IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 10 August 2023, accepted 29 August 2023, date of publication 5 September 2023, date of current version 11 September 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3312278

RESEARCH ARTICLE

Digital Twin-Based Healthcare System (DTHS) for Earlier Parkinson Disease Identification and Diagnosis Using Optimized Fuzzy Based k-Nearest Neighbor Classifier Model

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This work was supported by the Vellore Institute of Technology, Vellore, India.

ABSTRACT The Digital twin based Healthcare System is a demanding issue that can introduce improvements in the life of the elderly and disabled people living in remote places. More recently, modern Digital twin based Healthcare Systems have gained more attention and invitations from people due to the popularity of smart city establishment along with improvements in various healthcare services adapted in the smart phones. It is achievable because of the anytime, anywhere service access mechanism and machine-learning-based smart predictions over the cloud computing platform. The existing Healthcare System offers service to remote patients through continuous monitoring and tracking of physiological health records without live interaction and portability. Thus, the Digital twin based Healthcare System (DTHS) is proposed with smart virtual care facilities to enhance the earlier states of disease prediction and a patient-centric diagnosis mechanism from remote locations. Particularly, diseases such as Parkinson disease, identified as a severe neuro degenerative disorder worldwide, require such prediction and diagnosis at earlier stages. In this work, the experiments are focusing two voice based data sets namely DS1, and DS2 obtained from Kaggle, and UCI Machine learning repository. The proposed DTHS is developed over the cloud platform for Parkinson disease prediction using the Optimized Fuzzy based k-Nearest Neighbour (OF-k-NN) classifier model. It provides cumulative improvements against the existing Neural Network and Kernel-based SVM classifiers with respect to Prediction Time for DS1 as 0.00127 seconds, and DS2 as 0.00105 seconds, Prediction Accuracy for DS1 as 97.95%, and DS2 received 91.48%, F1-Score 0.98 for DS1, and 0.91 for DS2, and Matthews Correlation Coefficient of DS1 got 0.93675, and DS2 received 0.79816.

INDEX TERMS Digital twin based healthcare system, Parkinson disease identification, k-nearest neighbor classifier, remote patient monitoring, smart city and virtual care applications.

I. INTRODUCTION

The term Digital Twin (DT) was first coined by John Vickers of NASA in 2002. DT is a virtual replica of a physical entity. Using DT, any physical entity such as a human, building, city, etc., can be modeled using mathematical modeling and a digital replica of that object can be created virtually [1], [2]. With the advancements in technologies such as the Internet of Things (IoT), Machine Learning (ML), and Big Data Analytics (BDA) [3], [4], there has been a surge in the number of real-world applications based on DT recently. Using the DT technology, the behavior of the real-world objects are simulated in the digital replica. The responses of the real-world object to any change in the environment are captured through the sensors. The data captured from the sensors can be used to simulate the digital twin in the virtual world. The ML/BDA algorithms can be used to analyze the behavior of real-world objects, which can be used to train the digital twin by virtually. In this way, using DT technology, the virtual replica can be trained to respond to any changes

The associate editor coordinating the review of this manuscript and approving it for publication was Nazar Zaki.

TABLE 1. Important acronyms.

Acronym	Meaning
DT	Digital Twin
DTH	Digital Twin in Healthcare
DTHS	Digital twin based Healthcare System
OF-k-NN	Optimized Fuzzy based k-Nearest Neighbour
ML	Machine Learning
IoT	Internet of Things
HIoT	Healthcare Internet of Things
AI	Artificial Intelligence
BDA	Big Data Analytics
WSNs	Wireless Sensor Networks
BSNs	Body Sensor Networks
SVM	Support vector machine
ANN	Artificial Neural Network
k-NN	k-Nearest Neighbour
IEEE	Institute of Electrical and Electronics Engineers
EHR	Electronic Health Records
PA	Prediction accuracy
R	Recall
P	Precision
UCI	University of California-Irvine

in the environment. Hence, by integrating DT with IoT, ML, and BDA, penalized requirements of the physical object can be identified, and mass personalization can be achieved [5]. Many industries such as manufacturing, healthcare, agriculture can be benefited from the DT in providing personalized solutions to its customers [6]. DT has the potential to solve many problems prevailing in the healthcare industry today. DT can be used to provide personalized healthcare, precision healthcare, improving the efficiency of the hospitals, proactive remote monitoring of the patients, drug discoveries, designing the medical devices, etc. [7].

