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PATIENT MODEL BASED PERSONALIZED REMOTE HEALTH CARE FOR CHRONIC DISEASE

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A B S T R A C T

Recent advancements in wearable smart devices, medical internet of things, cloud computing, wireless communications, and AI-based technologies have enabled personalized remote health care for patients with chronic diseases. Covid pandemic period has exposed the shortfall of the healthcare system, where there was a massive shortage of doctors, nurses, medical supplies, hospital beds, and other healthcare infrastructure, which has affected many patients with chronic diseases who needed constant monitoring and consultation with doctors. This has affirmed the necessity of remotely monitoring the patients to predict their requirements for medicines, treatment, etc., and to avoid any unusual severe condition. In this work, we presented the Patient Model to monitor the patient's activities and remotely identify and fulfil their treatment requirements. The framework monitors the patients and depending on the diagnosis provides personalized remote health care services such as telemedicine, medical tests, diet plans, etc., along with an ambulance facility if needed. The proposed framework uses a CNN and other machine learning algorithm to predict the required personalized healthcare service requirements. The simulation results show that the proposed framework, using the patient's model, and CNN algorithm significantly improves the precision and recall of the prediction and reduces the time to predict the requirements.

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1. INTRODUCTION

Chronic diseases such as diabetes, hypertension, hyperlipidemia, cardiovascular diseases, etc., are diseases which are persistent, long-lasting and require constant medical treatment and sometimes immediate treatment during emergencies. Covid pandemic period has exposed the shortfall of health care system, where there was massive shortage of doctors, nurses, medical supplies, hospital beds, and other healthcare infrastructure, which has affected many patients with chronic diseases and who were in the need of constant monitoring and consultation with doctor (Javaid et al., 2022; Nitin Kumar Gupta, 2023). The recent advancement in wearable devices, Internet of medical things (Imo), cloud computing and AI, ML based technologies have enabled the prediction and early diagnosis of health care services by remotely monitoring the patients with chronic diseases (Zheng et al., 2013; Abiodun et al., 2022; Sun et al., 2010; Manjulatha & Pabboju, 2021; Wu et al., 2022). The health care service providers exploit the context awareness, AI, and machine learning tools to analyse the patient's information to identify the patient's condition and to provide suitable treatment without any intervention in their regular activities. Remote

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healthcare not only includes monitoring chronically sick patients, elderly people, but is also useful in tracking of pre/postnatal care and disaster victims. The personalized remote health care services not only benefits patients with doctor's advice on medicines, but also useful in diagnosis of medical tests requirements, suggesting diet charts or exercise routines based on the evaluation of vital parameters of the patients. The other advantages of personalized remote monitoring of patients are early and real-time prediction of diseases so as to prevent severe conditions and avoid hospital admissions (Zheng et al., 2013; Alanazi, 2022)

1.1 Proposed Idea

This paper introduces a personalized remote health care framework for patients with chronic diseases. The proposed framework continuously monitors the patient and predicts their requirements. The proposed framework makes use of the *Patient Mode*l and Machine Learning algorithms to provide personalized remote health care services. The proposed framework uses locally supervised metric learning to match the patient's information and CNN machine learning algorithm to predict the required personalized healthcare service. The simulation results show that the proposed framework, using the *patient's model*, and CNN algorithm significantly increases the precision and recall of the prediction and takes more time to predict in comparison to other machine learning algorithms.

1.2 Organization of Paper

The remaining part of the paper is structured as follows. Section 2 provides a brief overview of some of the related work. Section 3 explains the proposed *Patient Model.* Section 4 describes the framework of predicting *Remote Health Care Services*. Section 5 describes the simulation environment and results, followed by the conclusions in Section 6.

