A Graph Analytic Approach To Estimate The UserRisk Factor During Pandemic *

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I. Abstract :

***Abstract*—Pandemics are large-scale outbreaks of infectious diseases that can greatly increase the mortality rate over a wide geographic area and cause significant disturbance and loss economically, socially, and politically.**

The growth of epidemics such as COVID-19, 2020, the Asian Flu that began in East Asia in 1957, the Spanish flu 1918 due to the HINI virus, flu pandemic in 1968, which has hampered a large population of human life. Therefore, it is necessary to control the epidemic spreading in society. Only the Govt. initiative is not sufficient to control the epidemic spreading in a network. We only can control this pandemic with the help of individual person level.

In this project, our aim is to develop a framework that provides an interface for the users to see their epidemic risk factors and also pandemic-related information. In addition, we are going to develop an algorithm for estimating the risk factor of each user using social network theory.

Important features of the proposed framework:

- **Human Contact tracing using smart-phone's Bluetooth or WIFI .**
- **Indicates your health / risk status.**
- **Showcase Pandemic updates.**
- **Consists a list of helpline numbers.**
- **Notification Update.**

A. Keywords:

Complex networks , Degree Centrality measure , Graph Theory, Nodes and Edges Calculation.

II. Introduction

According to WHO, the occurrence in a community or region of cases of illness, specific health-related behavior, or other health-related events is clearly in excess of normal expectancy. The community or region and the period in which the cases occur are specified precisely. The number of cases indicating the presence of an epidemic varies according to the agent, size, and type of population exposed, previous experience or lack of exposure to the disease, and time and place of occurrence.The prediction of the future developments of a natural phenomenon is one of the main goals of science, but it remains always a great challenge when dealing with an epidemic.

This proved to be particularly true in the case of the COVID-19 global pandemic that the world is suffering since January 2020.Since then India has ridden out a host of lesser epidemics, from cholera to chikungunya, from the "Asian flu" of 1957 to the swine flu of 2009, without mortality on anything like 1918's apocalyptic scale.1915 - 1926: Encephalitis Lethargic is also known as lethargic encephalitis. It was an epidemic that spread around the world between 1915 - 1926. Encephalitis lethargic was an acute contagious disease where the virus attacked the central nervous system of human beings. The main characteristics of this disease were increasing languor, apathy, drowsiness, and lethargy.1961 - 1975: Cholera pandemic Since 1817, Vi brio Cholera (a type of bacteria) caused seven cholera pandemics globally. Within a time period of 5 years, this virus spread in parts of Asia from where it reached Bangladesh and India. The poor water sanitation practices in Kolkata made the city epicenter of the Cholera pandemic in India.1974: Smallpox Epidemic Smallpox was caused by either of the two virus variants: Various major or

Various minor. [1]

There are at least 26 mobile Apps for surveillance of epidemics, mostly free of charge and mostly for lay people. Among them,Health Map is the most comprehensive,but by far the greatest number of downloads war for a consumer App,Sick weather. Some Apps can provide real-time tracking and interactive maps.However, limitations included unavailability of Apps suitable for general public or surveillance of potential bio terrorism incidents limited geographic or disease relevance, and high cost for some Apps.

There is great potential to utilize existing Apps and develop new ones, especially which meet the needs of heath professionals and public heath authorities for real time disease surveillance. A review of Google play and the App store was conducted from June 2019 to August 2018 for Apps containing the words "epidemic", "outbreak","pandemic","public health ","infections diseases".,"bio terrorism" or "CBRNE"Surveillance".Available Apps were analyses by the intended user ,purpose , platform, functions and number of downloads some important apps in Epidemic are Arogyasetu App, Aaykar setu app, and others Epidemic simulator's. [2]

For same problem solving in epidemic we implement our App "Risk Factor Analyzer" which Analyzed the risk of a user by proposed method(Total weight of a node * Total Degree of a node) in composite graph.In this app,we contact traced by a Bluetooth device and getting this data ,Graph is generated.Appealing our proposed method in graph we get the risk factor of any user and know the status of risk (High or Low Risk). Our goal in this project is to provide a platform that gives people access to information about pandemics as well as their own epidemic risk factors. We will also use social network theory to create an algorithm for calculating each user's risk factor.Some important features of our App are :Human contact tracking using Bluetooth or WiFi on a smartphone. Indicates your risk and health status. Presenting pandemic updates,Nearby Hospital sources and Helpline benefit's.

III. Related Works/Literature Survey

IV. Weighted Networks Graph :

In many of the real time systems , the interactions between the nodes are not usually merely binary entities. To describe those relations we need to use weighted networks graph representation in the above networks . By **G(V, E)** we are representing an weighted in an undirected network, where **V** and **E** are the sets of nodes and there weightededges, respectively. Here the weight networks associated with a link quantifies the strength of the interaction between the two nodes and there edges. Representative weighted networks identifying the dense area network location , where the weight between two person is identifying by the numbers of most influential person by the disease on the basic of Degree Centrality Method , the scientific collaboration network where the weights are the numbers of coauthored papers, the neural network where the weights are the strengths of the interactions between the influential person.

Degree centrality is one of the easiest to calculate. The degree centrality of a node is simply its degree—the number of edges it has. The higher the degree, the more central the node is. This can be an effective measure, since many nodes with high degrees also have high centrality by other measures.

A. *Methods of Weighted Centralities :*

- **Weighted coreness:**

The k-core, a kind of structure of a graphs networks, this is a maximal connected subgraph's with the minimum degree greater than or equal to k .The maximum k such that a k-core contains u .

$$k(i) = \sum_{j=1}^{k} a_{ji} \tag{1}$$

The K value of u k-core, edge-weighted graph, core maintenance algorithm, hierarchical process. Most contemporary methods used to identify various influential spreaders are designed for unweighted networks and as the rapid development of communication equipment and Internet, tel-medicine has become a convenient way for the public to obtain valuable information and health consultation.

