Building a Patient-Centered Virtual Hospital Ecosystem Using Both Access Control and CNN-Based Models

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***Abstract*—Virtual hospitals empower traditional hospitals to deliver more accessible, affordable, and comprehensive patient-centered (PC) care services. However, the legacy information systems of traditional hospitals are ill-equipped to support the needs of virtual hospitals. We propose a holistic virtual hospital ecosystem design that addresses these issues. We have developed two models. The first is a *VHealth-CNN* model that extracts PC knowledge from multi-sourced biomedical big data by (1) extracting disease health-related features; (2) structuring the relevant health-related features as per the pre-identified factors; (3) training a convolutional neural network (CNN) double-layer structure, where we select significant health-related features in the first layer, and classify the positively and negatively correlated features in the second one; and (4) generating disease class outputs representing the PC knowledge. The second model is a granular *VHealth-AC* model that seamlessly grants healthcare practitioners at a hub hospital remote access to PC knowledge at the right point of care. We have deployed a granular 5-tier PC information classification scheme to enforce information security rules across hospitals. In addition, we examined the feasibility of the proposed design through a tele-monitoring service experimental case study for predicting obesity, hypertension, and diabetes. The experimental results show that the proposed model predicts obesity, hypertension, and diabetes diagnoses with 91.3%, 93.5%, and 95% accuracy, respectively. Finally, our ecosystem design should encourage the adoption of virtual hospitals and the adoption of virtual healthcare services as a new norm.**

***Index Terms*—Virtual Hospital, Virtual Healthcare Services, Patient-Centered Care, Tele-Monitoring, Access Control, Convolutional Neural Network.**

I. Introduction

Virtual health care is a fundamental care delivery model that is significantly shaped by eHealth technologies to achieve patient-centered (PC) care [1]. It refers to the actual provision of remote care to patients outside of a health setting. Similar to other healthcare delivery models, virtual healthcare maintains individualized care at the heart of its services to deliver a PC model of care [1] [2] [3]. PC care tailors health services around the patient's needs and current state and encourages healthcare practitioners to adapt to these needs by collaborating as a PC team [1] [4] [5] [6] and using shared decision-making processes to determine optimal treatment plans for patients they collaboratively care for [6]. Therefore, to enable this PC model, PC care seeks to connect healthcare providers, healthcare practitioners, and patients to allow a seamless flow of medical data to create a complete virtual electronic patient record. [1] [3].

Emerging digital technologies have disrupted healthcare and introduced the notion of virtual hospitals as novel ways to provide care to patients. Virtual hospitals were first introduced in 2015 with the establishment of the world's first healthcare facility fully dedicated to the provision of virtual healthcare services [7]. A virtual hospital is a dedicated network of secondary and/or tertiary care hospitals based on a "hub-and-spoke" [8] organized to equip specialized care services remotely in a "provider-to-provider" model (illustrated in Figure 1). In a virtual hospital setting, practitioners at a primary hospital (i.e., hub) provide inpatient and outpatient virtual healthcare services efficiently and effectively to patients at multiple secondary hospitals (i.e., spokes) [8]. Therefore, the ultimate goal of virtual hospitals is to empower traditional hospitals that offer limited healthcare services to deliver more accessible, affordable, and comprehensive PC care [7] [9].

Since COVID-19 pandemic, the global wave of interest in virtual healthcare practice has helped realize the potential of this model of care delivery to become the new norm [9] [10]. With limited medical resources and increasing healthcare pressure, many countries have rolled out virtual healthcare centers, programs, and solutions to deliver virtual healthcare services to assist in decision-making and overcome health-related challenges. Such countries include but are not limited

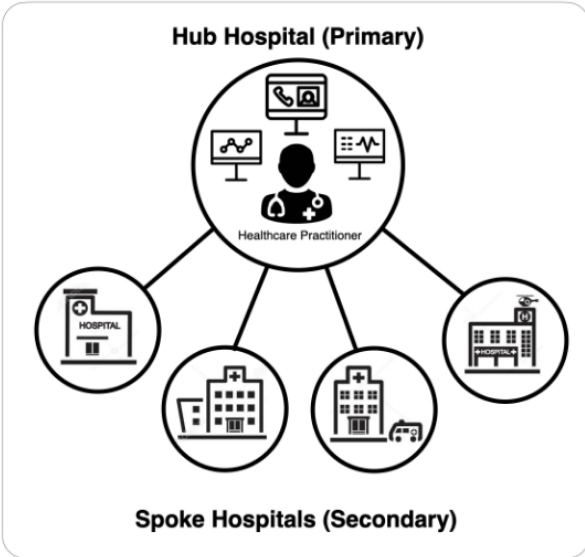

Fig. 1. Virtual hospital conceptual ecosystem.

to the South Pacific region [11], Vietnam [12], Saudi Arabia [13], Rwanda [14], China [15], Uruguay [16], Ghana [17], Kenya [18], India [19], South Africa [20], US [21], UK [22], Singapore [23], New Zealand [24], Israel [25], Chile [26], Korea [27], Japan [28], United Arab Emirates [29], Indonesia [30], and Argentina [31]. Consequently, this has pressurized regulators and policymakers worldwide to convene global experts to publish policy recommendations that can ensure virtual healthcare practice safety and effectiveness, while mitigating the potential risks of this newly adopted model of care [32] [33]. Finally, although there have only been a handful of fully established virtual hospitals since 2015 that are dedicated to virtual healthcare services, it is anticipated to be the future of healthcare post-pandemic [9].