In present era, Tele-HealthCare stretches beyond the usage of smart phone devices, which continuously connect the patient, physician and caregivers by combining digital and telecommunication technologies. By connecting patients and Tele-HealthCare providers, treatment can be improved due to real-time data gathering and continuous monitoring of remote patients. The need for DTHS is dramatically increasing on a daily basis due to the demands of remote Healthcare services. More recently, the World Health Organization has predicted that there will be 12.9 million healthcare worker shortages globally by 2035. In fact, that shortage number has already reached 7.2 million. Similarly, the association of American Medical College has also predicted an expected shortage of 61,700 to 94,700 physicians in the U.S alone for the next 10 years. Accordingly, the forecast prediction done by the U.S. Bureau of Labor Statistics has indicated that 1,000,000 nurses will be needed in 2022 [8]. Since healthcare centres are expected to be overwhelmed with many patients for medical care, we cannot expect nurses to be confined to patients with 24-hour monitoring to record physiological values for doctor's analysis. Due to the increasing demand of nurses, there is a possibility for human error in monitoring physiological parameters. There is also a need for a smart virtual care system for in-house patient monitoring in hospitals and said in monitoring remote patients to analyse the physiological parameters to achieve a diagnosis and to provide medical advice. Therefore, Tele-healthcare and smart virtual care are identified as the most important pillars for development. This critical problem motivates the concentration on DTHS for a better livelihood and lifestyle of human society. In this article, an comprehensive review of proposing DT for providing solutions to the problems in the healthcare industry is provided. The first objective of this research work was to design and develop an effective DTHS to provide a smart virtual care system that stretches beyond the usage of modern mobile devices or digital tools. Moreover, it continuously connects the patient, physician and caregivers by combining digital and telecommunication technologies. The second major objective was to design and develop an adaptive K-Nearest Neighbour classifier model to predict and identify the severity of patient diseases by analysing data generated from a smart virtual care device at the patient's side. In existing Tele-healthcare services, addressing various issues such as sensing and continuous monitoring of the patient become difficult for complex data management and computing capabilities due to the lack of a scalable and portable healthcare system for providing seamless service access to a large number of patients regardless of time and space limitations [9], and insufficient and ineffective healthcare services to satisfy the demands of the increasing ageing population with chronic diseases [10]. Tele-metrics gadgets include a wearable computer, ubiquitous computers, handheld devices such as personal digital assistants and mobile phones, which can record the cognitive, physiological, behavioural, environmental and affective data for humans [11]. Tele-pointer popular models such as the cursor, hand, laser and sketching have been used to improve the quality of healthcare by providing real-time positioning accuracy, even in rural areas [12]. Remote healthcare varies from continuous monitoring of ill and elderly patients to the victims of accidents. Similarly, the technology may vary from wireless body area sensors to ambient sensors attached to the monitoring environment [13]. According to recent research, the smart home (healthcare) video surveillance system addresses the use of robust and intelligent live video analysis using emerging edge-level computing technology [14], [15]. By connecting patients and smart virtual care providers, treatment can be improved due to real-time data gathering and continuous monitoring of remote patients. The major contributions of this research work includes the following:

1) Design and development of a patient-centric DTHS for earlier Parkinson disease identification and diagnosis over smart phones through continuous monitoring and analysis in the case of inadequate doctors in hospitals and remote villages;
2) Proposing optimized fuzzy based K-Nearest Neighbour classifier model for predicting Parkinson disease and its severity level by analysing the voice data of remote patients over smart phones;

3) Performance validation of the proposed K-Nearest Neighbour classifier model compared with existing models in terms of Prediction Time, Prediction Accuracy, F1-Score and the Matthews Correlation Coefficient.

Experimentation have performed in this work by using publicly available datasets like Cerrahpasa Faculty of Medicine, Istanbul University [16], and University of Oxford, consisting of voice samples collected from 195 subjects [17] that would help us to analyse and predict the Parkinson disease in earlier stages. These trained dataset are using for validating our proposed model, later it by using testing dataset the performance of proposed version will be evaluated. The paper is organized into five sections. The next section II provides a literature review of the different Digital twin based Healthcare Systems available in the market, comparative analysis of healthcare industry with and without digital twin features, and different classifier models involved in Parkinson disease prediction. Section III, provides a detailed explanation of the proposed DTHS architecture with appropriate modelling of the K-Nearest Neighbour classifier. In section IV, two benchmark datasets under experimental evaluation are briefly described with significant results and discussion. The final section V provides the conclusions and future enhancements of the research work.

II. LITERATURE SURVEY

Remote medical care is more crucial due to the ageing population. Recent advancements in IoT based healthcare technologies leverage the key components of intelligent pervasive systems to monitor and assist elderly people living independently in remote places [18]. In this section gives the brief review about how digital twin technology was used in existing health care services, beneficial comparison of health care with and with digital twin aided features, different existing Parkinson disease classifier models and their limitations.

A. DIGITAL TWIN BASED HEALTHCARE SYSTEMS

The fast world has led people worldwide to cope with all their needs in a faster and quicker manner. Due to this adaptation of the world, medical practitioners are also motivated to inherit various latest technologies in their treatment, monitoring, and diagnostic pattern [19]. This section discusses the various recent technology enhancements in the domain of healthcare. The wearable sensor may sometimes lead to inaccurate activity recognition and uncertainty in sensor measurements. According to an ambient assisted living report, Finland has facilitated the lives of disabled and elderly peoples to become more valuable by instituting smart devices only when combined with healthcare services including formal and informal support and disease prediction systems [20]. More recently, the vCare project was sponsored under the European Commission's Horizon 2020 [21]. This project was started in September 2017 by an international team consisting of twelve partners from seven European countries involving various researchers, industrial experts and healthcare providers. It aims to provide an advanced virtual coaching system to provide personalized rehabilitation for people that will lead to better quality of life and better continuity of care. Moreover, the vCare project ensures that patients' continuity of care shifts from classical professional treatment into the home environment by optimizing the economics of medical care treatment. St. Luke's Virtual Care Centre was established during the summer of 2018 to bring vital medical access to patients from rural and metropolitan areas [22]. Cameras and remote-monitoring devices were used at the patient end to connect people for medical diagnosis and treatment. At the hospital end, doctors and nurses will continuously monitor the patient's vital signs, watch criticality to support onsite caregivers, read results, order tests, and provide immediate evaluations of patients through specialists. The virtual care provider can continuously monitor vital signals such as the oxygen level, heart rate and blood sugar level using secure two-way audio and video communication devices in real time. Memorial Hermann Virtual Care remains one of the pioneers in health care [23]. The employees and affiliated physicians working at this institution continue to bridge the technology gap in health care. They continually seek new and innovative ways to bring their patients the most advanced care with accurate and nominal cost-effective service. Patients with chronic health concerns are remotely monitored through the use of smart phones, computers, telephonic devices, and customized home care kits. The care team recommends the set of treatment for various diseases including congestive heart failure, pulmonary conditions, diabetes and other endocrine disorders. The most complete and forward thinking Zipnosis Virtual Care platform offers transformative online virtual care tools along with traditional telemedicine software capabilities to provide outstanding clinical quality and strong financial returns [24]. Zipnosis delivers the widest range of virtual care services and technologies on the health care market. Starting from the simple to the complex care service is provided through multiple access points supporting patient access by dramatically improving clinician efficiency and high quality care. It provides a real-time connection between patients and health care providers through chat, phone and video communication. They have very good industrial marketing with other health care partners such as Allina Health, American Academy of Family Physicians, Scension, Bryan Health, CentraCare Health, Essential Health, Fairview, IHA, Inspira Health Network, John Muir Health, Lake Health, Lakewood Health System, Lexington Regional Health Centre, Memorial Health Care Systems, Methodist Medical Group, Mission Health, Multi Care, Musc Health, Olmsted Medical Centre, Prevea Health, Ridgeview Medical Centre, St. Luke's, St. Vincent's Medical Centre, and Summa Health. Several Digital twin based Healthcare Systems and classifier models have been discussed thus far based on different technologies to monitor remote patients in both indoor and outdoor locations by exploiting sensors, data communication technologies and other healthcare services. Our research work mainly focused on the design and development of DTHS using the

