Toward a trust-based Multi-layered network approach of Healthcare system's Architecture

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Abstract*—Medical Trust-Network is one of the most promising fields of study in network science. The establishment of trust within medical entities ensures better treatment and increases better medical facilities. The word 'Trust' signifies a very important behavioral aspect between any human entity, especially among doctors and patients. To represent such relationships Trust Network Models are built to express the interactions between human entities within such networks. Though the idea of a Trust-Network has traditionally been one of the major areas of research, yet the concept of a medical trust network model is relatively a new domain. .....this line may remove and may add in introduction part In this paper, we introduce an overall multilayered Trust Network to represent the entire healthcare architecture. More specifically, our model is based on an evolutionary graph system with a discrete relationship between the three most important entities of any healthcare system, namely – Doctors, Departments, and Hospitals. Observations based on our model indicate that the medical healthcare system is a multilayered model, unlike a feed-forward model as indicated by the previous studies. this line may remove and have to write one or two line for objective of the work and one or two line for conclusion or outcome

Keywords: ***Healthcare system, medical network, trust, network modeling***

I. Introduction

Today's healthcare services rely on popularity based assessment models [1], which undermines various good medical centers or doctors. However, relationships among healthcare facilitators are essential for functioning health care system efficiently. In a healthcare system, physicians rely on their relationships with physician colleagues for patient referrals [2], clinical advice [3], and information about the latest clinical advances [4]. However, the healthcare system is a part of social system, and it is represented using a social network in various existing studies [5]–[7]. In a recent study [8], Guo et al. proposed a model which incorporate the interconnectivity of individual medical entities like doctors, hospitals and departments. This model able to capture the interactive role of various medical entities in healthcare system to facilitate the medical services. Over the past, in social networks, social interactions is portrayed by friendship, closeness, trust, partnerships, and many more relationships [9]. However, in the recent studies, the researchers have shown more interest to develop the trust-based model of a social systems [5], [10]–[12].

Trust plays a crucial role in social interactions among the entities in any social system [13]–[15]. Existence of trust in various social systems had been one of the main interests of research of social scientist since a long back [16]–[18]. In literature [19], trust has been described as an aggregate of several incentives of social interactions. It may incorporate a plethora of distinct concepts such as the convergence of interests, compatibility of incentives, competence, and knowledge. There exists a plethora of works where trust has been used in the developments of various socio-economical applications [20]–[23].

In literature, many research works [5], [10]–[12] have been proposed where trust plays an important role in medical or healthcare networks. However, all the existing works [24]–[27] of healthcare systems that observe the existence of trust in the healthcare system, unable to cater a complete framework to capture the social interactions among the several existing medical entities. In a recent work [28], Mondal et al. proposed a multilayered trust-based model to capture the patient-doctor interactions on temporal basis and modeled the interaction episode as different layer to develop trust-based doctor recommendation system. Though they ignore the role of other various health care entities in their model. On the other hand, it is observed that, the proposed model by Guo et al. [8] neglects the social aspect of the interactions among the individual medical entities. Moreover, in some recent studies [8], [29], it is observed that patients tend to choose doctors based on the number of workplaces or hospitals they have worked in and also the number of several departments they are associated with. This nature of activities in healthcare system initiates the need of detailed study of interactions among the various medical entities for obtaining best possible solutions. Therefore, there is a strong requirement of suitable network model based on the social interactions among the various medical entities. The model does not only help to understand the social impact of their interactions but also give a strong base to develop social recommendation system in healthcare service. In fig1, we represent a schematic diagram to capture the various

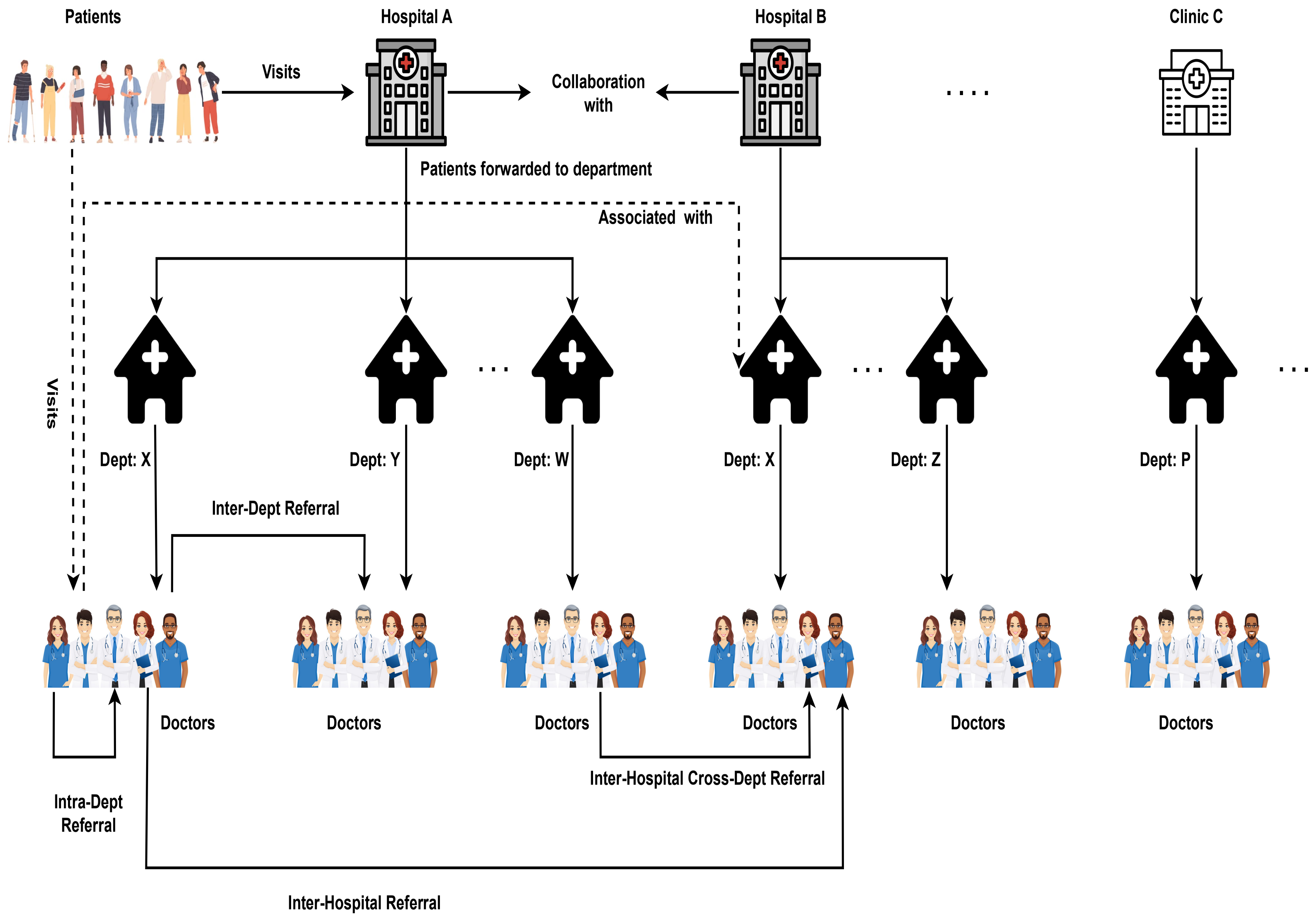

Fig. 1: Figure represents a schematic diagram of healthcare system. It shows the various interactions among the medical entities, including collaborations among the hospitals and clinics, doctor referrals, cross department referrals etc. in healthcare system

interactions among the several healthcare objects. This diagram not only help us to understand the interactions among the healthcare system objects but also gives us the perception about the layered architecture of healthcare system.

In this work, we propose a multi-layered healthcare framework that is able to capture the social interactions not only among the similar medical entities e.g., doctor-doctor, hospital-hospital interactions etc, but also interactions among the dissimilar entities e.g., doctor-hospital, hospital-department etc. Specifically, we propose a multi-layered network which capture the social interaction among the medical facilitators in the health care system. Further, we introduce mathematical model to formalize the social interactions among the medical entities. Based on the proposed multi-layered network, we further develop trust-network to capture the to trust relationship, amongst the medical entities, which influence any social interactions among the entities in a social system. In our proposed model, we specifically consider the relationship among three important medical entities – doctors, departments, and hospitals in healthcare systems as a multi-layered network. In our work, we introduce the concept of social score which is an aggregated social importance of any medial entity in the proposed multi-layered network. We specifically use *'page-rank'* kind algorithm to estimate the social score. This aggregated score not only consider the social interactions among the homogeneous entity e.g., doctor-doctor interactions, department-department interactions etc, but also it is estimated based on the interactions among heterogeneous entities e.g., doctor-department interactions, department-hospital interactions etc. Though the social score has been introduced in many social applications including financial system to measure the credit worthiness of any financial entity [30], academic social system to estimate academic impact of a researcher [23] etc., We hardly find any contributory work where social score has been introduced in medical healthcare system. The social score of medical entity in medical & healthcare system would not only helps in distinguishing important doctor, hospital etc., but also provide the platform for development of recommendation system in healthcare domain. Finally, we perform various experiments to measure the performance our proposed model. We initially do simulations to validate the proposed model. Further, the empirical analysis of the dataset reveal the nature of social score and usefulness of it. Patient is an integral part of any healthcare system. Therefore in some earlier works patient-doctor interactions has been separately modelled. Although we propose multi-layered network for healthcare system, the modelling of patient-patient social interaction might increase the complexity of the proposed model and insignificant from our proposed perspectives. Thus in model, we considered patient is an external entity in healthcare system. The contributions of the this work are summarized as follows:

- We develop a multi-layered medical network to model the social interactions among the various medical entities i.e., doctor, hospital and their departments. We further formalize the social interactions using a relational model.
- We propose trust-network model to capture the role of social interactions among the various medical entities exists in healthcare system under the influence of trust.
- In our work, We introduce social score of each medical entity based on the social trust relationship amongst the different medical entities in the healthcare system.
- We have collected the dataset of doctors along with the several departments of the hospitals where they are associated. We also collect the various detailed information of the hospitals also apart from the doctors details. We have given a major amount of effort to collect the data set. We use graph database to store the collected data to analyse the dataset properly.
- We simulate the proposed network model on synthetic data set to validate it. We also form multi-layered network using collected data set and analyse it to verify the proposed model.