A. Challenges in Incorporating Traditional Hospitals

Building virtual hospital ecosystems that incorporate traditional hospitals is challenging. This is because of key issues with the latter hospitals' legacy information systems that can interrupt patient treatment continuity in a virtual hospital setting. The term "biomedical big data" is used by the World Health Organization (WHO) to refer to data qualified as *health data* in today's evolving health data ecosystems [34]. This includes massive quantities of personal data about individuals from primary (e.g., health services, public health, and research) and secondary sources (e.g., environmental, lifestyle, socioeconomic, behavioral, and social) [35]. Such biomedical big data mostly contain a mixture of unstructured and lengthy free text, which can make it challenging and overwhelming to identify key and relevant information needed at a point of care to make speedy informed decisions that support virtual hospitals' PC model needs.

The WHO classifies health data as sensitive personal data or personally identifiable information. This emphasizes the need to attain the right balance between confidentiality, availability, and integrity of personal health data using information security mechanisms [6] [36] [37] [38]. Access Control (AC) is one of the most widely used security mechanisms deployed to control user actions in an information system to achieve information security goals [6] [39] [40]. However, many hospitals' legacy information systems were designed as autonomous discrete information systems at a time when disease-centered care was dominant [41]. Therefore, AC models deployed in such systems enforce an organization-driven information security policy that protects only local information resources [1]. Therefore, the physical perimeter restriction will only allow a single local point of control to meet information-sharing and security contexts of disease-centered care. Consequently, such legacy systems cannot comply with the emerging information security needs of PC care to allow information to flow beyond a specific information system [1]. Moreover, biomedical big data are also naturally disease-centered because they are collected to reflect the needs of the disease diagnosis, where care focuses mainly on the needs of the healthcare practitioner treating the disease [1] [6]. Ultimately, the above limitations in hospital legacy information systems demonstrate their inadequacies in extracting relevant medical data for PC care and sharing data securely with remote practitioners to support virtual hospital needs.

B. Our Objective and Contribution

This study aims to propose a novel holistic virtual hospital ecosystem design that addresses issues in legacy hospital information systems. The proposed solution comprises two models. The first is an intelligent *VHealth-CNN* model for extracting PC knowledge from biomedical big data. The second is a secure *VHealth-AC* model that allows granular cross-hospital sharing of PC knowledge. We conducted an experimental case study to evaluate the feasibility of our proposed models for enhancing disease prediction in a telemonitoring service. This virtual hospital ecosystem design should facilitate the adoption of virtual healthcare services in general and lay the foundation for the development of scalable, intelligent, and secure virtual hospitals. The technical contributions of this study are summarized as follows:

1) We have developed a holistic virtual hospital ecosystem design that incorporates hospitals' legacy information systems in harmony without interruption through two models: the *VHealth-CNN* model for PC knowledge extraction, storage, and classification, and the *VHealth-AC* model for PC knowledge access control.
2) In *VHealth-CNN*, we propose a new CNN-based learning model for knowledge extraction of correlated health-related features to reveal common co-occurring disease and symptom relationships.
3) We classify biomedical big data in the *VHealth-CNN* model using a double-layer CNN structure. In the first layer, we select significant health-related features to extract potential features. The selected data is structured and stored before being classified based on the degree of common correlated patterns in the second layer.

4) In *VHealth-AC*, we propose a new AC model based on a granular 5-tier information classification scheme designed to allow secure cross-hospital sharing with remote practitioners.
5) We create a neutral security domain in *VHealth-AC* that defines and enforces a neutral policy as long as the information resides across spoke hospitals' legacy systems for sharing; we enforce local policies as long as the information reside locally within the legacy systems.

II. Related Work

In this section, we shed light on state-of-the-art related work that addresses the two issues discussed above.

A. Knowledge Mining from Unstructured Big Data

There have been many significant artificial intelligence (AI) clinical applications for diagnosis and treatment decision making [42]. Although machine-learning models have been highly effective in healthcare and other fields, they still have limited applications in clinical decision support systems [43]. However, there are many effective deep learning models proposed in the literature on health data for personalized prediction of risks and abnormal health status [43]. Furthermore, deep neural networks have shown the same or better performance than clinicians for many tasks. CNN specifically has recently begun to penetrate various applications and has proven its effectiveness in unstructured biomedical big data [44]. CNN is a deep learning method that relies on nonlinear modules to learn multiple levels of representation from highly dimensional data without explicit feature engineering by humans [45] [46]. This renders CNN a potential method for knowledge mining from biomedical big data that can assist in disease prediction [44]. Handels *et al.* [47] proposed a new approach for computer-assisted analysis of skin cancers. This study looked at skin surface photos to identify "nevocytic," "nevi," and "malignant" melanomas. Genetic and greedy algorithms were used for feature selection to enhance the classification performance of the recognition system, and feature selection was viewed as an optimization problem. An accuracy of almost 98% was achieved through the optimization of the recognition system. Recently, a variety of methods have been proposed for optimizing the system performance. Karim *et al.*. [48] presented a novel, deep autoencoder (DA)-based architecture that aims to optimize the data processing capabilities of DAs. A DA-based architecture utilizes the Taguchi method for parameter optimization with this DL architecture. Using this architecture, various parameters are successfully optimized. Essentially, this increases the amount of measurable information and values extracted from a few experiments.