K-Nearest Neighbour classifier model, which can provide earlier Parkinson disease prediction and the diagnosis of remote patients.

During the recent era, there is a high rise in the IoT in almost all domains where there is a possibility for human-computer interaction. Out of the various real-time applications, healthcare is an essential domain in which IoT is being adopted for providing a better patient experience. When IoT is integrated with the healthcare domain, it is known as Medicine 4.0 recently. The initial era was called Health 2.0, where various diagnostic tools were designed and adopted in real-time to diagnose the patients' diseases. Health 2.0 was characterized by the utilization of certain diagnostic tools for detecting the disorders in the patients' health at an early stage and hence provided a well-planned treatment. The current shift is from Health 2.0 to Health 4.0 or Medicine 4.0, where the focus is to monitor the patients diagnosed with certain disorders and ailments are monitored remotely 24/7 [25], [26]. As a result of this, the doctors and healthcare professionals are aware of the state of the patient, even in a homely environment. This is also referred to as the Healthcare Internet of Things (HIoT) [27], [28].

Doctors are receiving the data through virtual mode by using digital twin environment. These data are collected by using different IoT connected gadgets. The backbone of IoT is the Wireless Sensor Networks (WSNs) which play a major role in interconnecting the smart devices as well as the sensors for the purpose of remote monitoring, gathering huge sensitive data, and sensing the environment. The HIoT utilizes the Body Sensor Networks (BSNs) as the underlying technology for the purpose of deploying the sensors over the body of patients [29], [30]. Currently, HIoT is adopted in real-time as wearable smart devices for the purpose of tracking general fitness. During the year 2017, the adoption of wearables in real-time showed an increase of 10.3% when compared to the previous year. Various companies like Apple, Fitbit and Xiaomi plays a vital role in the adoption of HIoT for the customers' space [31]. Though there is a huge response to this technology all over the world, the utilization of HIoT in diagnosis is still in a growing stage.

B. COMPARATIVE ANALYSIS OF HEALTHCARE WITH AND WITHOUT DIGITAL TWIN

Integration of DT with health care sector gives us an immense advantages in terms of lead new healthcare era. Recent decades many industries are incorporating the beneficial of DT into their working environment which helps them to make dynamic future decision and prediction. Similar to that incorporation of DT into healthcare domain gives the beneficial like tele-medicine, drug discovery, door step treatment, disease diagnosis, Treatment from any where in the world. This incorporation likewise makes a substantial asphalt for the scientists and clinical professionals to keep one stride ahead in finding and treatment as a result of the benefits as represented in Figure 1.

C. PARKINSON DISEASE CLASSIFIER MODELS

In the context of Parkinson disease, different types of classifier models are used in the Parkinson disease identification system. A classification scheme based on the Support Vector Machine (SVM) feature selection-based rotation forest ensemble classifier model is used to improve the prediction and diagnosis of Parkinson disease [32]. It plays an important role in the computer-aided diagnosis system used in emerging Tele medicine applications by improving metrics such as the classification accuracy and kappa error. A predictive Tele monitoring and diagnosis model is developed based on speech pattern analysis using the SVM classifier. Here, the SVM classifier with the linear kernel produced a higher prediction accuracy than the classical and K-Nearest Neighbours (k-NN) classifier [33]. Feature selection methods were applied with different classifiers using machine-learning methods to extract the necessary features from the time and frequency signals [34]. To diagnose the earlier stages of Parkinson disease, a local learning based feature selection method is applied to achieve the maximum classification accuracy by following optimal feature selection before starting the classification [35]. Therefore, it is more useful in voice signal-based remote monitoring and diagnosis of Parkinson disease in terms of economic cost. To select the top features, a logistic regression classifier generated using the cross-validation function with peak absolute weights is preferred for Parkinson medication [36]. Mostly, to distinguish Parkinson disease from a healthy normal condition, the SVM classifier (using Linear, Polynomial, Radial Basis and Sigmoidal Kernels) provides better performance than the Naéve Bayes, Boosted Tree and Random Forest classifiers in terms of accuracy, sensitivity, specificity and area under the ROC curve [37]. The multi-layer perceptron and radial basis function classifiers were designed based on the Artificial Neural Network (ANN) classification scheme [38]. They are the most powerful multi-classifiers compared with the perceptron by providing deviations in the classical linear perceptron with the non linear activation function used in feed-forward artificial neural network concepts. Therefore, the proposed research work concentrated on developing the OF-k-NN classifier model in the novel DTHS for earlier Parkinson disease identification and diagnosis remotely at an economical cost. The above literature about parkinson disease identification, earlier prediction, providing suitable diagnosis treatment plan, and the benefits of digital twin as well different existing classifier models gives the clear picture about gap in existing tele-medicine services in health care domain, and plan to propose a new model with the incorporation of digital twin in health care sector by using cloud environment.