We found a total of 106 Apps in an initial search, and of those 80 Apps did not meet the selection criteria and were excluded.Finally, this study includes 26 pertinent surveillance Apps, including 21 free and 5 premium Apps. 17 of these apps are for tracking a single disease, 7 are for tracking many diseases, and 2 are for learning about potential bio terrorism agents.App likes Health Map , .Arogya setu app,Corona Kovach and etc . These ara some Example of some of Application's as below ,

B. *Health Map:*

Mani-pal Health Map started in 2015, is the diagnostics arm of Mani-pal Group, which is one of the largest and most ethical healthcare institutions of India.Health Map is a freely accessible, automated electronic information system for monitoring, organizing, and visualizing reports of global disease outbreaks according to geography, time, and infectious disease agent,

C. *Arogya setu app :*

Arogya Setu : (translation from Sanskrit: the bridge to health) is an Indian COVID-19 "contact tracing, syndrome mapping and self-assessment" digital service, primarily a mobile app, developed by the National Informatics Centre under the Ministry of Electronics and Information Technology . The app reached more than 100 million installs in 40 days. On 26 May, amid growing privacy and security concerns, the source code of the app was made public.

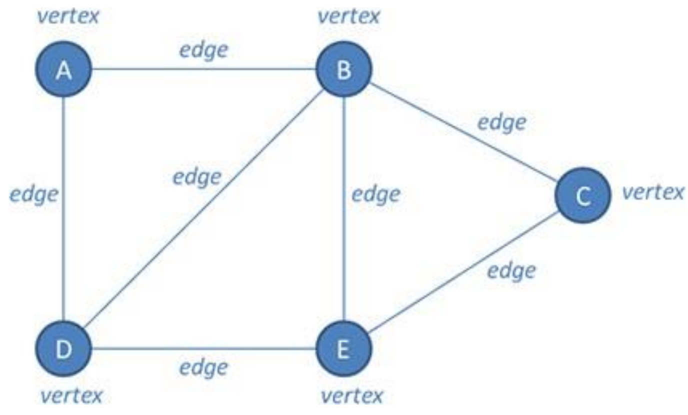

Fig. 1. Nodes and edges

D. Corona Kovach :

Released by the Union ministry of electronics and information technology in association with the ministry of health and family welfare, Corona Kavach is available on Google Play store. The highlight of the app is that it gives a real-time location of corona virus infected people. The app also keeps you updated about real-time cases, information, death cases and cured cases.

The composite graph is a node-weighted undirected graph associated with a given combinatorial optimization problem posed as a weighted constraint satisfaction problem. All the graphs considered are undirected connected simple graphs with order n and size m. Let u, v, w V(G). A composite labelling is a objective function f: (V(G) E(G)) → 1, 2, 3, ..., m + n, such that gcd(f(uv), f(vw)) = 1. A graph that admits composite labeling is known as a composite graph. We investigate composite labeling for some families of graphs and obtain certain labeling bounds for composite graphs.

V. Experimental Method/Procedure/Design :

Our project is mainly based on Graph Theory. We used many Graph properties in this project .In the method part we discuss the different types of Graphs and their Properties. a graph theory is the study of graphs, which are mathematical structures used to model pairwise relations between objects.A graph in this context is made up of vertices (also called nodes or points) which are connected by edges (also called links or lines).Brief discussion below :

A graph is a data structure that is defined by two components :

- A node or a vertex.
- An edge E or ordered pair is a connection between two nodes u,v that is identified by unique pair(u,v). The pair (u,v) is ordered because (u,v) is not same as (v,u) in case of directed graph.The edge may have a weight or is set to one in case of unweighted graph.

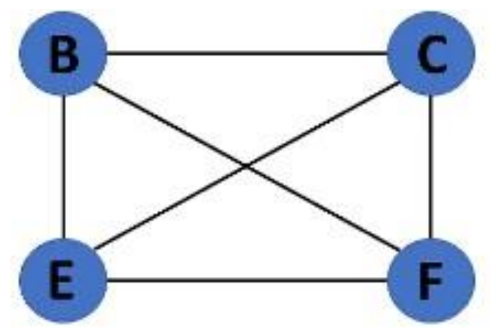

Fig. 2. Simple Graph

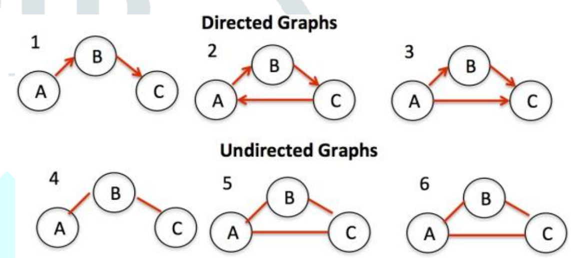

Fig. 3. Directed Graph and Undirected Graph

A. Different types of graphs which used in our Project:

1) Simple graph :: is a graph that does not contain more than one edge between the pair of vertices. A simple railway track connecting different cities is an example of a simple graph these refer a fig:3.1,as below. [3]

2) Directed Graph and Undirected Graphs:: Directed Graphs: A graph in which edges have a direction, i.e., the edges have arrows indicating the direction of traversal. Example: A web page graph where links between pages are directional refer a fig:3.2,as below ,

A graph in which edges have no direction, i.e., the edges do not have arrows indicating the direction of traversal. Example: A social network graph where friendships are not directional these refer a fig:3.2,as below..

3) Weighted Graphs:: A graph in which edges have weights or costs associated with them. Example: A road network graph where the weights can represent the distance between two cities these refer a fig:3.3,as below. [5]

4) Unweighted Graphs:: A graph in which edges have no weights or costs associated with them. Example: A social network graph where the edges represent friendships fig:3.4,as below.

