modal graph, labels each node with respect to the role played, and also labels edges as non-trust or trust, within the criminal network. “GraphExtract” at first level detect fragment of criminals and or functional groups of criminals that are profit-driven, at second level it depicts the detected functional group as a complete criminal network. And at third level, expressive data representation are created for evidence-based decision-making.

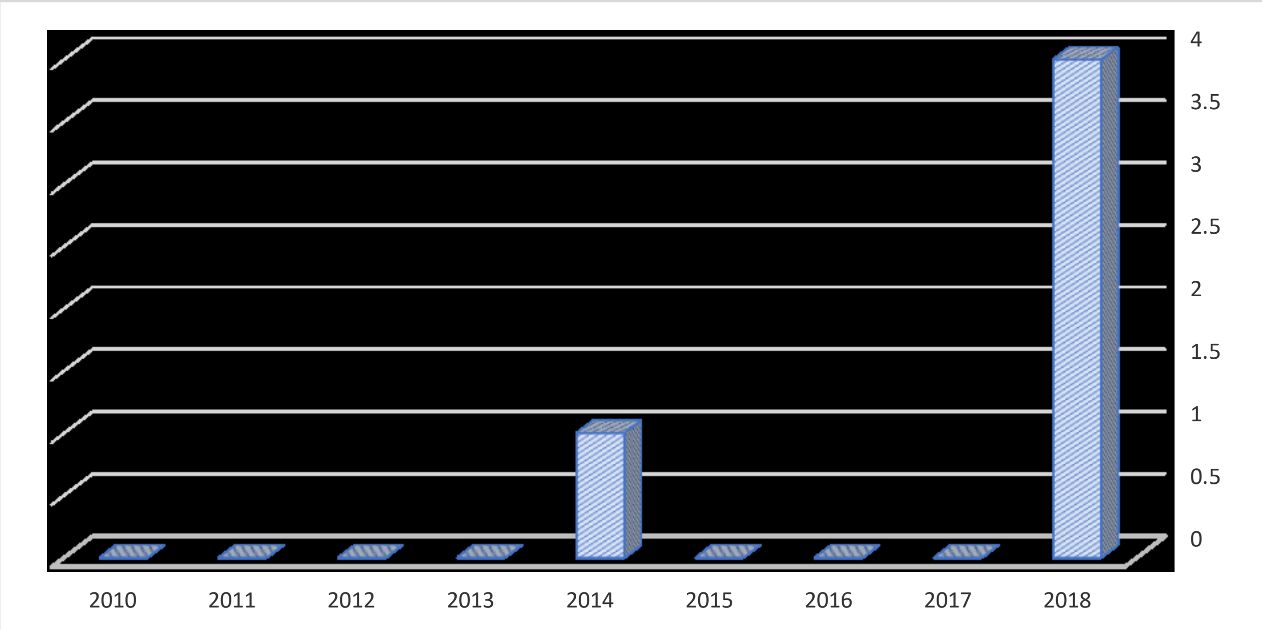

Figure 3. Timeline of literature on community's detection in a criminal network within the range 2010-2018

Figure 3 represents the research done by Calderoni et al [58] in the year 2014, and in 2018, Magalingam et al [52], Bahulkar et al [53], Robinson et al [54] ,Junjing at al [55], where they have used network graph analysis for community detection to identify clusters or communities from a covert dataset, these work proven its value in refining criminological concepts and theories to aid the understanding of social processes behind crime problems and to assist law enforcement agencies in enforcing crime. However, the Figure 3 above shows the gap identifies the less number of research done for the past decade.

Criminal network is made up of a series of association and not always isolated nodes and the application of community detection on criminal network is important for mining criminal gangs within the network [55]. The work further buttressed the fact that clustering method are being mostly used for community detection and that the better quality of the clustering method used, the better the detected communities with the network. With the aim of detecting suspect's society, reduce inspection targets, determine close suspects, and provisioning of intelligence decision support, the study presented a method based on nearest neighborhood shortest distance clustering technique used in conjunction with modularity function only when there exists a tie in distance between a node and two cluster centers. [56] This method for finding communities was implemented on communication records of criminal gangs made through telephone call in order to detect close links to suspected criminals for the identification of crime accomplices. The implementation resulted in creation of clusters with each cluster representing a community. More so, each community has varying node centrality resulting into varying size of node, as node with large centrality formed up small shape while node with small centrality formed up large shape. The level of centrality signifies the importance of the node in the network; thus, preference is given to nodes with large centrality. [57-61]