III. ARCHITECTURE OF CLOUD-BASED DIGITAL TWIN HEALTHCARE SYSTEMS

DT technology has been adopted tremendously in recent decades since it provides lot of solutions for existing challenges at different level of sectors such as

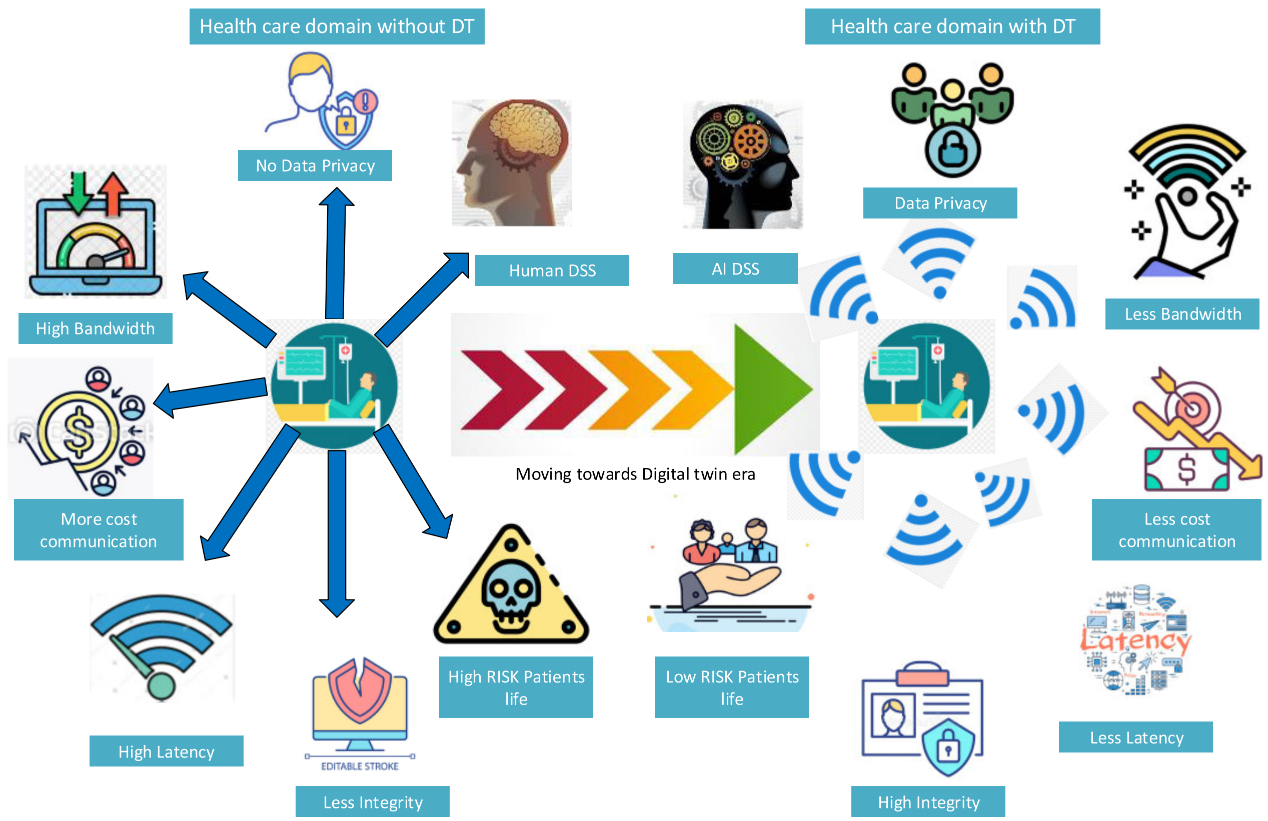

FIGURE 1. Health care with and without digitaltwin.

manufacturing/production industries, health care, sales force management, and so on [39]. Among these beneficial, the healthcare sector considered as crucial industry, since it gives the solutions to improve the quality of human-being lives. In order to achieve it, the health care industry have adopting tremendous innovations in their regular treatments inters of focusing patients' mortality rate mitigation. The incorporation of DT in health care domain helps us to create the tele-medicine solutions to the patient's health-related problems in virtual mode. The concept of DT was inherited from existing prominent models such as ML model, data analytical model, and many other simulation tool based models. These models are providing massive support for data maintenance, decision making, and prediction in health care organization [40]. However, in many cases the solution provided by these models are not in expected level such as anomaly detection for patient care, fault detection, and virtual support to the patient health monitoring. These critical issues could be addressed by means of integrating the features of IoT, machine learning, and big data into DT application. The architecture for DT services integrating with health care domain is represented in Figure. 2.

The proposed architecture of the Cloud-based Digital twin Healthcare System consists of three layers such as the End user layer, DTHS (DTHS Cloud layer), and service layers, as shown in Figure. 2. In the End user layer, Doctors' can get the patients' neuro degenerative disorder data either through physical mode or anyone of digital twin based applications present in DTHS Layer, and voice data from remote places are recorded through application, and send it to the cloud for further analysis and prediction. These voice data are analysed in the DTHS cloud layer for the analysis of Parkinson symptoms based on comparison to parameters with data available in the patient medical history. Next, the proposed OF-k-NN classifier model classifies the Parkinson disease into five stages according to their severity levels predicted by the decision support system. Based on the Parkinson severity stages, the Automated Care Service Negotiation System will attempt to negotiate with multiple cares service providers available on the market and suggest the appropriate care service to the remote patient by the experts available in Service Layer.