5) Multi Graph:: Any graph which contains some parallel edges but doesn't contain any self-loop is called a multi graph. For example a Road Map. Parallel Edges: If two vertices are

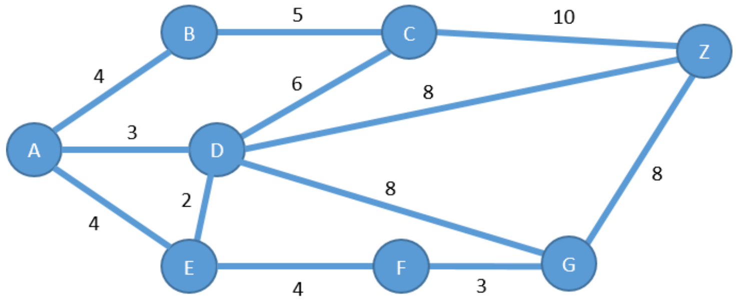

Fig. 4. Weighted Graph

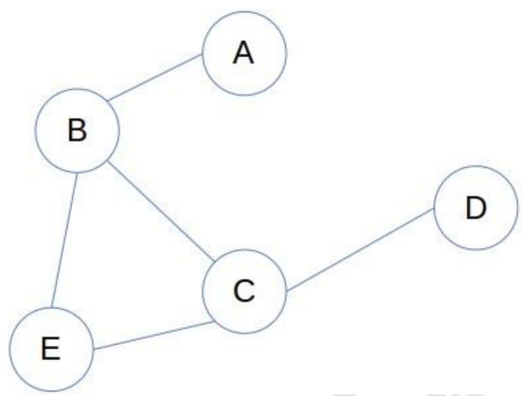

Fig. 5. Unweighted Graph

connected with more than one edge then such edges are called parallel edges that are many routes but one destination. Loop: An edge of a graph that starts from a vertex and ends at the same vertex is called a loop or a self-loop fig:3.5,refers as below.

6) Contact tracing Graph:: Contact tracing is the process of identifying persons who may have been exposed to an infected person ("contacts") and subsequent collection of

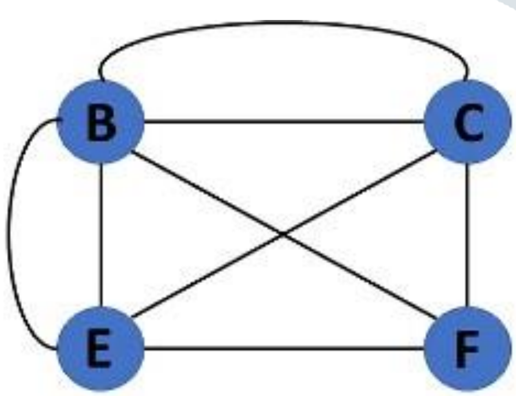

Fig. 6. Multi Graph

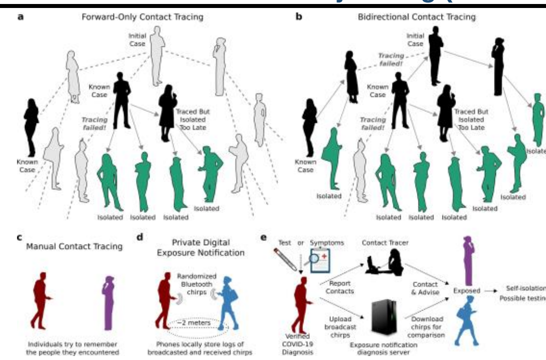

Fig. 7. Contact tracing Graph

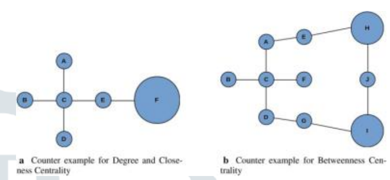

Fig. 8. Weight Centrality Graph :

further data to assess transmission.By tracing the contacts of infected individuals, testing them for infection, and isolating or treating the infected, this public health tool aims to reduce infections in the population.In addition to infection control, contact tracing serves as a means to identify high-risk and medically vulnerable populations who might be exposed to infection and facilitate appropriate medical care.In doing so, public health officials utilize contact tracing to conduct disease surveillance and prevent outbreaks.

7) Centrality : : Centrality measures have been proved to be a salient computational science tool for analyzing networks in the last two to three decades aiding many problems in the domain of computer science, Weighted centrality measures usually consider weights on the edges and assume the weights on the nodes to be uniform. One of the main reasons for this assumption is the hardness and challenges in mapping the nodes to their corresponding weights. while considering the weights on the nodes, there can be two possible extensions of the unweighted and edge-weighted centrality measures: Node-weighted centrality measures: consider only the node weights for the analysis while taking all edge weights as one.

8) Degree Centrality :: In an undirected simple network G(V, E) with V and E being the set of nodes and set of links respectively, the degree of a node vi, denoted as ki, is defined as the number of directly connected neighbors of vi. Mathematically, ki =Pjaij , where A = aij is the adjacency matrix, that is, aij = 1 if vi and vj are connected and 0 otherwise. Degree centrality is the simplest index to identify nodes' influences: the more connections a node has, the greater the influence of the node gets. [4]

Important Code and Out put: Simple Graph: import networkx as nx import numpy as np import matplotlib.pyplot as plt

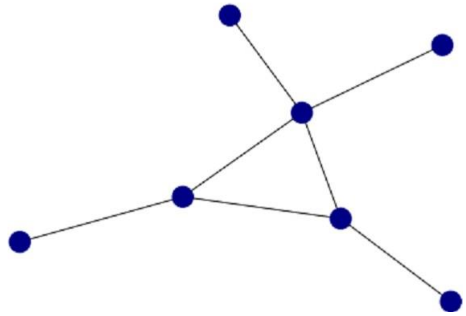

Fig. 9. Caption

G = nx.Graph() G.add_edges_from([(2, 1), (1, 3), (1, 4), (1, 5), (4, 5) 'A' : 1.0, 'D' : 0.5714285714285714, 'H' : 0.0values = [val_map.get(node, 0.25)fornodeinG.nodes()]nx.draw(G, cmap = plt.get_cmap('jet'), node_color = values)plt.show()