II. Related Work

In this section, we outline the works related to healthcare and medical service cater systems. Initially, we highlight some works related to healthcare systems and various behavioural activities of the several medical entities in the concerned system. Further we outline various works related to network models that incorporate the social interactions among those entities in the healthcare system. We also highlight some important related works which observes the social interactions from the perspective of trust. Finally, we outline some recent works related to application of social trust where social trust-based score has been used. In our work, we proposed a multi-layered network to represent the architecture of healthcare and medical services. Thus, we also highlight few works on multi-layered network. We carefully figure out the scope of our work that further justify the contributions.

Healthcare System & behavioural activities in it: The study of healthcare system to understand the underlying structure and behaviour of several entities in it was a strong interest of researcher from early age of science [31]–[33]. The referral process is one of the common phenomena of medical & healthcare system. A referral based network study [34], [35] show that the patients are referred by doctors within their personal networks.

In another earlier work [2], authors observe that the referral system in medical and healthcare system is influenced by the various factors. The one of the major factors is workplace influence i.e., hospitals. It plays an important influencing role in the referral system. In some other studies [3], [4], authors observed that doctors rely on their personal network among other doctors to seek clinical advice and advanced clinical information. Study from an another aspect of the healthcare system, authors revealed that doctor selection process by the patient is influenced by the popularity of the doctor measured in terms of the number association with the hospitals [29]. These observations figure out the need to detailed study of the interactions not only among the medical practitioners but also other medical entities e.g., hospital and department.

Network model of Healthcare systems: In pursuance of the strong requirement of detailed study of interactions among the several medical entities, people further observed the system as a network to model the interactions in it more systematically. In a work [6], Barnett et al. proposed a mapping for the network of physicians with the help of administrative data using a small-world network analysis. The study provided a detailed complex network of the physician networks. In another work [36], the authors confirmed that sharing patients is indeed a key factor influencing the medical doctor networks. In this work, authors observes that departments are also key players in a medical network. In some earlier works [7], [37] addressed the issue of lack of data in the study of medical network and have shown using Social Network Analysis(SNA) and ego mining studies that social media can be used to negate the problem of lack of data about physicians or hospitals.

The detailed overall network of medical entities like hospitals, doctors, and departments was presented by Guo et al. in [8], which provided the ground-work for establishment of any complex network of these said entities. Their study was based primarily on opinion leader based study [38], which made their study include only the key doctors, instead of all the doctors in any medical healthcare system. They did not explore the social aspect in their network modelling specifically in their work, as they primarily concentrated on establishing a recommender system.

Multi-layered Network Model:

Trust in Healthcare systems: The earlier studies [3], [4] reveal that overall approval of informal consultation among the physicians is strongly associated with beliefs about how it affects quality of care. This could be strong evidence of the need to explore healthcare network from the trust-based social aspect. Though trust networks in healthcare services relatively a new approach, still there are considerable foundation works [39]–[41] in this field. Traditionally *trust* has been a key role in assessing health care services, more specifically as a performance indicator [42]. The first apt comparative study on the role of trust affecting physician-physician relationship as well as the patient-physician relationship was studied in early 2000s by Pearson and Raeke [43]. Their work incorporated a synopsis of theories about patient trust and the evolution of methods to measure it. In another earlier work [44], incorporates the role of public trust for assessing the expertise of medical professionals.

Though the trust-based interactions has been explored in many social systems where a composite social trust value of the entities has been estimated, we find very few works in the health-care domain where social trust score of the health-care entities has been estimated. Earlier in some work [30], we find the credit worthiness has been measured based on the social trust-based score. In another work [23], Gayen et al. observed that trust-based score could be good indicator of academic productivity of the researchers and it could be used as a predictor of their future impact in their academic domain. In figure 2, we represent the various applications of trust in several domain.

In a recent work [28], Mondal et al. estimated the social trust score of the doctors based on the temporal model of patient-doctor interactions for doctor recommendation, though they failed to capture the patient referral among the doctors, collaborations among the hospitals etc. which are every frequent event in health-care domain. In an another earlier work [8], A feed-forward model of the medical healthcare system proposed by Guo et al. in 2016 which consisted of a 'patient-centered' model with a network study for each individual medical entity like hospitals, doctors, and their departments [8]. They failed to capture the social inter-relation among these medical entities, which could be efficiently explored by a trust-based multilayered network model. Thus there is a strong requirement of trust-based health-care framework which can capture the interactions not only between the doctor and patient but also the interactions among the doctor, department and hospital. However, our proposed model not only addresses the intra-dependability among the entities e.g, doctor-doctor, hospital hospital etc. but also the inter-dependability among medical entities like doctors, hospitals and departments as well.

III. Propose Work

In this section, we propose a multi-layered network model to represent systematically the existing healthcare system. We model the relations among the medical entities as a trust-network to explore the interpersonal activities amongst them and compute the social score of the healthcare entities. Finally we simulate the network and compute the experimental results.

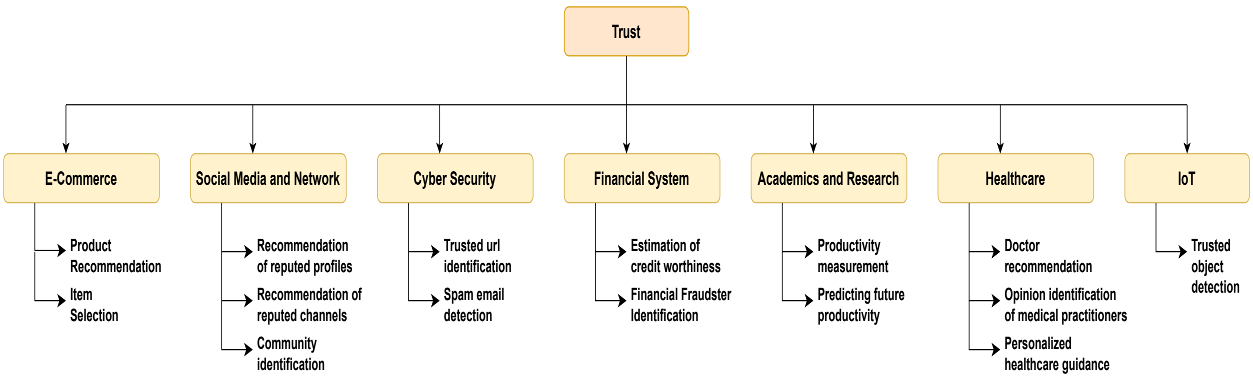

Fig. 2: Figure represents a schematic tree structure to show the several domain of application of trust. The main domains are represented in round rectangular box and the various important topics are shown below.

To understand the interpersonal relationship amongst the various entities of healthcare system, we propose a network model. The network model captures the interactions among the various entities exists in healthcare system and provides us a concise macro structure of large healthcare system. In our proposed network model, we specifically consider three healthcare entities, i.e., doctors, hospitals and the various departments of the hospitals. To capture interaction among the doctors in healthcare system, we propose a network amongst the doctors which is able to model the relationship among the doctors that reflects the social interactions among them for clinical advises, referrals and many more. In healthcare system, inter-department and inter-hospital clinical references, advises and collaborations are very common. To model this situation, we also establish the network among the various departments and hospitals. It emerges the view of various layers (doctor, department and hospital) in healthcare system. In our proposed network model, we consider the inter-layer network amongst the doctor-department-hospital that captures the impact of their interactions across the layers and also justify the 'belongs to' relationship among the doctor-department-hospital.

An interaction in any social system amongst the entities are based on mutual understanding and trust [26]. Thus, many works in literature, social interactions are modelled from the perspective of trust. In our proposed work, we further define social interactions among the various entities in micro level and capture the dynamics from the trust perspective among them. We model the interpersonal trust-relationship among the entities and propose various properties of it to support the trust dynamics in healthcare system. We further introduce a metric to rank the entities in our proposed work. We term it as 'social score' which is computed based on the social trust relationship among the entities. The social score of the various medical entities are computed in an unified method irrespective to type of entity. This score is further useful in various applications of healthcare system e.g., recommendation system etc.