2. RELATED WORK

In this section, we briefly discussed some works that address the handling of remote health care. Context-aware ML based healthcare identifies various treatment alternatives and personalized the treatment for patients and improves overall care of the patents by means of appropriate decision and prediction (Jen et al., 2012; Kumar et al. 2023; Erturkmen et al., 2019; Hegde & Mundada, 2020) Authors in (Javaid et al., 2022) discussed the importance of Machine Learning (ML) in healthcare systems along with its characteristics and usage. Nitin Kumar (Nitin Kumar Gupta, 2023) has discussed AI driven tools for chronic disease management. In (Zheng et al., 2013) authors have discussed emerging wearable devices for personalized health care. For prognosis of chronic diseases ML based approach is used. A decision tree-based prediction for chronic disease is used in (Qudsi et al., 2017) Authors found SVM model performs better in comparison to MLP, J 48, and KNN classification models. In (Lasorsa et al. 2016) ML-based remote triage scheme for tele-medicine (ML-ART)
is proposed to provide relatively importance to patients with multiple-chronic diseases for critical healthcare services. Rayan Alaniz has discussed to Identify Chronic Diseases using machine learning based approach in (Rao et al., 2022). Applications of Machine Learning Predictive Models in the chronic disease diagnosis is discussed in (Kadum et al., 2023). Gaiety et. al. has discussed the use of machine learning and IoT for healthcare applications. A ML based technique for remote health monitoring is proposed in (Battineni et al., 2020). Clinical trials are monitored using SVM and ANN classifiers where physiological datasets is obtained from the wearable devices. In (Galiveeti et al., 2022) survey of different artificial intelligence techniques is discussed to diagnose various diseases. Even with several existing approaches in the literature, the new approach of personalized remote health care of patients with chronic disease is still needed as providing personalized remote health care services is a compelling future to enhance their treatment experience. The proposed framework with the dynamic construction of the patient model improves the relevance of personalized health care services for the individual requirements of the patients.

In (Alanazi, 2022), CNN and KNN machine learning models are used for the Identification and prediction of chronic disease. Authors in (Rashid et al., 2022) have discussed an augmented artificial intelligence approach using an artificial neural network (ANN) with particle swarm optimization (PSO) for the prediction of five prevalent chronic diseases including breast cancer, diabetes, heart attack, hepatitis, and kidney disease. Authors in (Nanehkaran et al., 2022) have designed a medical recommender system for the identification and treatment of the chronic diseases by utilizing IoT devices. Authors have used the patient health record dataset from the Physio Net data repository. The patient's health records are obtained based on the identified diseases and the diagnosis of the physician. K-nearest neighbour classification method is employed for the identification of type of disease, and the collaborative filtering method is utilized to find the appropriate treatment for patients.

3. THE PATIENT MODEL

This section proposes a patient model. The patient model is designed considering the patient's personal information, analyzed context information and records of medical history of the patients. Based on the Patients Personal Information (PPI), Analyzed Context Information (ACI) and available Medical History (MH), The Patient Model (PM) is defined as given in Equation 1.

$$PM = \{\langle PPI\rangle, \langle ACI\rangle, \langle MH\rangle\} \quad (1)$$

Each of these terms is defined as follows.

Table 1. Medical Hostory of Pateints.

Patient-Id	Age	Gender	Location	BP	HR	Cholesterol	FBS	-----	Symptoms of Chest Pain (Yes/No)	Medicine
P1	50	F	Kitchen	140/90	95	190	200	-----	No	Glipizide
P2	70	F	Bedroom	150/80	70	220	120	-----	Yes	Ecosprin
P3	60	M	Bathroom	160/85	96	160	100			Captopril
-----	-----	-----	-----	-----	-----	-----	-----	-----	No	-----
-----	-----	-----	-----	-----	-----	-----	-----	-----	No	-----
P499	65	M	Balcony	130/70	88	200	110	-----	No	Losartan
P500	72	F	Garage	180/90	89	250	160	-----	Yes	Rosawell

3.1 Patients Personal Information (PPI)

The personal information of the patients such as age, gender, occupation, contact, address, etc., is obtained during registration of the patients to the health care services. The system maintains the personal records and provides unique Ids to the patients to explicitly monitor and provide remote health care services.