9) Weighted Graph ::

B. Weighted Graph :

import matplotlib.pyplot as plt import networkx as nx

G = nx.Graph() G.add_edge("a", "b", weight = 0.6)G.add_edge("a", "c", weight = 0.2)G.add_edge("c", "d", weight = 0.1)G.add_edge("c", "e", weight = 0.7)G.add_edge("c", "f", weight = 0.9)G.add_edge("a", "d", weight = 0.3)elarge = [(u, v)for(u, v, d)inG.edges(data = True)ifd["weight"] > 0.5]esmall = [(u, v)for(u, v, d)inG.edges(data = True)ifd["weight"] <= 0.5]pos = nx.spring_layout(G, seed = 7)positionsforallnodes − seedforreproducibilitynodesnx.draw_networkx_nodes(G, pos, node_size = 700)edgesnx.draw_networkx_edges(G, pos, edgelist = elarge, width = 6)nx.draw_networkx_edges(G, pos, edgelist = esmall, width = 6, alpha = 0.5, edge_color = "b", style = "dashed")nodelabelsnx.draw_networkx_labels(G, pos, font_size = 20, font_family = "sans − serif")edgeweightlabelsedge_labels = nx.get_edge_attributes(G, "weight")nx.draw_networkx_edge_labels(G, pos, edge_labels)ax = plt.gca()ax.margins(0.08)plt.axis("off")plt.tight_layout()plt.show()Result:ProposedWork/Method :

VI. Proposed Work:

In this Project,We mainly focused on the weighted graph and their degree and weight of each node and how each node is connected with other .Our proposed work based on the Graph Theory. Lets Discuss : Here ,we see a weighted Graph and its Nodes are “a,b,c,d,e,f”.Each node have their own Degree .The degree of a node is the number of connections that it has to other nodes in the graph.Each node have their weight . The weight of a node is the sum of the weights of the edges connected to the node.”a” is a node of this graph and its degree is “3” because its connected three nodes by edges. And its weight respectively for “d”,”c”,”b” are “0.3”,”0.2” and “0.6”.so “a” node total weight is (0.3+0.2+0.6)= 1.1 .Like this ,”b” node

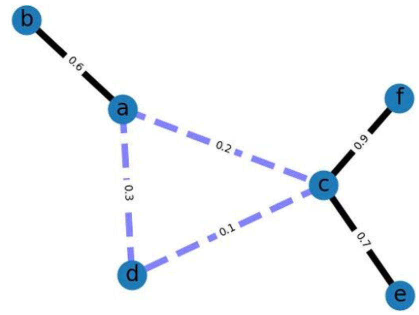

Fig. 11. Weighted Graph representation for proposed method :

Method of Risk Factor in pandemic Calculator

= Total Degree of a Node * Total Weight of a Node

Fig. 12. Caption

total weight is “0.6” and total degree is “1” . ”c” node total weight is “1.9” and total degree is “4” . ”d” node total weight is “0.4” and total degree is “2 . ”e” node total weight is “0.7” and total degree is “1” . ”f” node total weight is “0.9” and total degree is “1” . we get all nodes weight and degree now calculate the risk factor in Pandemic.Our propose method is based on the nodes total weight and total degree.This method calculated the risk factor of any user in Pandemic. Proposed Method is: Based on Our proposed method ,here we calculate node “a”’s risk factor = “a”;s total degree * “a”’s total weight = 3*1.1 =3.3. After get the value by this method we normalized the each of value upon max value. In this project,we consider a Range which help to know how much Risk are User in.The Range is 0.5 .After Calculation and Normalization all the risk factor .Which value of Risk Factor is Greater than or equal to 0.5 ,these user are in High Risk and Which value of Risk Factor is Less than 0.5 they are in Low Risk.

VII. Results and Discussions

Here we Discuss our Result part which we get based on our Proposed Method .

Now, We get an example and discuss main points of Example-1 : Above In this weighted graph,we see the five nodes and each node is a user (Preti,Arnab,Akash,Kaushik,Mozamil) and each nodes are connected to each other by edges.Distance between every

Normalization value of Risk Factor < 0.5 (Low Risk)

Normalization value of Risk Factor > =0.5 (High Risk)

Fig. 13. Caption

Our Proposed Method is = Total Degree of a Node * Total Weight of a Node

Fig. 14. Caption

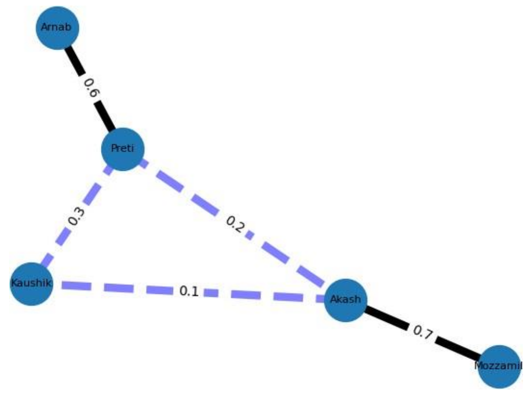

Fig. 15. Result Example Graph 1

User Name	Method of Risk Factor in pandemic Calculator(**= total degree of a node * total weight of this node)**	Risk Factor(From Proposed method)	Normalization the risk factor **(Risk factor/Max Risk Factor)**	How much User in Risk
Preti	3*0.6	1.8	1.8/3=0.6	High Risk
Arnab	1*0.6	0.6	0.6/3=0.2	Low Risk
Kaushik	2*0.4	0.8	0.8/3=0.26	Low Risk
Akash	3*1.0	3	3/3=1	High Risk
Mozzamil	1*0.7	0.7	0.7/3=0.23	Low Risk