In addition, CNN has been successfully utilized in a variety of healthcare services. Tariq *et al.* [49] used a CNN-based model for heart-sound classification. They proposed a classifier group combining the outputs of AdaBoost and a CNN for classifying normal and abnormal heart sounds. A time-frequency heat map indication was combined with a CNN by Rubin *et al.* [50] to create an automatic heart-sound classification algorithm. Deperlioglu [51] [52] used a CNN to classify segments and non-segments in phonocardiograms. Miotto *et al.* [53] developed a CNN model to automate diabetes detection using a combined network of a CNN-LSTM for abnormality detection in diabetes. Ebadollahi *et al.* [54] proposed a CNN-based brain tumor classification system for automatic learning of tumor regions. The system efficiently solves the problem of insufficient data availability using MRI images by learning and classifying tumor regions from such images. Ayala Solares *et al.* [43] proposed a deep generative learning model with 87.26% accuracy for detecting the use of traditional Chinese medicine from electronic health records. This model uses a CNN architecture to predict unplanned readmissions after discharge. The model directly maps the electronic health records of each patient's history to the predicted risk. Baek and Chung [44] proposed a CNN model for the prediction of chronic diseases. The model uses a CNN double-layer structure for factors classifications. In the first layer, the model selects significant health factors; however, in the second layer, the selected factor is analyzed. Using Pearson's correlation coefficient (PCF), factors with a positive correlation above 0.5 are selected as positive significant factors; factors with a correlation of less than 0.5 are classified as negative correlated factors. Associated rules are defined to classify and identify frequently occurring rules that may identify new knowledge from the classified dataset parameters.

The complex mix of methods and additional layers demonstrated the incredible ability of CNN's profound learning effectiveness with chronic disease diagnosis; however, it simultaneously; raised the complexity of analysis. Therefore, there is a need for a new CNN-based model that targets and detects based on the PCF and common behavior. The term 'common' refers to objects appearing in similar contexts. This would overcome the limitations and allow for detecting any abnormalities in the data for a PC knowledge extraction, turning big biomedical data into valuable insights that assist practitioners in making informed decisions without being overwhelmed.

B. Disease-Centered AC Models in Legacy Information Systems

An AC model rationalizes access decisions and enforces them based on predefined access rules stored in an information security policy [55] based on a deployed information classification scheme. This is achieved using three basic elements that are accountable for the decision, storage, and enforcement of these rules in a controlled environment (called the security domain). This is achieved through a policy decision point (PDP), a policy storage point (PSP), and a policy enforcement point (PEP). It ensures that an authenticated user only accesses what they should and determines if authorization should be granted or rejected [56] [57]. There are many proposals in the literature regarding approaches for cross-hospital information protection that range from unenforced and partially enforced to fully enforced protection approaches.

Traditional AC models [58] are not designed to share information across local AC model elements; thus, they surrender the security policy once the information is shared outside the original organization. Because the security policy cannot be enforced outside the organization, the result is the complete loss of control over its information when it leaves. Consequently, it is too risky to share information lest it contain even a small range of sensitive content; thus, the effectiveness of collaboration is hindered. Autonomous clinical portals deploy traditional AC models. They are web-based healthcare support systems that provide test results and letters to healthcare professionals at different National Health Service trusts or hospitals. Each hospital has its own separate implementation of clinical portal for viewing local clinical information within the hospital's perimeter, and although all the portals have similarities in fundamental concepts, look, and feel, each is a local implementation.

Pearson and Mont [59] and Sicari and Rizzardi [60] propose a "sticky policy" solution to help govern its sensitive information using its local rules, and thus a policy that reflects needs is passed to be enforced remotely. However, this system still does not have much control over its information because according to this proposal, it is left with no option but to rely on being a trusted authority. There is no guarantee that information will be protected in the same way or at the same level once it is located, because the AC model deployed may not be compatible with all rules [59] [60]. Yau and Chen [61] and Begum *et al.* [61] propose policy integration and conflict reconciliation solutions to enforce one and only one sufficient neutral policy in both security domains through integration [61]. This new policy aims to fully consider the local information security needs of both domains [61] while fulfilling the new sharing context essentials developed by collaboration to govern any future information [61]. Therefore, both domains must accept the resulting policy to govern all information resources used in the collaboration [61], which can be used locally without conflict. However, this might lead to misinterpretation due to the need to interpret inconsistent policies.