3.2 Analysed Context Information (ACI)

The patient's context information is obtained through the wearable, sensing, embedded devices or system APIs available throughout the environment of the patients. The information about patients' location, activity, time, enables the system to track the patient's routine, whether patient is in kitchen or balcony, relaxed or in doing exertion which in turn affect patients' vital parameters. The acquired context information is analysed and deduced over various combinations as a higher-level context information following a similar approach given in (Khanwalkar et al., 2020).

3.3 Medical History (MH)

The medical history of the patients includes past records of physiological information such as BP, Heart rate, blood glucose level, BMI, medicines, and information about previously conducted tests and accordingly prescribed treatments and medicines, historical records of patient's disease as given in history database as shown in Table 1. Usually, diseases may cause due to age, genetics or living habits and region related factors. Thus, along with disease related data other relative factors are also taken into consideration. Medical history enables the health care service professionals to correlate and predict the required treatment and medicines.

4. PROPOSED FRAMEWORK

We proposed a framework to provide the personalized remote health care service (*$RHCS_i$*) to patients with chronic disease using a *Patient Model*. As shown in Figure 1, it consists of patient information acquisition unit to gather the information personal, physiological, and medical history related information about the patients. The collected information is pre-processed and required features are extracted to design the patient model. Further, the Patient model is designed (see Section 3). The dynamic instance of a present *Patient Model* is matched against the existing medical records containing earlier designed *Patient Models*. After matching further, we use machine learning algorithms to predict the personalized healthcare service.

The proposed framework maintains the previous few years records of the patients in different scenarios and their respective treatments along with corresponding patients' model. The proposed framework maps the present instance of the *Patient Model (PM_j)* with the existing available case base of the Patient *Model (PM_K)* and automatically identifies a specific treatment for the patients as given in Equation 2

$$RHCS_i = argmax\ sim(PM_j, PM_k) \quad (2)$$

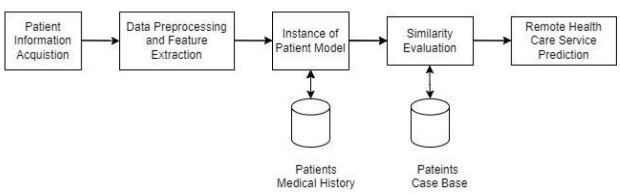

Figure. 1 Personalized Remote Patient Monitoring Framework

The existing patient's medical history records are used to train the model and for evaluating the patient's similarity. However, the similarity between patients' models may be dependent on several dimensions. The two patients may have few parameters similar whereas others might be different. For example, even though two patients are suffering from chronic heart disease, one may have a history of diabetes while the other may not. Thus, instead of common method of similarity evaluation using Euclidean or cosine similarity, we use locally supervised metric learning. $SIM_{LSML}(y_i-y_j)= [(y_i-y_j)^T ww^T(y_i-y_j)]^{1/2}$ (Sun et al., 2010), based similarity evaluation which is adaptive to the specific disease parameters, where x_i and x_j are the attributes of the Patient Model for ith and jth patients. and w is the transformation weight based on the disease parameters.

Next, the presented framework utilizes the CNN based ML algorithm for the prediction of personalized remote health care service for patients with chronic disease. Initially the information related to the patients is converted into vector form, then word embeddings is used such that features with similar meanings will have similar characterization in the vector space, and to consider null values for padding the information. Then, the processed information is passed to the convolution layer. The convolution layer output further passed to the pooling layer followed by the max pooling functionality. Then the output of max pooling layer is passed to the full connected layer, and in the end, the final layer gives the classified predicted output.

5. SIMULATION AND RESULTS

In this section we discuss the simulation and results of the proposed approach. In order to understand the functioning of the proposed framework we have simulated the framework using Python. We consider that patient data is collected through various wearable and sensing devices. The acquired data is further processed and based on the CNN machine learning algorithms the need for personalized remote health care service is identified. For the purpose of simulation, we consider the Kaggle dataset of chronic heart disease (Heart Disease Dataset, 2019). We evaluated the performance of the framework based on the remote healthcare service prediction time, Precision, Recall and F1-Measure. We compare performance of CNN with different machine learning algorithms, for example the Random Forest, Decision Tree and the Logistic Regression.