Fig. 16. Caption

nodes is called nodes weight and a nodes connect how many edges this is called their degree.Like a example,here “Preti” is a node and connect with other three other nodes(“Kaushik”,”Akash”,”Arnab”).so “Preti” node’s total degree is 3 and “ Preti” node’s weight respect to “Kaushik “ node is “0.3” same as with “Arnab” node weight is “0.1” and “Akash” node’s weight is “0.2” so “Preti “ node total weight is (0.3+0.2+0.1=0.6). [6]

Now We Calculate the Risk Factor and how much risk are they in : Our Proposed Method is = Total Degree of a Node * Total Weight of a Node Above Table we see the calculation and see how we calculate user risk factor and how muck risk are they in.now we briefly discuss the result, Previous discussion we see how get node’s weight and Degree .like this we get every node or user degree weight and degree.”Kaushik” node total weight is 0.4 and total Degree is 2.”Akash” node total weight is 1.0 and total Degree is 3.”Arnab” node total weight is 0.6 and total Degree is 1.”Mozzamil” node total weight is 0.7 and total Degree is 1 .Then we calculate the Risk factor by our Proposed Method .

For ,”Preti” Node = Total Degree of a Node * Total Weight of a Node = 3*0.6=1.8.

“Arnab” Node = Total Degree of a Node * Total Weight of a Node = 1*0.6 =0.6 “Kaushik” Node = Total Degree of a Node * Total Weight of a Node =2*0.4= 0.8 “Akash”Node =Total Degree of a Node * Total Weight of a Node = 3*1.0=

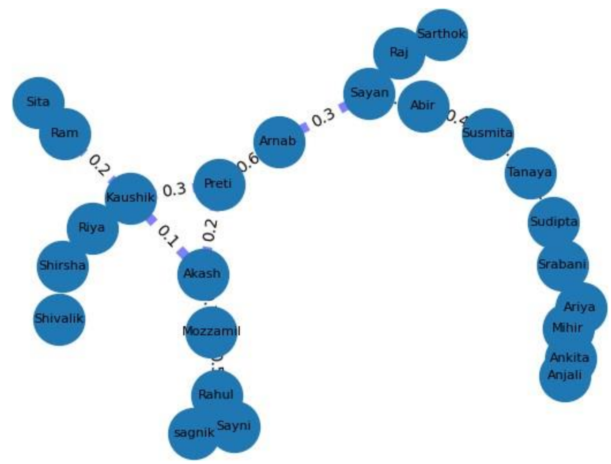

Fig. 17. Result Example Graph 2

3 “Mozamil” Node =Total Degree of a Node * Total Weight of a Node =1*0.7 = 0.7.

After Normalization the value of Risk Factor we see , “Preti” Node Risk Factor =”0.6”(High Risk) “Arnab” Node Risk Factor = “0.2”(Low Risk) , “Kaushik” Node Risk Factor=”0,26”(Low Risk),”Akash” Node Risk Factor= “1”(High Risk) , “Mozzamil”Node Risk Factor =”0.23(Low Factor) Here ,We assumed a range of risk factor,Greater than 0.5 range defines “High Risk” and Less than 0.5 range defines “Low Risk”. According to the table the descending order of User Risk Factor : Akash¿Preti¿ Kaushik¿Mozzamil ¿Arnab Example - 2 Now we consider a large Weighted graph and Calculated their every nodes Weight ,degree and their Risk Factor.

Above Discussion based on result ,we see that “Kaushik” has max Risk Factor and Probability of more Effective than other. Application Structure and Discussion:

Near By Bluetooth Devices:: Identifying influential nodes in complex networks has attracted much attention because of its great theoretical significance and wide application.Existing methods consider the edges equally when designing identifying methods for the unweighted networks. In this paper, we propose an edge weighting method based on adding the degree of its two end nodes and for the constructed weighted networks, we propose a weighted k shell decomposition method (W ks). Further investigations on the epidemic spreading process of the Susceptible-Infected Recovered (SIR) model and Susceptible-Infected (SI) model in real complex networks verify that our method is effective for detecting the node influence.

The unique nature of Bluetooth equipped devices has made it opportunistic to scavenge information that can be repurposed for applications other than initially intended. One such opportunity is in monitoring day to day epidemic infected person near by our house/society, whereby sampling of Bluetooth

User Name	Method of Risk Factor in pandemic Calculator(**= total degree of a node * total weight of this node)**	Risk Factor(From Proposed method)	Normalization the risk factor **(Risk factor/Max Risk Factor)**	How much User in Risk
Preti	3*1.1	3.3	0.58	High Risk
Arnab	2*0.9	1.8	0.32	Low Risk
Kaushik	4*1.4	5.6	1	High Risk
Akash	3*1.0	3.0	0.53	High Risk
Mozzamil	2*1.2	2.4	0.42	Low Risk
Sagnik	1*0.6	0.6	0.10	Low Risk
Riya	2*1.4	2.8	0.5	High Risk
Sayan	2*1.4	2.8	0.5	High Risk
Rahul	2*1.5	3.0	0.53	High Risk
Mihir	2*1.2	2.4	0.42	Low Risk
Anjali	2*1.5	3.0	0.53	High Risk
Ankita	2*1.0	2.0	0.53	High Risk
Srabani	2*1.2	2.4	0.42	Low Risk
Ram	2*0.8	1.6	0.28	Low Risk
Sita	1*0.6	0.6	0.10	Low Risk
Shivalik	1*0.3	0.3	0.05	Low Risk
Shirsha	2*0.9	1.8	0.32	Low Risk
Sayni	1*0.9	0.9	0.16	Low Risk
Raj	2*1.3	2.6	0.46	Low Risk
Abir	2*1.1	2.2	0.39	Low Risk
Sarthok	1*0.6	0.6	0.10	Low Risk
Susmita	2*0.9	1.8	0.32	Low Risk