Other proposals "stick" not only the policy with the information but also the AC elements. This maintains the same level of protection as the original rules over information remotely, even after it moves to the policy enforcement model. Digital Rights Management (DRM) in [62] is a well-known AC technology that remains applied to information after it has been copied, transferred, and stored on another organization's information system [62]. It is mainly used in the commercial sector because it is largely focused on payment-based dissemination controls by delivering licensed digital content, such as music, to the end user to reside on their machine and protect it using the original rules of the AC model even after dissemination [58] [62] [63]. However, this solution is limited to the machine that it resides on and the number of users having access to it. This is because this technology does not allow for policy update once the information leaves the physical perimeter [63] [64].

The Welsh Clinical Portal [65] solution helps maintain the information protection level even after information has been shared and can be changed remotely at any time. This solution is an electronic front door to various local autonomous clinical portals that creates a virtual electronic health record for the patient [65]. This solution allows it to move along with the information so that the unified AC can enforce it at any time and make it locally accessible for any later modification. This allows each domain to maintain its local policy such that users can only view information. Moreover, Park and Sandhu [58] proposed the usage control AC model to address the static policy issue by having two policy enforcement points in each domain that are linked together. This technique uses the concept of a "reference monitor" [58], which is an abstract Concept of controlling the rights and usage of rights on digital objects [58]. Usage control suggests having a reference monitor in the service provider named "server-side reference monitor," and another reference monitor named "client-side reference monitor" [58]. This provides s more flexibility by enabling both policy enforcement points to make access rights decisions for any number of access requests and enforce them equally in both domains to ensure consistency. However, like DRM, this technology cannot be used in collaborative environments of a heterogeneous nature, as it requires a piece of software to be used remotely and all systems must be compatible with this software.

Burnap and Hilton [66] proposed SPIDER, Self-protecting Information for De-perimeterized Electronic Relationships, and its extension for healthcare applications in [67] are examples of such holistic approaches. For SPIDER to meet the common information protection needs for the collaboration information security context, it uses a unified information classification scheme for collaboration. This scheme aims to classify information resources in collaboration based on their sensitivity level and assign the right protection level for each category. It provides guidance on what needs to be done to protect information resources. It is based on the widely used Traffic Light Information Classification Scheme [63]. SPIDER enforces this unified classification scheme and its protection levels to avoid the need for any organization to interpret the policy. Thus, it addresses the problem of misinterpretation of information security policies. It enforces the policy using a unified neutral AC model that allows users to label the information they want to share with the right class. Then, appropriate information security controls are placed to meet the protection level of classified information only around labeled content within the information resource, which then creates the proper access rules for this labeled information before sharing takes place. Once the information is shared, only the appropriate range of information is accessed by the user. The three AC elements are linked flexibly to ensure that rules are enforced remotely, anywhere the information may be accessed.

In summary, this section highlights a clear gap in the related work in the literature, where existing CNN and AC models cannot address the issues in traditional hospitals' legacy sys-

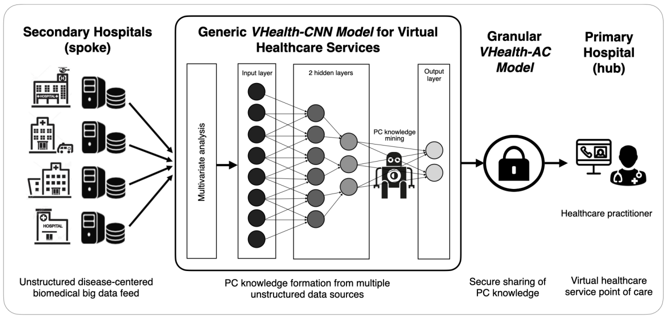

Fig. 2. Generic design of PC virtual hospital components and data flow.

tems to be incorporated into virtual hospital ecosystems.

III. Proposed Generic PC Virtual Hospital

The proposed novel PC virtual hospital ecosystem design for virtual hospital healthcare services comprises two components: one for PC knowledge mining and extraction from a medical dataset, and the second for access control to this knowledge through a novel granular AC model. On the one hand, PC knowledge is extracted from a large volume of biomedical big data collected from various sources using a *VHealth-CNN* model. This model uses multivariate analysis as a reduction technique on the collected unstructured biomedical big data to extract only the health-related features relevant to the virtual healthcare service provided and store the predefined features in a structured tabular format. This is intended to reduce the computational complexity and decrease the number of features efficiently without missing any important values. The *VHealth-CNN* model trains a CNN double layer structure; in the first layer, the significant health- related features to the virtual healthcare services from the collected data gets selected by the model and stores the collected features in a database. In the second layer, PCF analysis is conducted to classify the positively and negatively correlated features, and the final classification results are classified into three main categories: obesity, diabetes, and hypertension. This output represents the PC knowledge data for the tele-monitoring service. On the other hand, a developed fine-grained *VHealth-AC* model, based on a granular 5-tier information classification scheme, grants the health practitioner at a hub hospital this PC knowledge data seamlessly across hospitals at the point of care. Figure 2 illustrates the overview of the design components and data flow, which are further explained in the following subsections.