A. *Multi-layered network model*

We propose an undirected multi-layered weighted network where three different health care entities i.e., hospitals, doctors, and departments have been considered to form the network. In this proposed network, we consider the entities in health care system as the nodes in the network and edge represents the interactions in terms of similarity feature, 'belong to' etc. among the nodes. Our proposed multi-layered network of heathcare system broadly consists of two different parts i.e., intra-layer networks and inter-layer networks. The relationship in terms of feature similarity among the similar entities, we represent as intra-layer network whereas we represent inter-layer network between heterogeneous entities to capture the 'belong to' relationship between the entities of different layers. The relationship between similar entities has been represented as a network in one separate layer. We form three separate layers of intra-layer network, i.e., hospital layer, department layer and doctors layer. In proposed model, we consider similarity feature to measure the weight of the edges in intra-layer networks. Therefore, the weight of the edge is defined by the similarity values of the given two nodes. On the other hand, weight of the any edge in inter-layer network is estimated based on the importance of the entity perceived by the other entity in the 'belong to' relationship. In table I, we depict the several commonly used symbols in our work to describe the proposed model.

We define the multi-layer network $\mathcal{M}$=($\mathcal{G}$, $\mathfrak{I}$), where $\mathcal{G}$ represents the network and $\mathfrak{I} \in \Re$ is the number of layer. The network $\mathcal{G}$ decomposed into several layer networks $\mathcal{G}$ = $\{G_1, G_2 \ldots G_i\}$ where $i \in \mathfrak{I}$. In our case $\mathcal{M} = (\mathcal{G}, \mathfrak{3})$ and $\mathcal{G}$ = $\{G_1, G_2, G_3\}$, where G_1 denotes the hospital network, G_2 denotes the departmental net-

TABLE I: Symbols & Descriptions.

Symbols	Descriptions
$\mathcal{M}$	Multi-layer Network
Hosp_Name	Represent the name of the hospital.
Address	it represents the address of the hospital. It is a composite attribute, consisting of state, district, city, street name, street number, etc.
Rating	Floating point value representing the rating of the hospital out of 5.
stories_count	An integer value representing the number of stories i.e reviews written by the patients who visited the Hospital.
Doct_count	It represents the number of doctors in each of the department of the hospital.
Depart_Count	It stored the derived value from the department name of the hospital. It count the distinct departments of the hospital.
Location	This value is derived from the address of the hospital. It stores the categorical information regarding the location of the hospital i.e., Urban, sub-urban and rural.
Accreditation	In this field, we collect the accreditation(s) received by the hospital.

work and G_3 denotes the doctors network. We represent a schematic diagram of the multi-layer network $\mathcal{M}$ in figure 3 with small set of nodes in each layer. In next, we define the intra-layer and inter-layer network.

1) Intra-layer network: In this section, we define three intra-layer networks, i.e., hospital (G_1), department (G_2) and doctor (G_3) as follows:

Let H, D and P be the set of hospitals, departments and doctors respectively. The formal representation of these parameters are as follows:

$$H = \{h_1, h_2, ..., \ h_i\} \ where \ i \in \Re$$
$$D = \{d_1, d_2, ..., \ d_j\} \ where \ j \in \Re$$
$$P = \{p_1, p_2, ..., \ p_k\} \ where \ k \in \Re$$

a) G_1: Hospital Network: In this network layer, we create a hospital network, such that each hospital is considered as a node of a network and connection between two nodes are defined by the count of similar departments they have between any two hospital nodes. Let $h_1, h_2 \in H$ be two random hospitals. Let P_α = $\{\alpha_1, \alpha_2 \dots \alpha_n\}$ be the set of departments in h_1 and P_β =$\{\beta_1, \beta_2 \dots \beta_n\}$ be the set of departments in h_2. Then the similarity S_1 between h_1 and h_2 is defined as:

$$S_1 = |P_\alpha \cap P_\beta| \ \text{ where } \ P_\alpha \text{ and } P_\beta \in D \qquad (1)$$

In figure 3, we represent the schematic diagram of hospital layer with four hospitals h1, h2, h3 and h4 respectively. Each hospital nodes in the layer is connected to every other hospital nodes in this network with a set of edge based on their feature similarity. The edge is formed if the hospitals having common department/s. The weight of the edges are estimated as per the equation **??**.

b) G_2: Department Network: In this layer, we create the department network, such that each department is now considered as a node of the network and connection between two nodes are defined by the count of similar doctors working in different department nodes.

Let $d_1, d_2 \in D$ be two random departments. Let D_γ = $\{\gamma_1, \gamma_2 \dots \gamma_n\}$ be the set of doctors working in d_1 and D_δ = $\{\delta_1, \delta_2 \dots \delta_n\}$ be the set of doctors working in d_2. Then the similarity S_2 between d_1 and d_2 is defined as:

$$S_2 = |D_\gamma \cap D_\delta| \text{ where } \ D_\gamma \text{ and } D_\delta \in P \qquad (2)$$

In figure 3, we represent the schematic diagram of department layer with four departments d1, d2, d3 and d4 respectively. Edges among the department nodes in this layer are based on their common doctors between the departments. The weight of the edges are estimated as per the equation **??**.

c) G_3: Doctor Network: In this layer, we create the doctor network, such that each doctor is now considered as a node of the network and connection between two nodes are defined by the count of similar workplaces (they work in same hospitals).

Let $p_1, p_2 \in P$ be two random doctors. Let H_η = $\{\eta_1, \eta_2 \dots \eta_n\}$ be the set of hospitals where doctor p_1 work in and H_ψ = $\{\psi_1, \psi_2 \dots \psi_n\}$ be the set of hospitals doctor p_2 work in. Now the similarity S_3 between p_1 and p_2 is defined by the number of hospitals present in the intersection of H_η and H_ψ which is represented as:

$$S_3 = |H_\eta \cap H_\psi| \ \text{ where } \ H_\eta \text{ and } H_\psi \in H$$

We represent the schematic diagram of doctor layer with five doctors p1, p2, p3, p4 and p5 respectively in figure 3. Edge in the layer is formed between any two nodes if the two doctors work at one or more than that number of hospitals together. The weight of the edges are estimated as per the equation **??**.

2) Inter-layer Network: In this section, we establish the inter-layer edges amongst the layer $\mathbf{G}_1$ & $\mathbf{G}_2$, and $\mathbf{G}_2$ & $\mathbf{G}_3$ to captures the 'belongs to' relationship between the entities of different layers. Though there exists the inter-

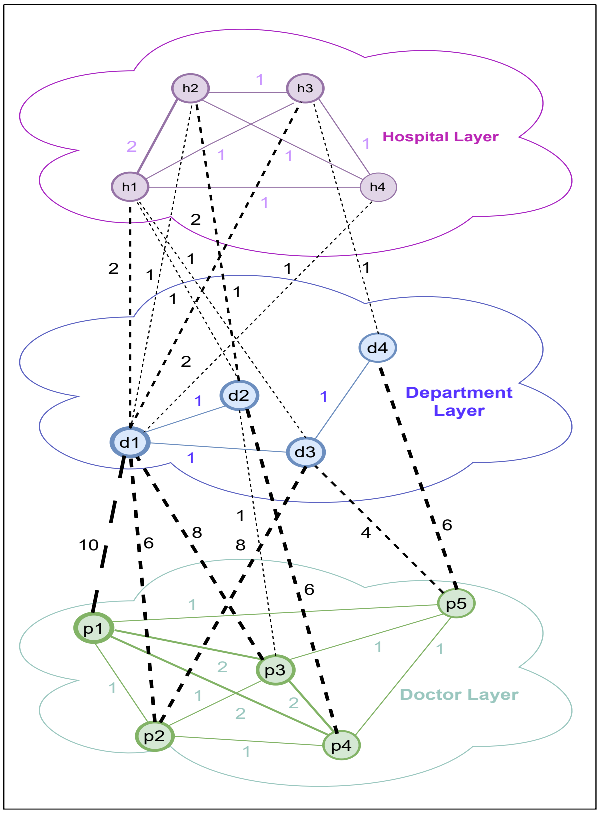

Fig. 3: Figure represents a schematic diagram of Multi-layered Network. It shows three layers; hospital, department and doctor layers in three different colors. Edges are also colored in the same as nodes of that same layer. Inter-layer edges are black colored dashed line. Edges are comparatively bold according to their edge weight.

layer edges amongst the layer $\mathbf{G}_1$ & $\mathbf{G}_3$ logically, as this relationship is recursively computed, we sincerely ignore this relationship in our network. We specifically consider inter-layer edges amongst the layer $\mathbf{G}_1$ & $\mathbf{G}_2$, and $\mathbf{G}_2$ & $\mathbf{G}_3$. Further, this inter-layer network representation would be able to capture the impact of interpersonal relationship amongst the entities of a layer into other layers and vice-versa.