A. FORMULATION OF DTHS CLOUD LAYER

The traditional k-NN classifier will treat all the neighbors equally where us the Fuzzy based k-NN classifier will exploit the fuzzy membership function to impose the appropriate weight on all the k nearest neighbors. Like k-NN has different variants such as Adaptive, Locally adaptive, Mutual,

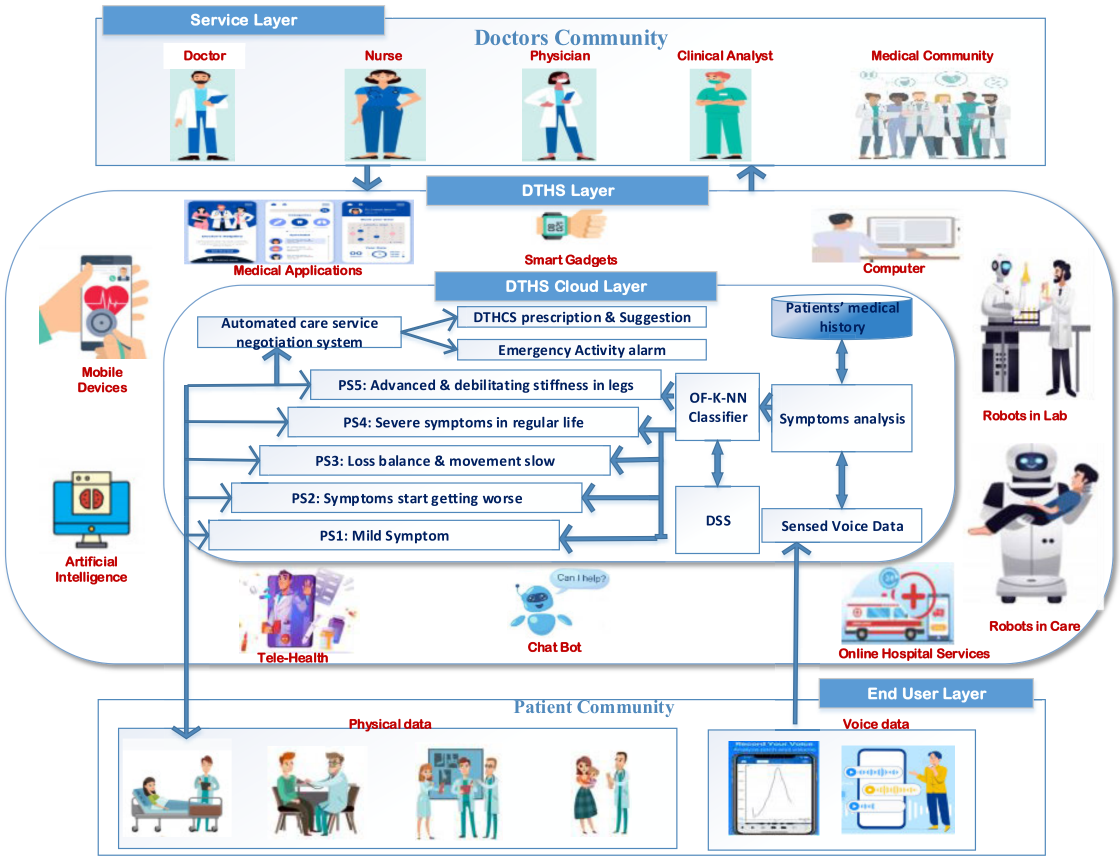

FIGURE 2. Architecture of cloud-based digital twin healthcare systems.

Ensemble, k-means clustering, Hassanat, and Generalised mean distance k-NN. Choosing of k-NN variants is getting differ based k parameters to run [41]. Thereby additional dependent parameters unlike k are not considered in those classifiers in optimizing the required data. Also the effect of representative features may be redundant and noisy which may not be appropriate to correctly classify the class. Therefore the proposed research work attempt to optimize the class specific features to be enforced in OF-k-NN classifier model by selecting appropriate set of class reliant optimum fuzzy weight and optimum value of k. Let X be dataset, Ψ be the set of class labels and C(.) be the classification task to identify many-to-one-mapping from X to Ψ as formulated as $C : X \rightarrow \Psi$. This classification problem is solved by the proposed OF-k-NN classifier model under supervised learning mechanism. It takes the set of training data $TR \in X$ containing the data point $x \in X$ whose classification value C(x) is known. By exploiting the training set TR, the proposed classifier is expected to predicts the class label of any new instance of testing set TE. To get better classification accuracy, both features weights and k values are optimized simultaneously in the proposed OF-k-NN classifier model. In case of existing classifiers, optimization is achieved by improving either the value of k or feature weights. Therefore, the existing classifiers may misclassifies the testing instances in some cases due to globally optimized weights of attributes.