After the details of the proposed generic ecosystem design for virtual hospitals' healthcare services, we use a case study as a specific service (namely, tele-monitoring service) to validate the design concepts and implementation in a real medical dataset relevant to the chosen virtual healthcare service.

IV. Experimental Case study: Tele-Monitoring Healthcare Service

The designed tele-monitoring case study is mainly used for chronic disease prediction to assist in validating design concepts and evaluating their feasibility. For our case study, we used real-world biomedical big data from the Korean National Health Nutrition Examination Survey [69], which contains the lifestyle and health-related features of 10,806 Korean patients. This dataset was collected from the Korean Centers for Disease Control and Prevention to resemble the unstructured biomedical dataset for our tele-monitoring service case study experiment.

A. Design Component 1: VHealth-CNN Model

The*VHealth-CNN* model targets a detection and recognition model based on the PCF and common recording behavior. This model comprises three correlated steps, as shown in Figure 2:

1) Multivariate analysis for chronic disease and symptom concepts extraction: Raw patient medical data were collected from multiple resources and then preprocessed using multivariate analysis. This was done to extract potential features related to health conditions and lifestyle parameters and select the most important features as inputs and disease classes as outputs. Such features can detect the relationships among specific diseases relevant to the tele-monitoring service provided in our case study. As a first step in data preprocessing, we reduced the high dimension (49 features) of the collected dataset to 20 health condition and lifestyle features as input (listed in TableI) and three disease prediction classes as output (listed in TableII).

2) PCF analysis for input data classification: PCF analysis presented in [70] to determine the significant relationships between the selected features to identify the positively and negatively correlated features. This prevents overfitting when recognizing the selected health features. If the significance level of an item is greater than 0.1, the item is considered a significant enough feature. This ensures that the selected item is correlated, thereby eliminating the problem of overfitting. To test the degree of correlation between features F_1 and F_2, the *PCF* can be calculated as follows:

$$\rho_{F_1,F_2} = \frac{Cov(F_1,F_2)}{\sigma F_1 \sigma F_2} = \frac{\sum \mid (F_1 - \mu F_1)(F_2 - \mu F_2) \mid}{\sigma F_1 \sigma F_2}$$

where the coverage of F_1 and F_2 is defined as $Cov(F_1; F_2).F_1$ and F_2 represent the deviations of σF_1 and σF_2 , respectively, whereas μF_1, and μF_2 are the respective means. In our experiment, factors with *PCF* levels of 0.5 are extracted to test the relationship between input features and output classes. Furthermore, if $PCF < 0.1$, then we say that F_1 and F_2 do not have a strong negative correlation with each other. Understanding the behavior of the collected medical data features should greatly enrich the monitoring and analysis of patients' chronic disease status. For example, if some symptoms related to a specific disease are recorded repeatedly for a period of time (common pattern), then it can be expected to have a serious effect; Alternatively, if a specific health-related feature

TABLE I
CNN MODEL INPUT FEATURE LIST WITH CORRESPONDING RANGE OF VALUES

Factor	Range
V_EG: Energy intake (g)	[Num]
V_FT: Fat intake (g)	[Num]
V_WT: Water intake (g)	[Num]
V_PT: Protein intake (g)	[Num]
V_CHK: Cholesterol intake (mg)	[Num]
V_CB: Carbohydrate intake (g)	[Num]
B_SEX: Sex	[Male, Female]
B_PL: 60-s pulse	[Regular, irregular]
B_CH: Family history chronic disease	[Yes, no, no-response]
B_TSS: Time to sit and spend (h)	[Num, N/A, non-response]
B_PHC: Physical activity time (min)	[Num, N/A, non-response]
B_WD: Walk duration (min)	[Num, N/A, non-response]
B_SM: Average smoking per day	[Num, N/A, non-response]
B_ASLD: Average sleep time/weekend (min)	[Num, N/A, non-response]
B_ASLW: Average sleep time/weekday (min)	[Num, N/A, non-response]
R_DBP: Diastolic blood pressure (mmHg)	Low $\leq$ 80 Normal 80 - 90 Above $\leq$ 90
R_SBP: Systolic blood pressure (mmHg)	Low $\leq$ 120 Normal 120 - 140 Above $\leq$ 140
R_BMI: Body mass index (kg/m2)	Low $\leq$ 18.5 Normal 18.5 - 25 Above $\leq$ 25
R_FSUG: Fasting blood sugar (mg/dL)	Low $\leq$ 100 Normal 100 - 126 Above $\leq$ 126
B_DR: Drinking	[1-10, N/A, non-response]

TABLE II
CNN MODEL DISEASE CLASSIFICATION OUTPUT

Factor	Range
Presence of hypertension	[Normal, pre, high]
Presence of obesity	[Low, normal, obesity]
Presence of diabetes	[Normal, moderate, diabetes]

changes over a specific time frame (daily, weekly, or monthly), this may provide important insight into an individual's health status. Therefore, analyzing health records involves examining common behavioral features; for instance, a patient with disease x may have a temperature and heart rate increase three times in one month. Tracking and analyzing such unusual events may help identify cardiovascular risk and prevent a heart attack related to a diabetic patient. Therefore, we incorporated a common-pattern analysis module in the second layer of the *VHealth-CNN* model by searching for the common pattern among the selected features based on the user-defined normality threshold value defined by healthcare givers. Using a normality threshold, we can detect relationships between health features and understand the characteristics that are consistent with the data collected, which would help explore more possibilities.