The edge is formed between the two nodes which are belong to any two different layers of G_1 & G_2 or G_2 & G_3. Weight of the edges in inter-layered network is based on the importance of the node in the 'belongs to' relationship. Importance of the various nodes can be captured by several features of the node, e.g., importance of a department in a hospital can be computed by the number of doctors in that department, number of special equipment available in the concerned department, etc. Similarly importance of doctor in a department in a specific hospital can be measured by tenure of association as well as his / her qualification etc. The other face of 'belongs to' relationship can be explored as a importance of a node in that layer perceived by the node of other layer. A hospital could have distinct importance of the several departments, in vice-versa this relationship also explore the importance of a hospital with respect to a specific department. This relationship could be useful for further analysis to develop healthcare recommendation system. This kind of relationship is similarly applicable in G_2 & G_3 layer edges. Though the importance of the nodes in their 'belongs to' relationship can be captured by the rating of external sources, e.g., rating by patients, others ranking framework by professional bodies, etc., we have used parameters of the medical entities considered in our network model to mitigate it from external influences and biases.

In figure 3, we have used weighted dotted lines to represent the inter-layer network edges between hospital layer to department layer and department layer to doctor layer respectively. The line width of each inter layer weight is in accordance with their corresponding edge weights. Let us assume that a hospital h_1 having a set of departments $P_\alpha = \{\alpha_1, \alpha_2, \alpha_3\}$, where $P_\alpha \subset D$. Thus there will be three edges between the G_1 and G_2 layers to captures the 'belongs to' relationship. In similar way we could have the inter-layer network between G_2, G_3. Our proposed model efficiently mitigate the issues of 'patient-centric' feed-forward model. Though, our model consider the dependency among the different layers, the layers feed the connected layer/s which actually deduce the impact of one layer to other layer recursively. Thus, the vice-versa impact of the layers are observable rather that feed-forward nature. On the hand, this model is not a single entity centric like as of earlier model [8] where entire model is 'patient-centric'. This model able to capture the importance of the medical entities in every layer where the plug-in came from any of the layer, e.g., important hospital based on a specific department, important doctor of a specific department, important hospital among the hospitals where a doctor is associated, etc.

B. *Formalization of Relations*

In the section, we propose the relational theorem to capture the interactions among the several medical entities. We define relationship to understand the interactions within intra-layer (homogeneous relationship) and inter-layer (heterogeneous relationship) entities in the network.

1) Intra-layer relationship: In this section we propose the relational theorem of intra-layer network. Initially we propose a general theorem for each layers of the network. We further use weighted adjacency matrix to capture the overall view of the each network.

Definition 1: In a layer $G_\alpha = (X_\alpha, E_\alpha)$, where X_α are the nodes and E_α are the edges in that layer α and P_α is the set of total parameters of the X_α, then between any two nodes in the layer the relation:

$$W_{ij}^{\alpha} = n(X_i^\alpha \cap X_j^\alpha)$$

holds true where, W_{ij}^α is weight of edge E_{ij}^α , $i \neq j$ and the parameters of nodes are represented by $X_i^\alpha, X_j^\alpha \in P_\alpha$.
In layer G_α we have the graph structure $G_\alpha = (X_\alpha, E_\alpha)$, where X_α are the nodes and is given by $X_\alpha = \{X_1^\alpha, ..., X_{N_\alpha}^\alpha\}$ and the E_α are the edges in the layer α. We can calculate the value of similar parameters possessed by any two arbitrary nodes of G_α from the expression $n(X_i^\alpha \cap X_j^\alpha)$, where $1 \leq i, j \leq N_\alpha$ and $1 \leq \alpha \leq M$. Now the term $n(X_i^\alpha \cap X_j^\alpha)$ will be greater if X_i^α and X_j^α share more parameters between them. We have the total set of parameters P_α of layer G_α, then the following relation has to be true:

$$\bigcup_{k=1}^{N_\alpha} X_k^\alpha \subseteq P_\alpha$$

Now, the adjacency matrix of the layer G_α can be defined in the following way. The adjacency matrix for layer G_α is represented as $A^{[\alpha]} = (a_{ij}^\alpha) \in \Re^{N_\alpha \times N_\alpha}$ given by:

$$(a_{ij}^\alpha) = \begin{cases} W_{ij}^\alpha & , if (X_i^\alpha, X_j^\alpha) \in E_\alpha \\ 0 & , otherwise \end{cases}$$

where $A^{[\alpha]}$ is a symmetric matrix, $1 \leq i, j \leq N_\alpha$ and $1 \leq \alpha \leq M$.

$$A^{[\alpha]} = \begin{bmatrix} a_{11} & a_{12} & \dots \\ \vdots & \ddots & \\ a_{N_\alpha 1} & & a_{N_\alpha N_\alpha} \end{bmatrix}$$

$$A^{[h]} = \begin{bmatrix} 0 & 2 & 1 & 1 \\ 2 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} ; A^{[d]} = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$A^{[p]} = \begin{bmatrix} 0 & 1 & 2 & 2 & 1 \\ 1 & 0 & 1 & 1 & 0 \\ 2 & 1 & 0 & 2 & 1 \\ 2 & 1 & 2 & 0 & 1 \\ 1 & 0 & 1 & 1 & 0 \end{bmatrix}$$

where, $A^{[h]}$, $A^{[d]}$, $A^{[p]}$ are the adjacency matrix of hospital layer, department layer and doctor layer respectively of the network represented in the figure 3.

2) *Inter-layer relationship:* In this section we propose the relational theorem of inter-layer network. Initially we propose a general theorem for each layers of the network. We further use weighted adjacency matrix to capture the overall view of the each network.
Definition 2: In a layer $G_{\alpha\beta} = (X_{\alpha\beta}, E_{\alpha\beta})$, where $X_{\alpha\beta}$ are the nodes of the inter-layer network, $X_{\alpha\beta} \subseteq X_\alpha \cup X_\beta$ and $E_{\alpha\beta}$ are the edges between the layer α & β and P_β is the set of total parameters of the X_β, then between any two nodes in the layer the relation:

$$W_{ij}^{\alpha\beta} = n(P_j^\beta)$$

holds true where, W_{ij}^α is weight of edge E_{ij}^α, P_j^β is set of parameters of X_j^β, $P_j^\beta \subseteq P_\beta$, $i \neq j$.
The inter-layer adjacency matrix can be defined given by $A^{[\alpha\beta]} = (a_{ij}^{\alpha\beta}) \in \Re^{N_\alpha \times N_\beta}$ where,

$$(a_{ij}^{\alpha\beta}) = \begin{cases} W_{ij}^{\alpha\beta} & , if\ (X_i^\alpha, X_j^\beta) \in E_{\alpha\beta} \\ 0 & , otherwise \end{cases}$$

where $A^{[\alpha\beta]} \neq [A^{[\alpha\beta]}]^T$, where $1 \leq i \leq N_\alpha$, $1 \leq j \leq N_\beta$ and $1 \leq \alpha, \beta \leq M$.

$$A^{[\alpha\beta]} = \begin{bmatrix} a_{11} & a_{12} & \dots a_{1N_\beta} \\ \vdots & \ddots & \\ a_{N_\alpha 1} & & a_{N_\alpha N_\beta} \end{bmatrix}$$

$$A^{[hd]} = \begin{bmatrix} 2 & 1 & 1 & 0 \\ 1 & 2 & 0 & 0 \\ 2 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix} ; A^{[dh]} = \begin{bmatrix} 2 & 1 & 2 & 1 \\ 1 & 2 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$A^{[dp]} = \begin{bmatrix} 10 & 6 & 8 & 0 & 0 \\ 0 & 0 & 4 & 6 & 0 \\ 0 & 8 & 0 & 0 & 4 \\ 0 & 0 & 0 & 0 & 6 \end{bmatrix} ; A^{[pd]} = \begin{bmatrix} 10 & 0 & 0 & 0 \\ 6 & 0 & 8 & 0 \\ 8 & 4 & 0 & 0 \\ 0 & 6 & 0 & 0 \\ 0 & 0 & 4 & 6 \end{bmatrix}$$

where, $A^{[hd]}$, $A^{[dp]}$ are the inter-layer adjacency matrix of hospital-department layer and department-doctor layer respectively of the given network represented in figure 3. We find that $A^{[dh]}$=$[A^{[hd]}]^T$ and $A^{[dp]}$=$[A^{[pd]}]^T$, where, $A^{[dh]}$ and $A^{[dp]}$ represent the vice-versa relationship between the concerned two layers respectively. In our proposed model, we have considered the number of doctors in the department in a hospital as the edge weight of the hospital-department inter-layer network, whereas we have considered the qualification of the doctor quantified in terms of number as the edge weight of department-doctor inter-layer network. We have considered the qualification importance in a scale of five, e.g., Bachelor degree in specialized domain can be scaled as 4 out of 5, similarly Master degree in specialized domain can be scaled as 4 and where as diploma in specialized domain can be scaled as 2.