In addition to optimization of k value, feature weights can be optimized in the proposed classifier through class specific feature weights of attributes. Here, the set of training points $TR = x_1, x_2, \ldots, x_n$ and testing points $TS = y_1, y_2, \ldots, y_m$ are defined as set of real valued data points $X \subset (R^d)$ in d-dimension. i.e. $TR, TS \subseteq X$. Now the d-dimension vector $a \in R^d$ can be represented as $a = [a^{(1)}, a^{(2)}, \ldots, a^{(d)}]$. Each data points on X belongs to any one of the class label from $\Psi = \Psi_1, \Psi_2, \ldots, \Psi_c$. Any training point $x_i \in TR$ on sample will have the known class sample $c_\Psi(x_i)$, where the taken testing point $y_j \in TS$ is predicted by the proposed OF-k-NN classifier as $\vec{c}_\Psi(y_j)$. i.e. $\vec{c}_\Psi(x_i)$, $\vec{c}_\Psi(y_j) \in L$. Let $\Omega_k(S, a)$ defines the k-neighborhood of point a in the set S and $|S|$ defines the number of elements in the set S. The distance between any two points a and b can be measured as $\delta(a, b)$. A classifier model C(.) can be significantly defined with set of parameters as $C_y(TR, y_j)$. Thus the classifier can be further expressed as $\vec{c}_\Psi(y_j) = C_y(TR, y_j)$. In the OF-k-NN classifier, optimized fuzzy membership function of any sample instance are assigned as per formation given in equation 1.

$$u_i(x) = \frac{\sum_{j=1}^{k} u_{ij}(1/||x - x_j||^{2/(m-1)})}{\sum_{j=1}^{k}(1/||x - x_j||^{2/(m-1)})} \tag{1}$$

where i=1,2,…,c denotes the number of classes and j=1,2,…,k denotes the number of nearest neighbors. The fuzzy parameter $m \in (1, \infty)$ represents the strength of weighted distance calculation during neighbors contributing to membership value. Let $\|x - x_j\|$ be the distance calculation between x and its nearest neighbor x_j. Next, the constrained fuzzy membership of x_k among k nearest neighbor to each class i is assigned as shown in equation 2.

$$u_{ij}(x_k) = \begin{cases} 0.51 + (n_j/k) * 0.49, & ifj = 1 \\ (n_j/k) * 0.49, & ifj \neq 1 \end{cases} \tag{2}$$

where n_j represents the number of neighbors belonging to class j. The membership function should satisfies the constraints such as $\sum_{i=1}^{c} u_{ij} = 1, 0$ less than $\sum_{j=1}^{n} u_{ij}$ which is lesser than $n, u_{ij} \in [0, 1]$ and j=1,2,…,n. The proposed OF-k-NN classifier will returns a set $M(y_j) = \mu_1(y_j), \mu_2(y_j), \ldots, \mu_c(y_j)$ for testing the point $y_j \in TS$ in which the $\mu_p(y_j)$ represents the probability of y_j belonging to p^{th} class as defined in equation 3.

$$\mu_p(y_j) = \frac{\sum_{x_i \in \Omega_k(TR,y_j)} u_{ip} \delta(Y_j, X_i)^{\frac{2}{1-m}}}{\sum_{x_i \in \Omega_k(TR,y_j)} \delta(Y_j, X_i)^{\frac{2}{1-m}}} \tag{3}$$

Let the parameter m denotes the performance controller and the value of m > 1. To get high classification accuracy, assign the computed membership of sample query to the class containing highest membership value. If you higher the value of m, correspondingly more number of neighbor will be equally weighted without bothering their distance measurement from y_j. After computing the value of $M(y_j)$ the class label $\Psi(y_j)$ which need to be predicted can be depicted in equation 4.

$$\psi(y_j) = arg_{i=1}^{c} max(\mu_p(y_j)) \tag{4}$$

Next, the class based weighted feature measurement is proposed for estimating distance between training instance and another instance as expresses in equation 5.

$$\delta_w(x_i, y_j) = (\sum_{d=1}^{k} w_{pd}(x_i^{(d)} - y_j^{(d)})^2)^{\frac{1}{2}} \tag{5}$$

Let $w_{x_i \to l_p}$ express the weight of training point x_i belonging to class label l_p at d^{th} dimension. therefore the weight parameter can be represented as $W = \left[w_{pd}\right]_{c*k}$. Initially, optimal features were selected from the Parkinson data set for selecting the most informative features at first stage. Then, train the proposed OF-k-NN classifier with training data set TR using optimal fuzzy strength parameter m, number of classes C and optimal rounded k nearest neighbor via 3-fold cross validation at later stages. Finally, predict the class label of test set TS using trained OF-k-NN classifier model. For making optimized prediction accuracy PA, compute the fitness value f as stated in equation 6.

$$f = mean(PA) = \frac{\sum_{fold=1}^{3} test(PA_{fold})}{3} \tag{6}$$

In optimization context, each Parkinson data is treated as a particle in the d-dimensional space. Here, each i^{th} particle is represented by the position vector $P_i = p_{(i,1)}, p_{(i,2)}, \ldots, p_{(i,d)}$ and the corresponding velocity vector $V_i = v_{(i,1)}, v_{(i,2)}, \ldots, v_{(i,d)}$. The position and velocity of the particle are frequently get updated as defined in equation 7 and 8 respectively.

$$p_{i,j}^{n+1} = p_{i,j}^{n} + v_{i,j}^{n+1}, j = 1, 2, \ldots, d \tag{7}$$

$$v_{i,j}^{n+1} = \omega * v_{i,j}^{n} + c_1 * r_1(b_{i,j}^{n} - p_{i,j}^{n}) + c_2 * r_2(b_{g,j}^{n} - p_{i,j}^{n}) \tag{8}$$

Let the vector $B_i = b_{(i,1)}, b_{(i,2)}, \ldots, b_{(i,d)}$ denotes the i^{th} particle best fitness value of previous position. It is also called as personal best position $b_{personal}$. Similarly, the vector $B_g = b_{(g,1)}, b_{(g,2)}, \ldots, b_{(g,d)}$ denotes the best particle among the population. Hence, it is called as global best position b_{global}. Then, the acceleration coefficient c_1 and c_2 is defined to balance the space between local and global exploration for ensuring better search solutions. The random numbers r_1 and r_2 are uniformly generated in the range as $r_1 \in [0, 1]$ and $r_2 \in [0, 1]$ respectively. But, the velocity $v_{(i,j)}$ is generated with restricted range such as $[-v_{max}, v_{max}]$. The inertial weight ω is formulated according to varying time period with current iteration t and maximum number of iterations t_{max} as shown in equation 9. where ω_{max} and ω_{min} represents the predefined maximum and minimum value of ω.