Fig. 18. Caption

Fig. 19. Register Page and Login Page

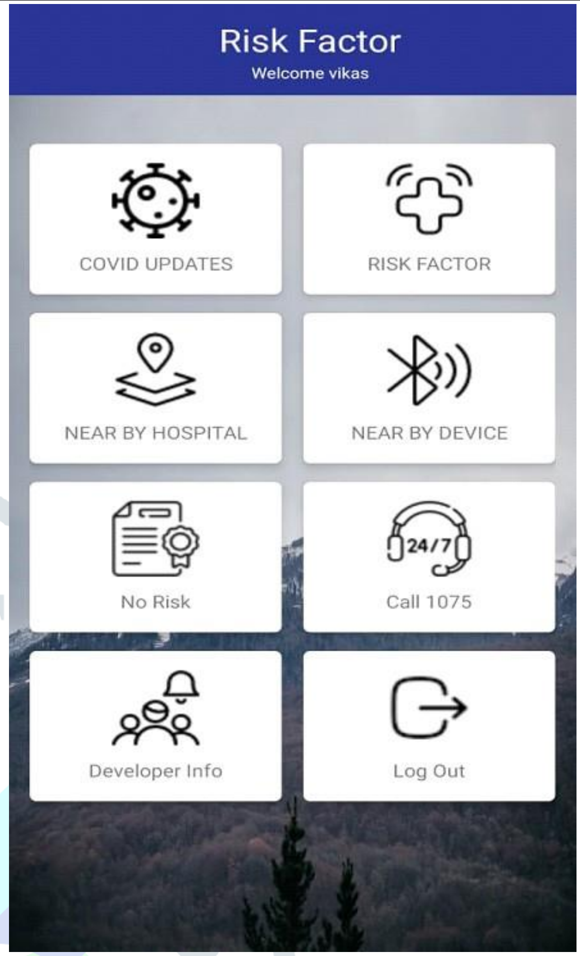

Fig. 20. Application Dashboard :

radios serve as proxies for desiccates and consequently for epidemic density and flow. [13] This paper discusses a complete data collection system developed at the University of JIS under MACKUT UGC University that utilizes a variety of wireless networking technologies and devices to collect inferred traffic data at an intersection along a major thoroughfare in an urban setting. Specifically, a wireless sensor network of slave probes was designed and implemented with the objective to collect Bluetooth device information for this purpose.

Data from each slave probe is communicated to the master node through for future communication, where it is stored on a secure digital (SD) memory card before being transmitted to a central server every five minutes over a global system for mobile communications (GSM) cellular network.The server parses the data received and stores it in a database. Consumer and corporate websites may then access this database to display archived data or current data in real-time to various users.

Monitoring user risk factor of a epidemic Despises using Bluetooth MAC addresses has been intensively studied for a decade.Nevertheless, estimation of the Original-Destination volume is still challenging, because of the unstable nature of the detection.With the aim to reveal the factors affecting the detection probability of MAC addresses from moving Bluetooth device, this study conducted a series of driving tests to collect detection samples under various scenarios.The data was then utilized to develop a Logistic Regression Model to estimating detection probability considering the installation positions of the scanner.

The results agreed on the contribution of distance and angle between them is scanned. This study further identified the contribution of driving direction,and height and timeout duration of these scanner.The proposed model successfully estimated the detection probability with reasonable accuracy.

VIII. Case Study

A. Application Features

1) Covid Updates:: COVID-19 tracking tools or contact-tracing apps are getting developed at a rapid pace by different governments in their respective countries. This study explores one such tool called Aarogya Setu, developed by the Government of India. It is a mobile application developed under the Health Ministry, as a part of the E-Governance initiative, to track and sensitize the citizens of India in a joint battle against COVID-19 spread. The study aims to understand

Fig. 21. Covid Updates

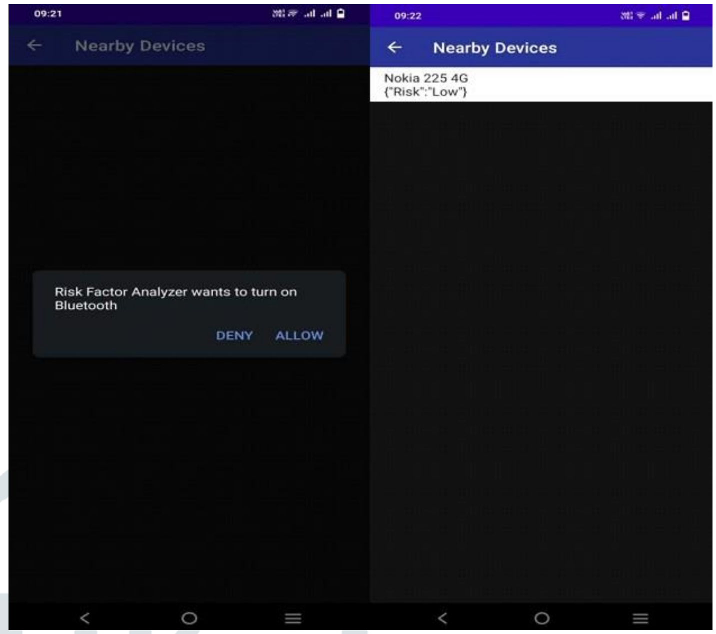

Fig. 22. Nearby Devices(Bluetooth)

various useful features of this tool and to present different concepts of data science applied within the application along with its importance in managing the ongoing pandemic. The App uses Bluetooth and GPS technologies to alert a user when they are nearby a COVID-19 infected person. The application uses various Data Science concepts such as Classification, Association Rule Mining, and Clustering to analyze COVID-19 spread in India. The study also shows potential upgradations in the application, which includes usages of Artificial Intelligence and Computer Vision to detect COVID-19 patients. The study would be useful for mobile technology professionals, data science professionals,medical practitioners, health-related front line workers, public administrators, and government officials and will be available in more Indian languages soon. [7]

The application has been designed in such a way that it informs the users through notification if they cross paths with a COVID-positive person. The tracking is accomplished with the help of Bluetooth technology and location-generated social graphs or GPS, which shows the user's interaction with anyone who has been tested coronavirus positive and notifies them. It detects and tracks the user's movement with the help of GPS and Bluetooth sensors.