C. Trust Network

The social interactions are based on trust relationship between the entities in any social system. In this section, we define trust in the context of interactions between the medical entities of the proposed network in healthcare system. We initially categorise the trust into two different types : a) Intra-layer trust and b) inter-layer trust, to explore the two different kinds of interactions in the proposed multi-layered network, i.e., intra-layer and inter-layer interactions. We further define intra-layer and inter-layer trust matrix to represent the trust network which is derived out the proposed weighted multi-layered network.

1) Definition of Trust: We define trust (τ_{ij}) as a perceived importance of an object j by an another object i. It can be defined as follows:

$$\tau_{ij} = \frac{W_{ij}}{\sum_{k=1}^{\phi} W_{ik}}$$

where, ϕ be number of node adjacent to node i.

Based on the definition of trust, we build the directed trust network which is a shown in the figure 4. Node of the network represent the medical entities of the healthcare system and the trust relationship is representing the edges among them. Though the definition of trust is generic across the intra-layer and inter-layer network, the properties of their representative trust matrix have distinct properties. Therefore, we separately define trust matrix of intra-layer and inter-layer in the next.

a) Intra-Layer Trust: The intra-layer trust network can be represented as a square non-symmetric matrix. It can be represented as follows:

$$\tau^{[\alpha]} = \begin{bmatrix} \tau_{11} & \tau_{12} & \dots \\ \vdots & \ddots & \\ \tau_{N_\alpha 1} & & \tau_{N_\alpha N_\alpha} \end{bmatrix}$$

where $\tau^{[\alpha]}$ is a trust matrix of α layer, $1 \leq i, j \leq N_\alpha$, $1 \leq \alpha \leq M$ and $\sum_{k=1}^{\phi} \tau_{ik} = 1$. Every element of each row i represent the trust of node i on other nodes.

$$\tau^{[h]} = \begin{bmatrix} 0 & 0.5 & 0.25 & 0.25 \\ 0.5 & 0 & 0.25 & 0.25 \\ 0.33 & 0.33 & 0 & 0.33 \\ 0.33 & 0.33 & 0.33 & 0 \end{bmatrix}$$

$$\tau^{[d]} = \begin{bmatrix} 0 & 0.5 & 0.5 & 0 \\ 1 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 0.5 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\tau^{[p]} = \begin{bmatrix} 0 & 0.17 & 0.33 & 0.33 & 0.16 \\ 0.33 & 0 & 0.33 & 0.33 & 0 \\ 0.33 & 0.17 & 0 & 0.33 & 0.16 \\ 0.33 & 0.17 & 0.33 & 0 & 0.16 \\ 0.33 & 0 & 0.33 & 0.33 & 0 \end{bmatrix}$$

Here, $\tau^{[h]}$, $\tau^{[d]}$, $\tau^{[p]}$ represent the trust matrix of hospital layer, department layer and doctor layer respectively of the figure 4.

b) Inter-Layer Trust: The inter-layer trust network can be represented as a rectangular matrix. It can be represented as follows:

$$\tau^{[\alpha\beta]} = \begin{bmatrix} \tau_{11} & \tau_{12} & \dots \tau_{1N_\beta} \\ \vdots & \ddots & \\ \tau_{N_\alpha 1} & & \tau_{N_\alpha N_\beta} \end{bmatrix}$$

where $\tau^{[\alpha\beta]}$ is a trust matrix of the inter-layer trust network of α, β layers, $1 \leq i \leq N_\alpha$, $1 \leq j \leq N_\beta$ and $1 \leq \alpha, \beta \leq M$ and $\sum_{k=1}^{\phi} \tau_{ik} = 1$.

$$\tau^{[hd]} = \begin{bmatrix} 0.5 & 0.25 & 0.25 & 0 \\ 0.33 & 0.67 & 0 & 0 \\ 0.67 & 0 & 0 & 0.33 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

$$\tau^{[dh]} = \begin{bmatrix} 0.33 & 0.17 & 0.33 & 0.17 \\ 0.33 & 0.67 & 0 & 0 \\ 1.00 & 0 & 0 & 0 \\ 0 & 0 & 1.00 & 0 \end{bmatrix}$$

$$\tau^{[dp]} = \begin{bmatrix} 0.42 & 0.25 & 0.33 & 0 & 0 \\ 0 & 0 & 0.4 & 0.6 & 0 \\ 0 & 0.67 & 0 & 0 & 0.33 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\tau^{[pd]} = \begin{bmatrix} 1.00 & 0 & 0 & 0 \\ 0.43 & 0 & 0.57 & 0 \\ 0.67 & 0.33 & 0 & 0 \\ 0 & 1.00 & 0 & 0 \\ 0 & 0 & 0.40 & 0.60 \end{bmatrix}$$

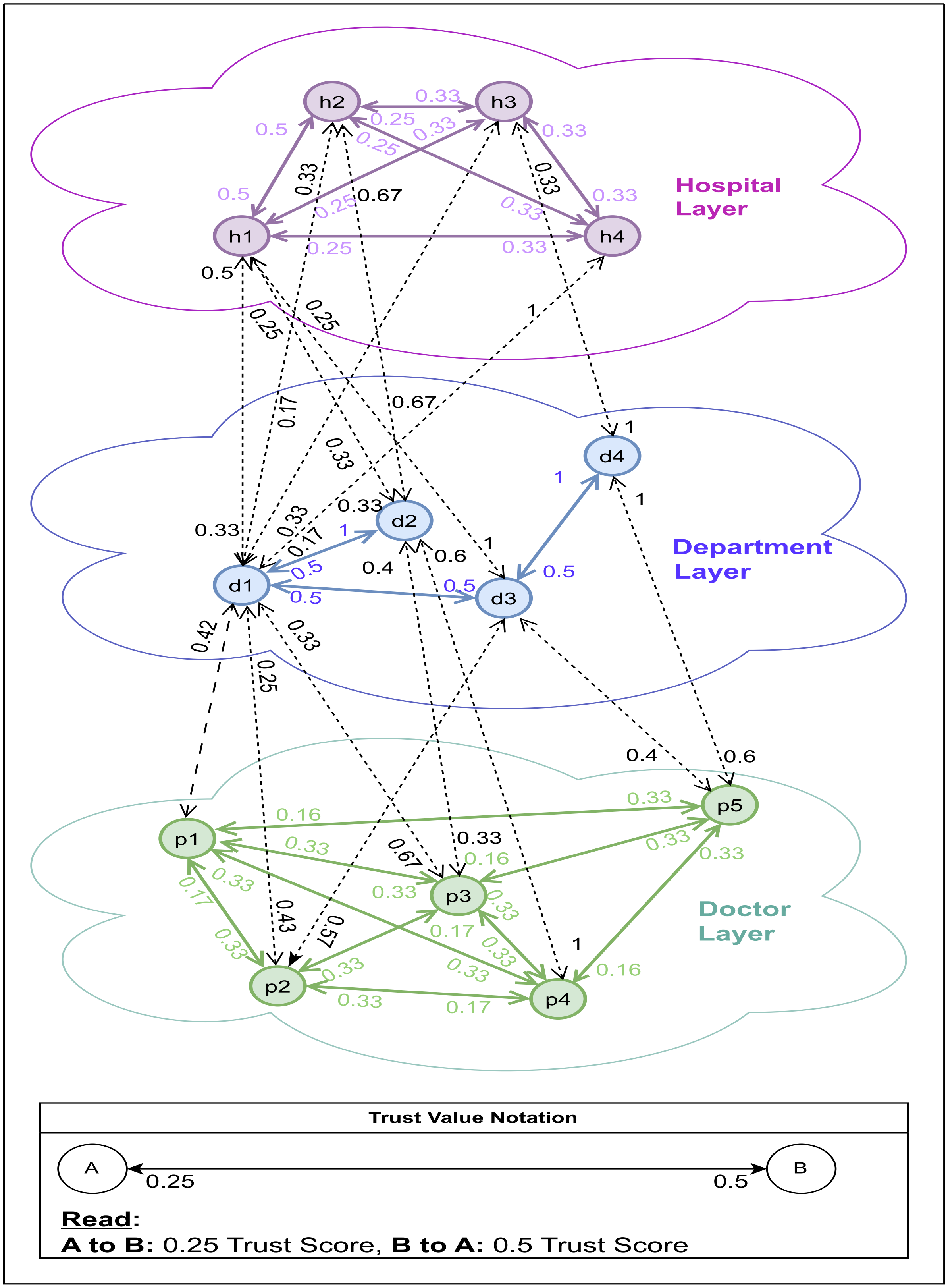

Fig. 4: The figure represents the Multi-layer Trust Network with Hospital, Department and Doctor layers.The nodes and edges of same color signify they all belong to same layer. Inter-layer edge is represented by doted line. The edge weigh represents the trust value of the directed edge.

where, $\tau^{[hd]}$, $\tau^{[dp]}$ represent the inter-layer trust matrix of hospital-department layer and department-doctor layer respectively of the network given in the figure 4.

In the next section, we introduce the concept of social sore and discuss the estimation of social score based on trust.