3) CNN-Based Model For PC Knowledge Mining: The common concurring features are selected in this final step, and the final results are classified into three main categories: obesity, hypertension, and diabetes, which derive the required PC knowledge needed for informed decision making at the point of care. The *VHealth-CNN* model trains a CNN double-

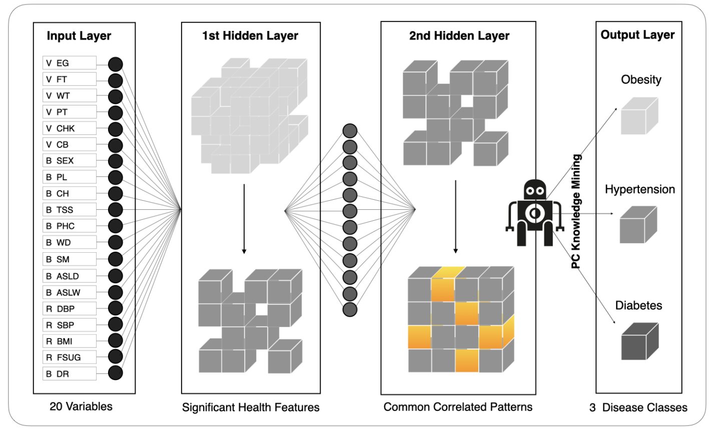

Fig. 3. PC-CNN-VHealth Model for Tele-Monitoring Services.

layer structure, as illustrated in Figure 3.

B. Design Component 2: Fine-Grained VHealth-AC Model

We consider the following scenario for a virtual hospital service collaboration between a spoke and hub hospital security domain, D_S, and D_H, respectively, to deliver a virtual healthcare service to an outpatient in a spoke hospital. Each hospital has its own local information security policy that protects its local information and is enforced by an AC model in a single local point-of-control, AC_S, and AC_H, respectively. The AC models of both hospitals were independent and may be inconsistent. If D_S shares the patient's medical information, I_S, with D_H, then this information must be protected when it leaves D_S's local point-of-control to reside in D_H. To bridge this gap in the literature, there is a need for a fully enforced AC model AC_V that incorporates heterogeneous disease-centered legacy information systems. This ACV model should enforce a neutral virtual hospital-driven (i.e., collaboration-driven) policy P_V that takes control of the information IS wherever it resides within the collaborative environment (i.e., virtual hospital ecosystem) security domain D_V. In addition, this AC_V model should not interrupt traditional hospital-driven (i.e., organization-driven) policies of disease-centered AC_S models in legacy information systems governing such information with local policiesP_S as long as it is used locally withinD_S. This guarantees that all spoke hospitals' information systems enforce the neutral policy P_V defined by VHealth-AC through the AC_V model as long as the information resides in D_V, whereas it enforces PS through the AC_S model as long as it resides in D_S (Figure 4). This allows the VHealth-CNN model to attain the right balance of I_S information security in its targeted security domains without interruption.

Defining this collaboration-driven context should require access to information strictly on a "need-to-know" basis, which complies with healthcare regulations and data protection laws [71] [72]. Therefore, in order to provide the right set of data to the right care team member at the right time of treatment on a "need-to-know" basis, we propose a fine-grained *VHealth-AC* model that achieves this goal. Therefore, we define access rules for the *VHealth-AC* model based on the following five key interrelated elements (as illustrated in Figure 5): patient, PC care team assigned to this patient, PC care team's member role, treatment plan, and virtual healthcare point of care. These elements define an information classification scheme suitable for the *VHealth-AC* model, where

1) Each patient is looked after by at least one specialized PC care team that includes all specialized healthcare practitioners caring for that particular patient to treat their disease or condition. This means that if a patient has comorbidities (that is, they suffer from more than one condition or disease and are therefore following more than one treatment path), they may have more than one PC care team.
2) Each authorized PC care team member (i.e., healthcare practitioner) should access PC knowledge only for patients they cares for and in whose treatment plan they play a role.
3) Ultimately, at a virtual healthcare service point of care, PC knowledge should be accessible to each PC care team member who needs to access it to play their role in the current treatment plan for the provided service.