The application uses both Bluetooth and GPS-generated data for contact-tracing to alert users if they come in contact with a person suffering from COVID-19 or with someone who is at high risk of getting COVID-19. The Bluetooth and GPS of the user's device must always be turned on for the App to function correctly. Bluetooth access is a significant key for the application to build up information on proximity between two individuals. At the point when two cell phones, which have the App installed, come in one another's Bluetooth range, the application collects data. If anyone of the users is tested positive, the App cautions the other user, and this helps the government in keeping track of potential COVID-19 cases in all over the world .

2) Near By Hospitals:: In this features we represent a demonstrator application for a real-world m-Health scenario: medical emergency management in through the urban area's and as well as in rural area's. Medical emergencies have a high priority given the potential life risk to the patients.

The demonstrator is implemented using the THOMAS approach to open multiagent system based on an organisational metaphor. This metaphor is very suitable for capturing the nature and the complexity of the mobile health domain and, thus, it provides an appropriate mechanism for developing next generation m-Health applications.

In the healthcare domain the management of medical emergencies has a huge social impact given the immediate threat to a patient's life or long term health. Such extreme circumstances demand the usage of the appropriate resources within a limited response time in order to provide an efficient assistance .

A typical medical emergency assistance starts when a patient calls SUMMA112, asking for assistance. The call is received by an Operator, who gathers the initial data from all the patient.Analysing this typical scenario, we have determined basically the following actors which are involved along the whole process: patients, coordinator staff, physicians, ambu-

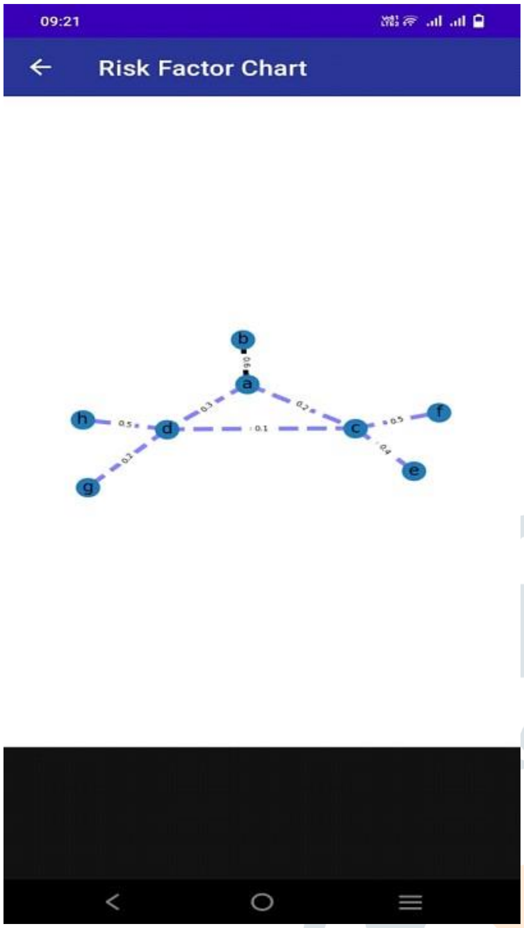

Fig. 23. Risk Factor Chart

lances and hospitals. [8]

3) Risk Factor Updates:: In these features we are going to introduced the Risk factor spreading processes of epidemic and information attract increasing attention in complex network studies],and the researchers tried to find the reason why information spread so quickly as well as how to decelerate the spreading Among many ingredients for quick and wide spreading, influential spreaders play a major role to these. [10] Accordingly, immunization on large-degree nodes(they are usually considered to be more influential)is a highly efficient method to control epidemic spreading having a few highly influential neighbors may be more influential than a node having a larger number of less influential neighbors Numerous real-world networks such as air traffic networks,road networks email networks,and collaboration networks, social network are complex and weighted networks complex networks by employing word-of-mouth strategy and mutual trust between the network users.

A weighted complex network can be represented as a graph

$$(2)$$

G = (V , E, W), where V represents a set of people who are members of the network, E denotes edges, and W is a weight function from E to the set of real numbers R. In case of social networks, there is an edge between two nodes if they are related by a relation, such as friendship, follower, or follow.

Influence maximization is an important research problem in the field of network science because of its business value.It requires the strategic selection of seed nodes called "influential nodes,"such that information originating from these nodes can reach numerous nodes in the network. Many real-world networks, such as transportation,communication, and social networks, are weighted networks.Influence maximization in a weighted network is more challenging compared to that in an unweighted networks. [12]

4) User Risk::

- Pandemics have occurred throughout history and appear to be increasing in frequency, particularly because of the increasing emergence of viral disease from animals.
- Pandemic risk is driven by the combined effects of spark risk (where a pandemic is likely to arise) and spread risk (how likely it is to diffuse broadly through human populations).
- Some geographic regions with high spark risk, including Central and West Africa, lag behind the rest of the globe in pandemic preparedness.
- Probabilistic modeling and analytical tools such as exceedance probability (EP) curves are valuable for assessing pandemic risk and estimating the potential burden of pandemics.
- Influenza is the most likely pathogen to cause a severe pandemic. EP analysis indicates that in any given year, a 1 percent probability exists of an influenza pandemic that causes nearly 6 million pneumonia and influenza deaths or more globally.

Impacts

- Pandemics can cause significant, widespread increases in morbidity and mortality and have disproportionately higher mortality impacts on LMICs.
- Pandemics can cause economic damage through multiple channels, including short-term fiscal shocks and longer-term negative shocks to economic growth.
- Individual behavioral changes, such as fear-induced aversion to workplaces and other public gathering places, are a primary cause of negative shocks to economic growth during pandemics.
- Some pandemic mitigation measures can cause significant social and economic disruption.
- In countries with weak institutions and legacies of political instability, pandemics can increase political stresses and tensions. In these contexts, outbreak response measures such as quarantines have sparked violence and tension between states and citizens.