D. Social Sore

In this section, we initially define the social score. In this context, we also introduce the concept of residual social score. Further we estimate the social score based on the residual social score and trust relationship among the entities in the network which has been defined in the earlier section.

Definition of Social Score: We can define Social Score (S_i^α) of an entity i in a layer α as the estimated social importance of the entity based on its social interaction in the multi-layer network. More specifically, it could be cumulative weighted trust of other connected entities of the entity i in a layer α. It defines that how one entity is perceived in the network by other entities.

We represent the social score of entities in a layer α as a vector (S^α).

$$(S^\alpha) = \begin{bmatrix} s_1 & s_2 & \cdots & s_{N_\alpha} \end{bmatrix}$$

Definition of Residual Social Score: Residual social score of any entity δ_i^α in a layer α can be considered as importance of an entity which has been based on their own feature presumed to be with the entity from its inception.

For example, a hospital's residual social sore can be estimated based on the location of the hospital, associated brand name, type of the hospital etc. Similarly, each department has its own importance could be measured by its number of patients, importance of organs or body section dealt by the department etc., on the other hand, doctors residual social score can be estimated based on his/ her affiliation, work tenure etc.

We represent the residual social score of entities in a layer α as a vector (Δ^α).

$$(\Delta^\alpha) = \begin{bmatrix} \delta_1 & \delta_2 & \cdots & \delta_{N_\alpha} \end{bmatrix}$$

Estimation of Social Score: In this section, we estimate the social score of the entities of any layer based on residual social score of the entities and trust matrices of the multi-layered network. We propose the algorithm 1 to compute the social score of the entities as follows:

We can estimate the initial social score(S_0^α) as follows:

$$S_0^\alpha = \Delta^\alpha + \Delta^\beta * \tau_{\beta\alpha}$$

where, layer α and layer β are adjacent to each other in the multi-layer network $\mathcal{M}$. We take feed of the residual social score of layer β to layer α to estimate the initial social score vector of layer α. We further solve the recurrence relation, $S_{r+1}^\alpha \leftarrow S_r^\alpha * \tau_\alpha$ using the method of substitution to estimate the social score. Thus, further S_r^α can be measured as follows:

Algorithm 1 Estimation of Social Score

Input: Δ^α, Δ^β, $\tau_{\beta\alpha}$
Output: S_r^α
Initial: $S_0^\alpha \leftarrow \Delta^\alpha + \Delta^\beta * \tau_{\beta\alpha}$
while $True$ **do**
  $S_{r+1}^\alpha \leftarrow S_r^\alpha * \tau_\alpha$
  $\gamma \leftarrow S_{r+1}^\alpha - S_r^\alpha$
  if $\gamma \leq 0.001$ **then**
    $break$
  end if
end while

$$S_r^\alpha = S_0^\alpha * (\tau_\alpha)^r$$

Analysis of Algorithm: In the above algorithm, we find that initially, we perform a matrix multiplication of $\Delta^\beta * \tau_{\beta\alpha}$ to estimate the initial social score. In this multiplication involves into two matrices whose order are 1 x N_β and N_β x N_α. Thus the time complexity of the initial score calculation would be $O(n)$. Usually, Time Complexity of matrix multiplication is $O(n^3)$. However, in the above algorithm, a vector(1 x N_β) is multiplied with a square matrix(N_α x N_α). Thus the resulting time complexity is $O(n^2)$. The convergence of social score estimation depends on γ.Thus, if convergence occurs in r-th iteration,then matrix multiplication occurs r times. Thus, time complexity of the algorithm: $O(r * n^2)$. For the high dimensional multi-layered network, we can consider that $r \ll n$. Hence, overall time complexity of the algorithm deduce to $O(n^2)$. Though for the $\lim \gamma \to 0$, the time complexity would be deduced to $O(n^3)$, where $r \approx n$. We compute the social score of hospital nodes of network depicted in figure 3 based on the proposed algorithm 1 and shown the the convergence of social score in each iteration in figure 5.

E. Dataset

In this section, We initially, describe the dataset collected in our work. Further, we have develop a graph database to store the collected data as in our work relationship among the data plays a significant role. We have collected the dataset from Practo [45], an online doctor consultation application. Initially, we have manually collected the information regarding the doctors, their workplaces i.e., hospitals and the several departments with which the doctors are associated. Later on we have

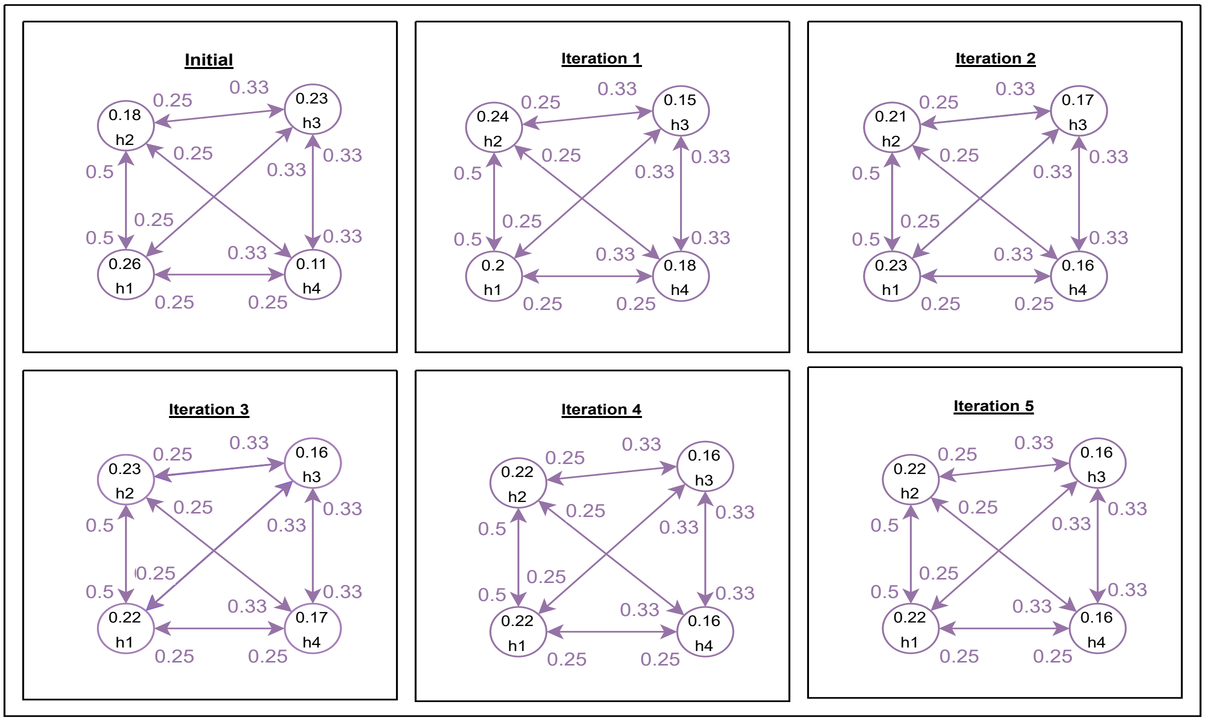

Fig. 5: The figure represent the iterations followed to estimate the social score of the hospital layer nodes of the network shown in figure 3. It shows the initial social scores of the hospitals of the network in top left box and then the changes of the social score of the each node in each iteration is shown in the subsequent boxes.For this simulation, we have considered the uniform distribution of residual social score($\delta_h = 0.2$ and $\delta_d = 0.2$).

used web scraping technique to collect data not only from the Practo but also from several websites of the hospitals. To store and retrieve the various relational information very quickly from the dataset, we have implemented Neo4j graph database. We have run several queries to evaluate some parameters of the healthcare entities as well as the weight of the relationship of proposed multi-layered network.

1) Dataset collection Method: In figure 6, we represent the schematic diagram of data collection and further data cleaning process which leads to compilation of hospital, department and patient dataset to form a graph database. In Practo web application, we can search doctors based on location(city), hospital name, department etc. Initially, we set a specific location (City) to list down the doctors. On the basis of the city, it provides the list of doctors that are available in practo. We manually collect around 330 doctors profile which contains the following information regarding the doctors—name, associated hospital / clinic name, qualification, experience (overall experience as well as experience in specialized domain), department(s) associated with, percentage of like received from the verified patients measured by the number of up and down vote received. We recursively, do this method to collect the doctors from several hospitals at their different departs. Thereafter, based on the listed doctors in our dataset, we collect the detailed information regarding the hospital e.g., name, rating, stories count of the hospital. We also collect the information regarding the departments in which the listed doctors are associated. Though we are not able to find the rating or review of the department, we further compute that based on the other information collected related to department, e.g., number of reviews received by the doctors in the department. We also collect the hospital address and accreditation visiting the corresponding hospital official websites. We also category manually the location(Urban/ sub-urban/ rural) of the hospital based on the address collected from the websites.