C. Putting All Components Together in a Secure and Intelligent Virtual Hospital Ecosystem Implementation

To implement both *VHealth-CNN* and *VHealth-AC*, in a unified ecosystem design, a technical wrapper is designed on top of traditional hospital legacy information systems to represent the neutral collaboration context security domain (i.e., virtual hospital ecosystemD_V) where the points of care are held following a patient's treatment plan. In this technical wrapper, the *VHealth-AC* creates the PSP_V, PDP_V, and

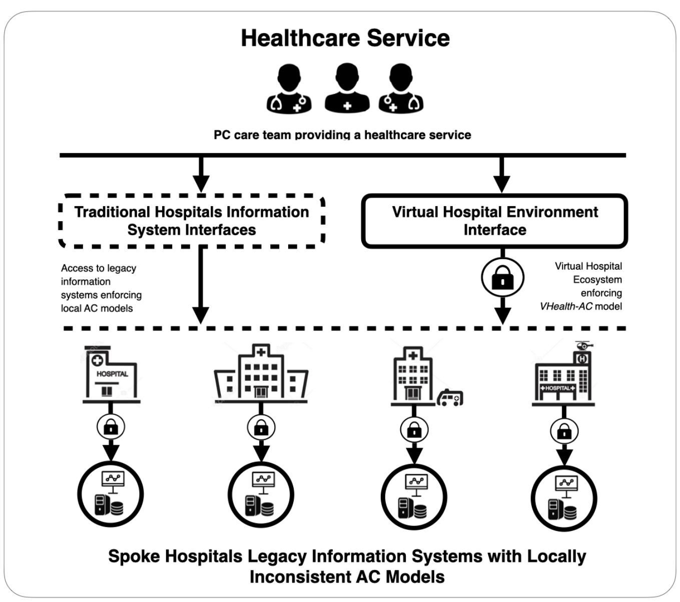

Fig. 4. *VHealth-AC* Model

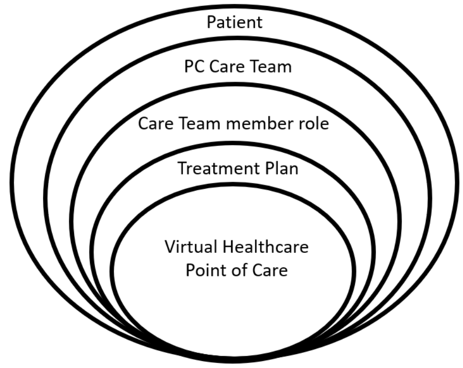

Fig. 5. 5-Tier Information Classification Scheme for *VHealth-AC* Model.

PEP_V elements for this security domain and enforces access decisions in P_V for any PC care team member requesting access to a PC knowledge I_S. This knowledge is formed by *VHealth-CNN* from legacy spoke hospital information systems that deploy the security domain D_S locally. Through this wrapper, the *VHealth-AC* model controls what may be viewed by the PC care team member ensure the availability of patient knowledge while preserving patient privacy.

Finally, both *VHealth-CNN* and *VHealth-AC* models should provide a secure, intelligent ecosystem that can transform traditional hospitals with unstructured disease-centered medical data and limited cross-hospital information sharing into a secure and intelligent ecosystem.

V. Performance Evaluation

Performance evaluation was carried out on a 64-bit Core i5 processor running Windows 10 Pro, with 12 GB of RAM, using the software SPSS. In this study, a multivariate analysis was conducted using SPSS to extract health-related features and lifestyle attributes from the dataset of 10,806 patients. This efficiently reduced the computational complexity and decreased the number of attributes from 49 to 20 without missing any important values. To analyze the model efficiency, various features that affect obesity, hypertension, and diabetes were explored. The selection of the health features was based on the correlation between features. We calculated the correlation coefficient of each feature, and a correlation co-efficient of 0.5 or more was extracted. In this case, obesity, high blood pressure, and diabetes disease prediction attributes were selected first. Subsequently, the correlation between the selected attributes were calculated and classified into positive and negative relationships. Monitoring such important positively correlated data could improve a person's daily activities by identifying positively related factors. The PCF study determined the significant relationships between the selected attributes. An efficient way to analyze regular correlations between the selected health factors is to use PCF to define the strength of the connection relationship between two variables. Additionally, any abnormality can be predicted by monitoring the negatively correlated feature values. A CNN was used to subdivide them. Moreover, the common factor behavior was analyzed to discover any additional feature behaviors among the selected correlated features. This reveals which attributes feature a common or abnormal correlation. Therefore, the characteristics of the collected features were analyzed and classified as obesity, hypertension, and diabetes. This could significantly enhance health status before it happens by understanding such diseases and their causes.

For the experiments, we used 4,759,777 records in appropriate data formats and excluded data with no responses and missing values, which was 1,499,423 records. The collected records were divided into 70% training data and 30% test data. A 10-fold cross-validation algorithm was used to optimize the hyperparameters (such as early stopping for training). Moreover, The model accuracy was measured by root mean square error (RMSE). For each model, the RMSE, calculation speed, and complexity were calculated using the proposed *VHealth-CNN* model. In addition, we recorded the same evaluation criteria in the general CNN model for the prediction of obesity, hypertension, and diabetes. RMSE was used to measure the difference between the predicted and observed values [73]. The RMSE was evaluated as follows:

$$RMSE = \frac{\sqrt{\sum_1^n (P_K - O_K)^2}}{n}$$

A smaller value of RMSE indicates a high accuracy of the model prediction; however, an increase in the RMSE value indicates a low prediction capability of the model. For the three identified diseases, if obesity was predicted and the value was 3, applying our model, the actual observed value was 2 and the error was 1. Table III lists the RMSE results for the *VHealth-CNN* model. The predicted RMSE of our model was compared with that of the general CNN model for the prediction of obesity, hypertension, and diabetes. The calculation speed of the proposed model was calculated using the two hidden layer and the complexity was also calculated. For each diagnosed disease, the general CNN model has a high RMSE value, which indicates a low prediction accuracy with high calculation speed and complexity. For example, the RMSE of the general CNN model was approximately 0.87 with 1.1 complexity. However, the maximum RMSE of the proposed model prediction was 0.2562 for diabetes. Furthermore, to compare the performance of our algorithm, we trained the following general models:

1) *Model1*: *VHealth-CNN* model (our proposal).
2) *Model2*: Long Short-Term Memory (LSTM) model which is known for its efficiency in finding correlated data.
3) *Model3*: Support Vector Machines (SVM) model.
4) *Model4*: Traditional neural network.

Owing to the effect of the CNN structure accuracy and efficiency, we constructed a CNN model with two layers to extract and classify regular health-related data. Using multivariate analysis, the proposed method extracted all relevant information from the training dataset without transforming it and then passes it to the deep learning system for feature extraction and classification. In addition, accurate knowledge was obtained from n the collected information. A health factor that is important for health status analysis was extracted through multivariate analysis. To identify chronic diseases related to obesity, high blood pressure, and diabetes, the correlation between f the collected factors was determined d. Finally, the regular behavior of each disease factor and the knowledge related to the regular co-occurring health factors were analyzed.

TABLE III
ACCURACY OF *PC-CNN-VHealth* MODEL

Disease	RMSE		Complexity		Calculation speed	
	Apply	*None*	*Apply*	*None*	*Apply*	*None*
Presence of hypertension	0.1793	0.2027	0.454	0.956	16.452	52.27
Presence of obesity	0.0919	0.7681	0.452	1.100	15.525	36.681
Presence of diabetes	0.2562	0.5976	0.654	1.923	16.964	62.13

TABLE IV
DIFFERENT LEARNING MODEL ACCURACY COMPARISON

Disease	Learning Model			
	Model1	*Model2*	*Model3*	*Model4*
Presence of hypertension	93.5	90.01	91.3	73
Presence of diabetes	95	91	60	82
Presence of obesity	91.3	89	76	73

We propose a *VHealth-CNN* model for the diagnosis of three common chronic diseases by discovering the common behavior of correlated health features. By exploiting this knowledge of common correlated features, our model demonstrated competitive analysis performance for 4,759,777 medical records. Table IV presents the performance analysis of the model. The results show that the proposed model predicts obesity, hypertension, and diabetes diagnoses with 91.3%, 93.5%, and 95% accuracy, respectively. In contrast, *Model2* (LSTM model), when trained with the collected data after preprocessing and removing only irrelevant data, proved to not be as effective as our proposed model *Model1*. Moreover, the model represents a potential accuracy when compared with other traditional machine-learning algorithms' (*Model3* and *Model4*) learning model. Therefore, effective knowledge mining and analysis of biomedical big data are of great significance for the discovery and diagnosis of health status and medical conditions. The proposed model can extract features from the collected data, which enables it to deliver accurate and robust results to deduce the presence of obesity, hypertension, or diabetes.

VI. CONCLUSION AND FUTURE WORK

In this article, we proposed a holistic virtual hospital ecosystem design that can help address the inadequacy of hospitals' legacy information systems that hinder the flow of medical data for PC care continuity. In this study, we developed two models. First, the *VHealth-CNN* model extracts PC knowledge from multi-sourced biomedical big data to extract disease health-related features and then trains a CNN double-layer structure. The second model is a granular *VHealth-AC* model that seamlessly grants healthcare practitioners at a hub hospital remote access to PC knowledge at the right point of care. Moreover, the feasibility of the proposed design was examined through a tele-monitoring service experimental case study to predict obesity, hypertension, and diabetes. We used real-world biomedical data containing health-related and lifestyle behavioral data features. The experimental results showed that the proposed model predicts obesity, hypertension, and diabetes diagnoses with 91.3%, 93.5%, and 95% accuracy, respectively. Finally, the results showed that effective PC knowledge mining and analysis of biomedical big data are of great significance to the prediction and diagnosis of health status and medical conditions. Therefore, our novel virtual hospital ecosystem design should empower patients, healthcare providers, and healthcare practitioners to deliver accessible, affordable, and comprehensive PC care.

However, there are some potential limitations to the performance of this ecosystem. First, bandwidth limitations due to the extensive sharing of huge amounts of data over the cloud between the hub and spoke hospitals may cause delays in data delivery. Therefore, we plan to improve the performance of this system in the future by using fog computing and non-real-time edge computing to enhance factors such as limited bandwidth and capacity. Moreover, we plan to optimize the CNN to improve the learning accuracy using various recently published pattern classifiers or by adding multiple classifiers and evaluating the performance accordingly and studying multimodality data and preprocessing methods.

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