$$\omega = \omega_{min} + (\omega_{max} - \omega_{min}) \frac{(t_{max} - t)}{t_{max}} \tag{9}$$

The major idea of time varying acceleration coefficient is to show that the value of c_1 decreases from c_{1i} to c_{1f}, whereas the value of c_2 increases from c_{2i} to c_{2f} as mathematically expressed in equation 10 and 11.

$$c_1 = (c_{1f} - c_{1i}) \frac{t}{t_{max}} + c_{1i} \tag{10}$$

$$11.c_2 = (c_{2f} - c_{2i}) \frac{t}{t_{max}} + c_{2i} \tag{11}$$

where c_{1i}, c_{2i}, c_{1f} and c_{2f} are constants. In binary optimization, velocity is transformed from continuous to probability space using Sigmoid function as given in equation 12.

$$sig(v_{i,j}) = \frac{1}{1 + exp(-v_{i,j})}, j = 1, 2, \ldots, d \tag{12}$$

To ensure the velocity update given in equation (8), bit is transfer between 0 and 1 with positive probability. Further, the value of $v_{(i,j)}$ is limited by introducing v_{max}. Therefore, the new optimization is introduced using the rule shown in equation 13.

$$p_{i,j}^{n+1} = \begin{cases} 1 & if\ rand < sig(v_{i,j}) \\ 0 & if\ rand \geq sig(v_{i,j}) \end{cases}, j = 1, 2, \ldots, d \tag{13}$$

Let rand be the uniform random number generated in the range of [0,1], and the value of $sig(v_{(i,j)})$ is computed as stated in equation 12. Finally obtain the optimal value of k, m and feature from global best particle position b_{global}.

TABLE 2. Parkinson datasets description.

Datasets	Subjects			Training Voice Samples	Testing Voice Samples	Affected Samples		Non-Affected Samples		No. of Features considered
	Parkinson subjects	Normal subjects	Total subjects			Training samples	Testing samples	Training samples	Testing samples	
The Cerrahpasa Faculty of Medicine, Istanbul University (DS1)	23	8	31	195	88	147	62	48	26	23
University of Oxford (DS2)	147	48	195	435	246	353	210	82	36	22

TABLE 3. Performance comparisons of various classifier models.

Classifier Models	Prediction Time in Seconds		Prediction Accuracy		F1-Score		Matthews Correlation Coefficient	
	DS1	DS2	DS1	DS2	DS1	DS2	DS1	DS2
Neural Network [42]	2.13489	3.33686	97.0052	85.10638	0.97	0.85	0.91725	0.63732
Linear Kernel SVM [42]	0.00370	0.00254	89.79592	78.72340	0.89	0.77	0.66152	0.44776
Polynomial Kernel SVM [42]	0.00174	0.001406	79.59184	70.21276	0.71	0.58	0.0	0.0
Radial Basis Kernel SVM [42]	0.00197	0.00179	79.59184	70.21276	0.71	0.58	0.0	0.0
Sigmoidal Kernel SVM [42]	0.00289	0.002892	79.59184	70.21276	0.71	0.58	0.0	0.0
Proposed OF-k-NN	0.00127	0.00105	97.95918	91.48936	0.98	0.91	0.93675	0.79816

B. SUCCESS PERFORMANCE MEASURE OF CLASSIFIER

To measure the success performance of proposed OF-k-NN classifier against the existing classifiers, an evaluation metrics such as prediction time, prediction accuracy, F1-score and Matthews correlation coefficient are selected for comparative results. Prediction Accuracy metrics PA is defined as the effective measurement of ratio of properly classified occurrence to the total presented occurrence as shown in equation 14.

$$PA = \frac{TP + TN}{TP + FP + TN + FN} \tag{14}$$

Let TP, TN, FP and FN represents the amount of true positives, true negatives, false positives and false negatives respectively. Advance measurement can be made through F1 score computation as a weighted average performance in the form of the Precision (P) and Recall (R) as defined in equation 15. It can be otherwise called as balanced F-score or F-measure on which can reaches its best score at 1 and worst value at 0. But, the value of F1 score is equal in case of the relative assistance of precision and recall value measurement. In case of multi-label and multi-class consideration, this will be measured in terms of weighted average of F1 score of every class. Next, the precision and recall parameter can be further formulated as shown in equation 16 and 17 respectively.

$$F1 = 2 * \frac{(P * R)}{(P + R)} \tag{15}$$

$$P = \frac{TN}{TN + FP} \tag{16}$$

$$R = \frac{TP}{TP + FN} * 100\% \tag{17}$$

Further, the Matthews's correlation coefficient metrics M can be computed directly from confusion matrix which gives the correlation coefficient among the predicted and observed binary classification. It helps to define the actual quality of classification exploited using machine learning mechanism and it can be formulated as shown in