2) Data cleaning: At the time of manual data collection process, finally we have removed those doctors profile which are ‘unclaimed’ or ‘not-verified’ from our listed raw dataset. We have further removed those doctors profile whose some of the details are missing from our dataset. Further based on the filtered dataset of doctors, we have collected the hospitals and the departments of those doctors. We removed those hospitals/ clinics which are not rated. In table II, we show the general statistics

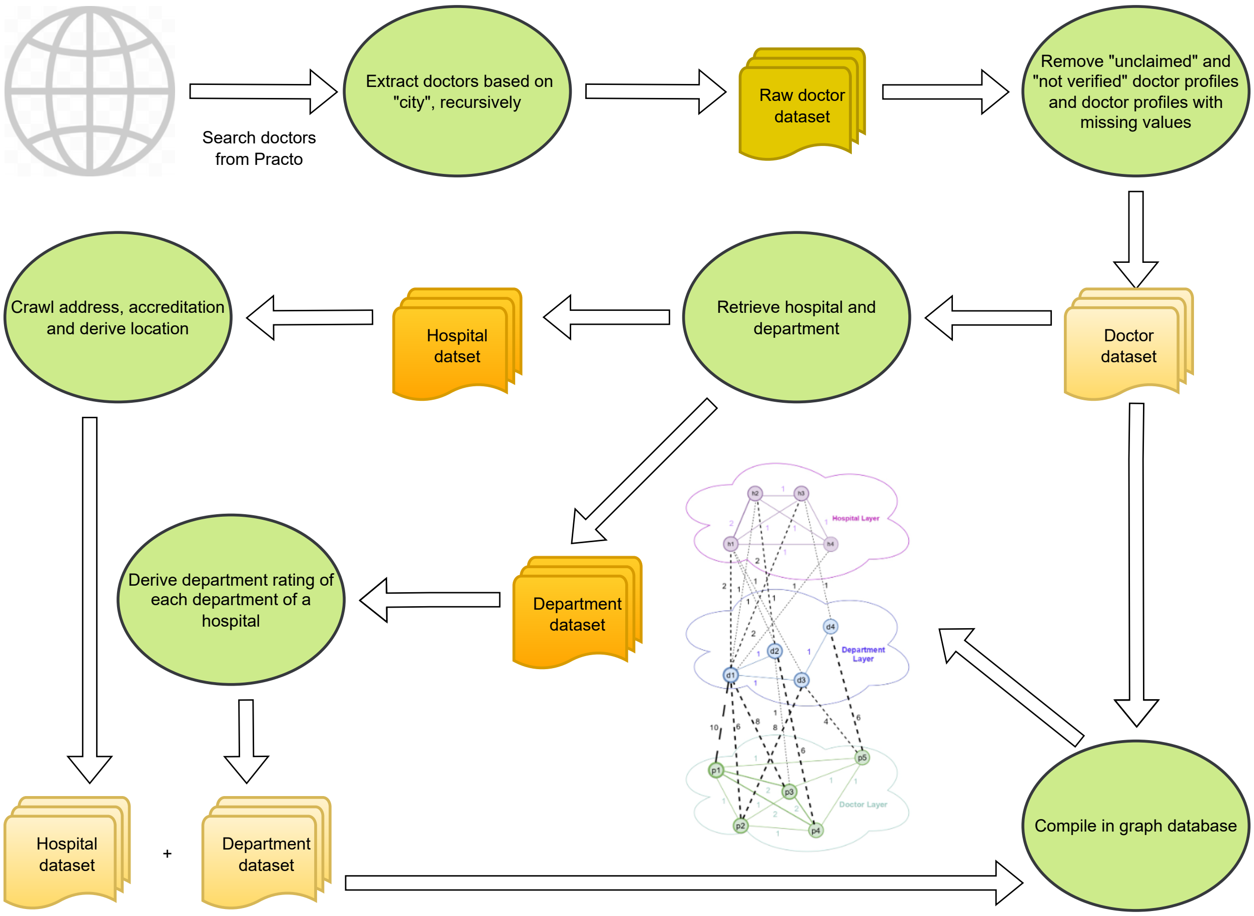

Fig. 6: The figure represent the schematic diagram of the work flow which is to be followed to collect the data and finally to develop the graph database using Neo4j.

of our collected dataset.

Manually collected					
Doctor		Hospital		Department	
Raw	Filtered	Raw	Filtered	Raw	Filtered
330	160	24	22	53	32
Data collected(Web scrapping)					
Doctor		Hospital		Department	
Raw	Filtered	Raw	Filtered	Raw	Filtered
330	160	24	22	53	32

TABLE II: General Information of Dataset.

3) Formation of Graph Database: In this section, we form graph database using hospital, department and doctor dataset collected. We present the attributes and their brief description of the hospital, department and doctors in table III,IV and V respectively. Initially, We added doctor ID, department ID and hospital ID for each of the records. We depict an ER diagram in figure 8 to represent the relationship among the entities. We used Neo4j version: Desktop-1.5.7 to implement the graph database to store the relational graph data.. To perform it, we have used a system with following specification— Processor: Intel(R) Core(TM) i3-6006U CPU @ 2.00GHz 2.00 GHz, Installed RAM: 4.00 GB, Operating system: Windows Edition: Windows 10 Home Single Language Version: 21H2. In the figure 7, we show an example of the Neo4j graph database with some real collected data. This example shows the only a small part of the large database. In In the table XI, XII and VIII, we show the hospital, department and doctor nodes records required to develop the graph database. In table IX, X, we show the edge information of the graph database.

4) Query on Neo4j: In this section, we list down the queries developed to retrieve the various parameters values of the several healthcare entities. We categories the queries into two types: (a) queries to compute the derived features of the entities (b) queries to compute the weight of edges on the proposed multi-layered network.

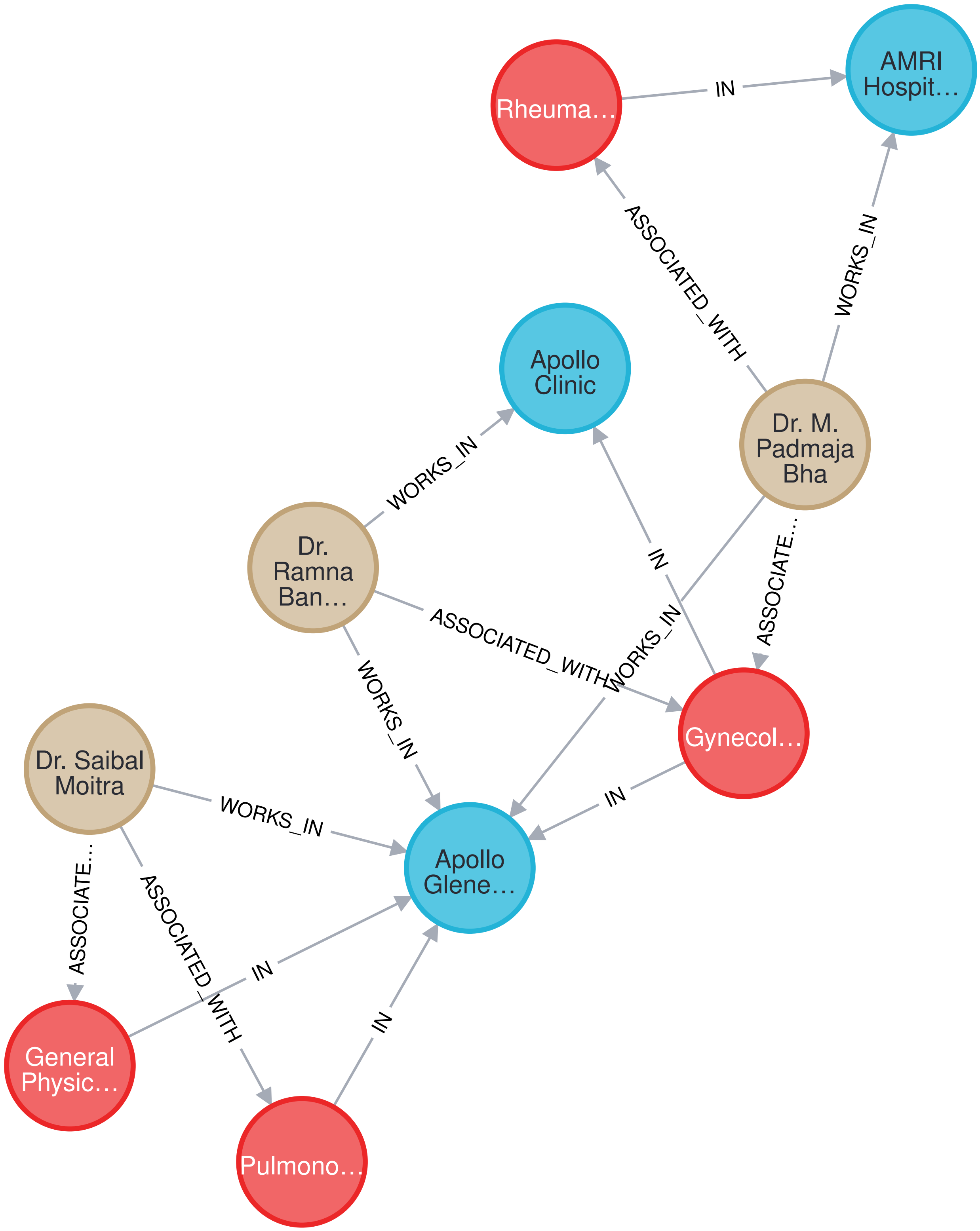

Fig. 7: The figure represent the graph diagram of the graph database using Neo4j. In the figure, it represents the hospitals nodes, department nodes and doctor nodes in different colors. The names of the corresponding nodes are written on the nodes and the relationship type is also written along with the edges shown.