A case study of communities in criminal networks was carried out by [5] in which community analysis of Ndrangheta dataset was carried out. The dataset represents criminals' co-participation in meetings, drawn from "Operazione Infinito" that tacked a Calabria mafia organization. The study emphasized the clustered nature of criminal network as well as the associations of communities with criminal network. It further revealed that criminal network structure can be exist as ethnic, functional, or hierarchical units and also, this type of network are usually locally clustered but globally sparse network. [62-66] In the study, the Louvain method for community detection was used and it resulted in the detection of seven (7) clusters [67]. It was reported that all clusters are strongly cohesive, ranging from small or medium-large. It is noteworthy to mention that the criminal dataset used possess weighted nodes and it is a typical undirected network. [68-71]

We have organized the collection of facts which is closely related to our area of research, which is criminal communities' detection. in Table 3 below. A critical analysis has been done and represented facts such as dataset used, the strengths, and the limitation and future work is represented in Table 3

Table 3. Review of Related Literatures on Criminal Communities Detection

S/N	Reference	Community Detection Method Used	Potential Implementation	Strengths	Limitation and Future Work	Dataset
1.	(Calderoni, Piccardi & Milano 2014) Reference [58]	Max-Modularity (Louvain method)	Positive Programming Possibility Computations Spanning tree based community detection	Detected communities closely similar to known criminal gang 90% precision in node classification	Deeper structural analysis is required to assess if unique structural attributes are recurrent	Ndrangheta
2.	(Magalingam, Davis & Rao 2018) Reference [52]	Shortest paths network search algorithm (SPNSA), and network centrality measure	Shortest network paths Modelling pathway of diseases/cures Ranking importance level	Outperformed *k*-neighborhood detection method. Applicable to one-to-one or one-to-many relationships Allow feeding in of early suspects or suspicious entity Reveals abnormalities within communities Extracted communities are small and sparse, easy to understand and probe further.	No future work or limitation was highlighted	Enron Email (Money Laundering)
3.	(Bahulkar et al. 2018) Reference [53]	Louvain, SpeakEasy	Edges augmentation Mapping the human brain's cortical-subcortical People search	Augmentation of covert links to facilitate network restoration Stable networks were detected	Investigation of methods for edge augmentation based on the position and roles of entities.	Caviar, Ndrangheta gang datasets (Chalonero and Stupor Mundi)
4.	(Robinson & Scogings 2018) Reference [54]	GraphExtract	Analyzing Architechtures Network Topology Modelling Topic Propagation Using Percolation Theory	A generic tool for mining intelligence and executing investigative process on criminal network, based on graph-mining technique.	Adoption of classification approach to improve "entities of interest" identification Improvement of Subgraph extraction algorithm	Criminal intelligence data, suspicious transactions, sanctions data, offshore leaks database, national companies register
5,	(Junjing 2018) Reference [55]	Nearest neighbor hierarchical clustering method based on shortest distance core mining method, modularity function	Detecting Community Structure in Complex Networks Enterprise business intelligence system Graph Partioning	Threshold to control the size of the community or automatic size selection. Community detection can be performed on weighted and undirected social network Uses modularity function to break ties when two node has equal distance value to two clusters.	No future work or limitation was highlighted	Criminal suspects communication data.

6. Developing ideas to reduce the problems

It was established in the papers we reviewed above have shown strong evidence that identifying of communities within a criminal network that will enable disrupting operations within the network and to detect communities is more difficult in a criminal network than any other social network as criminal links are usually covert i.e. intentionally hidden by members to reduce exposure of law enforcement agents. By carefully reading the pros and cons listed above a researcher with enough knowledge in this domain will be able to use his critical thinking skills to use one or more of the algorithms to come up with a insight. On the other hand, our team is coming up with a new method and developing a new algorithm that can be used to detect communities within a criminal network. The method we are about to deploy will differ from the traditional method by allowing law enforcement agencies to be able to compare the detected communities and thereby be able to assume a different viewpoint of the criminal network. We will consider and come up with a method as an alternative or an addition to the traditional community detection methods mentioned earlier as it allows, and assists in, the detection of different patterns and structures of the same community by enforcement agencies and researches.

8. Conclusion

This paper presented a comprehensive review of community detection algorithms and to highlight the strength and limitation of these algorithms. Community detection were vividly discussed and the essence of detecting communities within a graphically represented network was established. Also, the broad categorization of community detection algorithms was discussed as well as the foundational method for mostly used community detection algorithm was mentioned.

As a result of this, popularly used community detection algorithms, as used for various type of social network, were discussed in text and summarized in table, after which strict review of community detection analysis in criminal network was carried out in order to know the extent at which research is being carried out in this area as well as identify major researcher gap that are available and also, to see if major advancement can be made on existing method of community detection algorithm, particularly for criminal networks. As revealed through the detailed review of the community detection analysis for criminal network and found rare researches in this domain. This rises a high demand to further explore this research area in several aspect, and specifically on community detection using graph analysis for criminal network. This will help to address the current era issue raised by the available researchers.

Future work

More on these findings, we are working to develop a wide range community detection algorithm which may address these raised issues.

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