As shown in Figure 2, we evaluated remote health care service prediction time, and found that due to several layers CNN algorithms takes little, longer time for prediction in comparison to linear regression and random forest and decision trees.

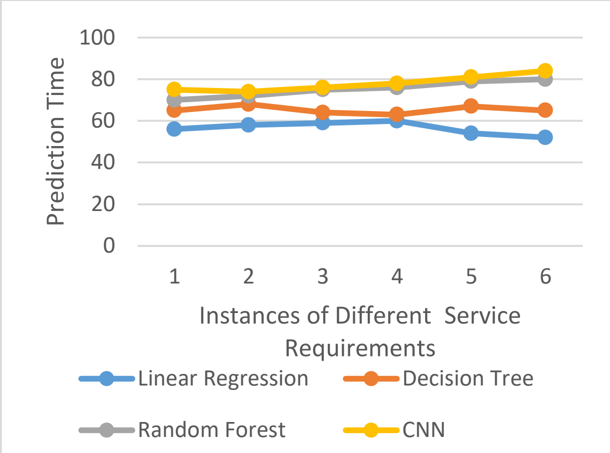

Figure 2. Remote Health Care Service Prediction Time of Linear Regression, Random Forest, Decision Tree, and CNN Algorithms

We evaluate the performance of the presented framework by considering precision and recall of the identified remote health care services. *Precision* measures the fraction of relevantly identified services among the total identified service as given by the Equation 3

$$Precision = \frac{|\{Relavant\ Services\ \cap Identified\ Services\}|}{|\{Identified\ Services\}|} \quad (3)$$

Recall measures the fraction of the identified service which are considered to be relevant for the patients over the period of time as given in Equation 4.

$$Recall = \frac{|\{Relavant\ Services\ \cap Identified\ Services\}|}{|\{Relavant\ Services\}|} \quad (4)$$

F1- Score is based on the precision and recall as given in Equation 5.

$$F1 - Score\ =\ 2 * \frac{Precision * Recall}{Precision + Recall}. \quad (5)$$

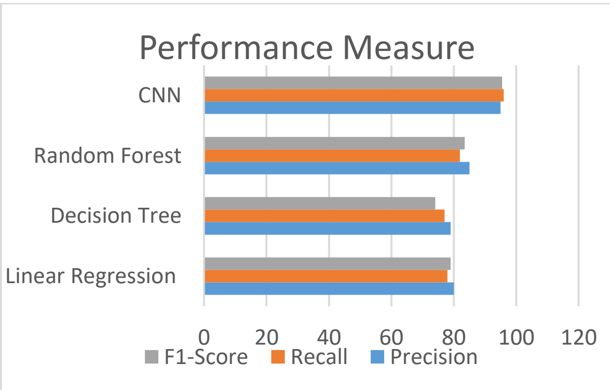

Figure 3. Performance of Linear Regression, Random Forest, Decision Tree, and CNN Machine learning model

Figure 3 indicates the comparative results of precision, recall, and F1-score for the CNN, linear regression, random forest, and decision trees. As shown in Figure 3 the CNN algorithm with higher precision, recall and F1-score as 95%, 96% and 95.49% performs better in comparison to the linear regression, decision trees and random forest.

6. CONCLUSION

In this paper we have discussed the framework for personalized remote health care of patients with chronic diseases using patient model. The proposed framework continuously monitors the patient and predicts their requirements. The framework makes use of the *Patient Mode*l and Machine Learning algorithms to provide personalized remote health care services. The proposed framework uses locally supervised metric learning to match the patient's information and CNN machine learning algorithm to predict the required personalized healthcare service. The simulation results show that the proposed framework, using the *patient's model*, and CNN algorithm significantly improves the precision, recall and F1-Score of the prediction and takes more time to predict in comparison to other machine learning algorithms.

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