TABLE III: Hospital dataset attributes.

Attribute Name	Attribute description
Hosp_ID	Primary key added to the data set to uniquely identify the each hospital.
Hosp_Name	Represent the name of the hospital.
Address	it represents the address of the hospital. It is composite attribute, consists of state, district, city,street name, street number etc.
Rating	Floating point value representing the rating of the hospital out of 5.
stories_count	An integer value representing the number of stories i.e reviews written by the patients who visited the Hospital.
Doct_count	It represents the number of doctors in each of the department of the hospital.
Depart_Count	It stored the derived value from the department name of the hospital. It count the distinct departments of the hospital.
Location	This value is derived from the address of the hospital. It stores the categorical information regarding the location of the hospital i.e., Urban, sub-urban and rural.
Accreditation	In this field, we collect the accreditation(s) received by the hospital.

TABLE IV: Department dataset attributes.

Attribute Name	Attribute description
Dept_ID	Primary key added to the data set to uniquely identify the each department.
Dept_Name	Represent the name of the department.
Rating	Floating point value representing the rating of the department out of 5 in a hospital. It may differ from hospital to hospital.

a) Computation of derived features:

b) Computation of weight of edges:

TABLE V: Doctor dataset attributes.

Attribute Name	Attribute description
Doct_ID	Primary key added to the data set to uniquely identify the each doctor.
Doct_Name	Represent the name of the doctor.
Specialisation	it represents the domain of specialisation(s) of the concerned doctor.
Quali	This field store the qualification(s) of the doctor.
Yr_As_Spe	It represents the experience in terms of number of years in a specialisation domain of a doctor.
Ovr_Exp	It represents the overall experience in terms of number of years of a doctor.
Review_Count	It stores the count of reviews given by the patients who visited the concerned doctor.
Vote_Count	It stores the total count of the vote received by the concerned doctor given by the patients. It includes total number of up vote and down vote.
Like_Percentage	In this field, we collect the like of the doctor by given the patients. It is shown in % and calculated in terms of number of up vote received out of total vote received.
Other_Clinics	It stores the name of the other clinic(s) where the specific doctor also visits.

F. Results & Discussion

In this section, we show the various results observed in our work. We initially observe the estimated social scores of the hospitals for the network shown in figure 3. Further, we estimate the social scores on some synthetic networks. Finally we observe the results on empirical dataset.

1) Synthetic Network Analysis:

a) Uniform Distribution of residual social score:

b) Normal distribution of residual social score:

c) Skewed distribution of residual social score:

2) Empirical dataset analysis:

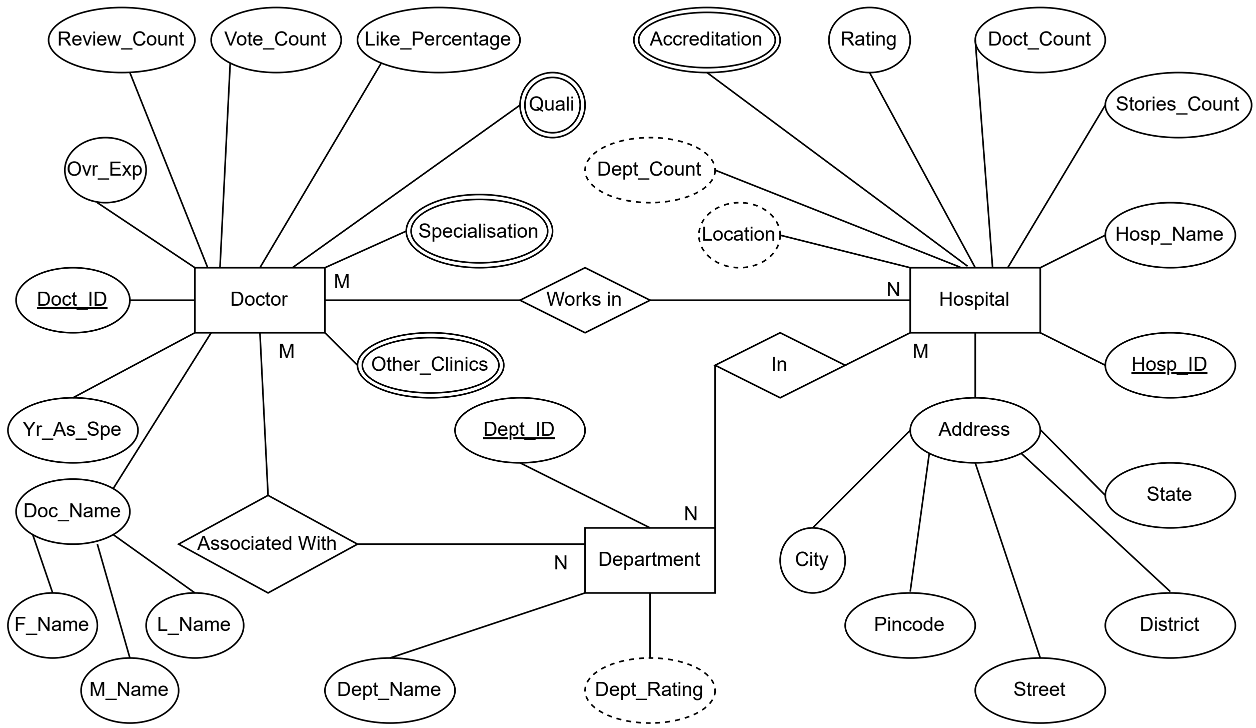

Fig. 8: The figure represents the Entity Relation Diagram of the Hospital- Department-Doctor Dataset.

TABLE VI: Hospital-Department dataset attributes.

Attribute Name	Attribute description
Hosp_ID	This attribute stores the hospital identification number for which we keep the details of the concerned department information.
Dept_ID	Represent the identification number of the department. In this field, we keep those department ID which departments are existing in the concerned Hospital.
Doct_count	This field stores the count of the doctor of the department of the concerned Hospital.

TABLE VII: Hospital-Doctor dataset attributes.

Attribute Name	Attribute description
Doct_ID	This attribute stores the doctor identification number of the specific department of any hospital with which he / she is attached.
Hosp_ID	It represents the specific hospital ID of the doctor attached with.
Dept_ID	It keeps the specific Department ID of the department with which doctor is attached.

TABLE VIII: department node properties.

Dept_ID	Dept_Name	Rating
12	General Physician	4.4
15	Gynecologist or Obstetrician	4.5
29	Pulmonologist	4.5
30	Rheumatologist	4.4

IV. Conclusion and Future Work

We have proposed a medical Trust Network model using multilayered complex network. Our approach relied on the observable characteristics like doctor names, departments and hospital records to model discrete relationship between these entities. Our proposed centrality measure can be used to study the nature of our multilayered network in much more depth. This centrality measure is derived from n-partite multilayered graph system. We validated our model by calculating its computational complexity, which we have found to be much better

TABLE IX: Hospital-department edge properties.

Hosp_ID	Dept_ID	Doct_count
2	15	28
6	30	23
3	15	3
2	12	28
2	15	28
2	29	28

TABLE X: Hospital-Doctor edge properties.

Doct_ID	Hosp_ID	Dept_ID
6	2	15
6	6	30
5	3	15
5	2	15
11	2	12
11	2	29

than the previously proposed models. Although our multilayered network model has been designed considering there exist discrete relationships between medical entities, however we could possibly use other relationships like stochastic functions to describe such interactions. Finally, the proposed Trust-Network can be explored further by studying the nature of stochastic or probabilistic interactions between the medical entities using scale-free random models. Valles-Catala et al. [**?**] and Levent et al. [**?**] explores how stochastic block models or SBMs can be used to reveal the multilayered structure on any complex network. If we can introduce stochastic or probabilistic functions to describe the interactions between our network entities we will certainly be one step closer in modeling a scale-free network, which is considered elegant and versatile.

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TABLE XI: Hospital node properties.

Hosp_ID	Hosp_Name	Address	Rating	stories_count	Doct_count	Depart_Count	Location	Accreditation
2	Apollo Gle-neagles Hospitals	Salt Lake	3.5	543	28	34	Suburban	JCI,NABL,ISO
3	Apollo Clinic	Lake Town	–	6	3	5	Suburban	NABL
6	AMRI Hospitals	Salt Lake	4.5	405	23	30	Suburban	NABH

TABLE XII: Doctor node properties.

Doct_ID	Doct_Name	Speciali.	Quali.	Yr_As_Spe	Ovr_Exp	Review_Count	Vote_Count	Like_Percent.	Other_Clinics
Hosp_ID	Primary key	added to	the data set	to uniquely	identify	the	each	hospital.	

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