Mitigation

- Pathogens with pandemic potential vary widely in the resources, capacities, and strategies required for mitigation. However, there are also common prerequisites for effective preparedness and response.

- The most cost-effective strategies for increasing pandemic preparedness, especially in resource-constrained settings, consist of investing to strengthen core public health infrastructure, including water and sanitation systems; increasing situational awareness; and rapidly extinguishing sparks that could lead to pandemics.
- Once a pandemic has started, a coordinated response should be implemented focusing on maintenance of situational awareness, public health messaging, reduction of transmission, and care for and treatment of the ill.
- Successful contingency planning and response require surge capacity—the ability to scale up the delivery of health interventions proportionately for the severity of the event, the pathogen, and the population at risk.
- For many poorly prepared countries, surge capacity likely will be delivered by foreign aid providers. This is a tenable strategy during localized outbreaks, but global surge capacity has limits that likely will be reached during a full-scale global pandemic as higher-capacity states focus on their own populations.
- Risk transfer mechanisms, such as risk pooling and sovereign-level catastrophe insurance, provide a viable option for managing pandemic risk.

[11]

5) Near By Bluetooth Devices:: Identifying influential nodes in complex networks has attracted much attention because of its great theoretical significance and wide application.Existing methods consider the edges equally when designing identifying methods for the unweighted networks. In this paper, we propose an edge weighting method based on adding the degree of its two end nodes and for the constructed weighted networks, we propose a weighted k-shell decomposition method (W ks). Further investigations on the epidemic spreading process of the Susceptible-Infected-Recovered (SIR) model and Susceptible-Infected (SI) model in real complex networks verify that our method is effective for detecting the node influence. [13]

The unique nature of Bluetooth equipped devices has made it opportunistic to scavenge information that can be repurposed for applications other than initially intended. One such opportunity is in monitoring day to day epidemic infected person near by our house/society, whereby sampling of Bluetooth radios serve as proxies for desicuses and consequently for epidemic density and flow. [14] This paper discusses a complete data collection system developed at the University of JIS under MAKAUT UGC Universiy that utilizes a variety of wireless networking technologies and devices to collect inferred traffic data at an intersection along a major thoroughfare in an urban setting. Specifically, a wireless sensor network of slave probes was designed and implemented with the objective to collect Bluetooth device information for this purpose.Data from each slave probe is communicated to the master node through XBee for future communication, where it is stored on a secure digital (SD) memory card before being transmitted to a central server every five minutes over a global system for mobile communications (GSM) cellular network.The server parses the data received and stores it in a database. Consumer and corporate websites may then access this database to display archived data or current data in real-time to various users.

Monitoring user risk factor of a epidemic Deasises using Bluetooth MAC addresses has been intensively studied for a decade.Nevertheless, estimation of the Original-Destination volume is still challenging, because of the unstable nature of the detection.With the aim to reveal the factors affecting the detection probability of MAC addresses from moving Bluetooth device, this study conducted a series of driving tests to collect detection samples under various scenarios.The data was then utilised to develop a Logistic Regression Model to estimating detection probability considering the installation positions of the scanner.The results agreed on the contribution of distance and angle between them is scanned. This study further identified the contribution of driving direction,and height and timeout duration of these scanner.The proposed model successfully estimated the detection probability with reasonable accuracy. [15]

*6) 24*7 Toll free No::* In this article the document practices of globalization in a newly emerging transnational labour force – call centre workers in kolkata, India, who provide voice- to-voice service to clients dialling toll-free numbers in North America.Recent theorists have focused on how capitalism is continually under construction, and how heterogeneous groups of workers play active roles in relation to transnational corporate processes. Accordingly, I trace three practices that constitute transnational callcentre work –scripting, synchronicity and locational masking– and examine how Indian workers negotiate these practices. I argue that the transnationalization of voice-to-voice process service work provides the opportunity for Indian workers to construct 'Americans' and situate their own jobs within global markets accross the world . [9]

IX. Conclusion and Future Scope

We used Graph to summarize the body of evidence related to Epidemic risk and protective factors reported in recently published literature. We identified research areas where there exists a moderate body of literature and a follow-up review, such as a systematic review, may be informative and also areas where evidence is lacking (i.e., risk factors in susceptible sub-groups, risk factors of user). The automation technologies applied to this graph in the screening and tagging process can be used to periodically update this evidence base and track scientific knowledge as it evolves, We used our proposed method to use the risk factor of the User's.

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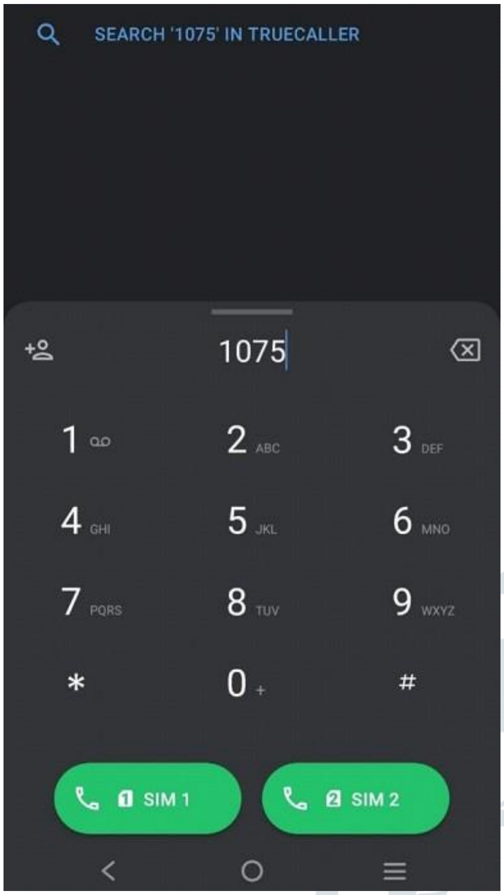

Fig. 24. Helpline Number

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