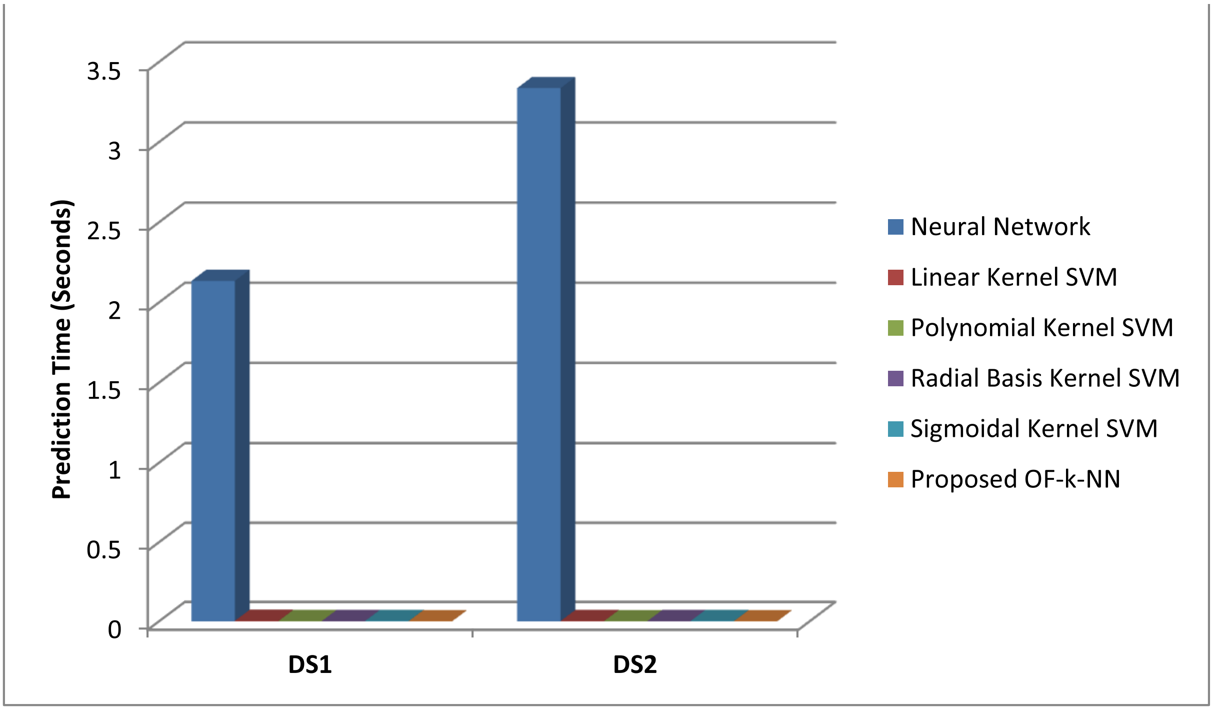

FIGURE 3. Prediction time performance of classifiers.

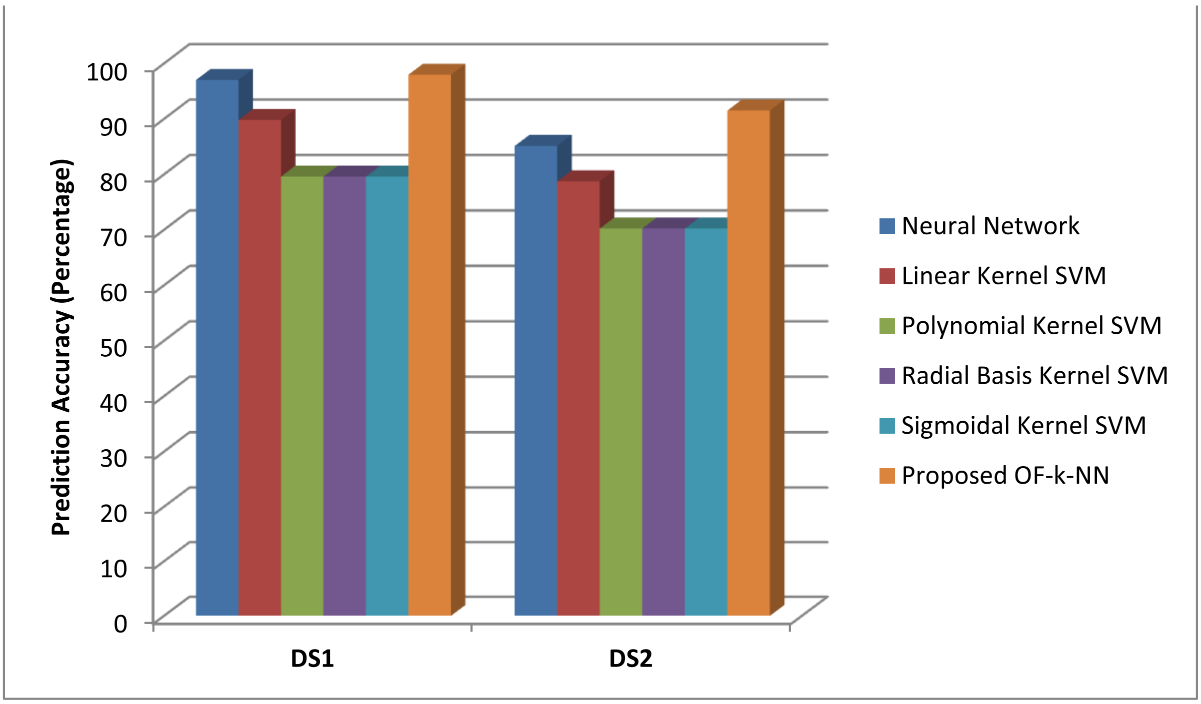

FIGURE 4. Prediction accuracy performance of classifiers.

equation 18.

$$M = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (18)$$

here, the assessment of M will ranges between -1 and $+1$. Therefore, value -1 indicates that the classifier predictions is disagree, value $+1$ indicates that the classifier predictions is perfect and finally value 0 indicates that the classifier has no healthier predictions than the accidental predictions.

IV. EXPERIMENTAL EVALUATION

A. EXPERIMENTAL SETUP

The experimental setup of proposed DTHS will capture the voice data of remote patients through the healthcare apps used

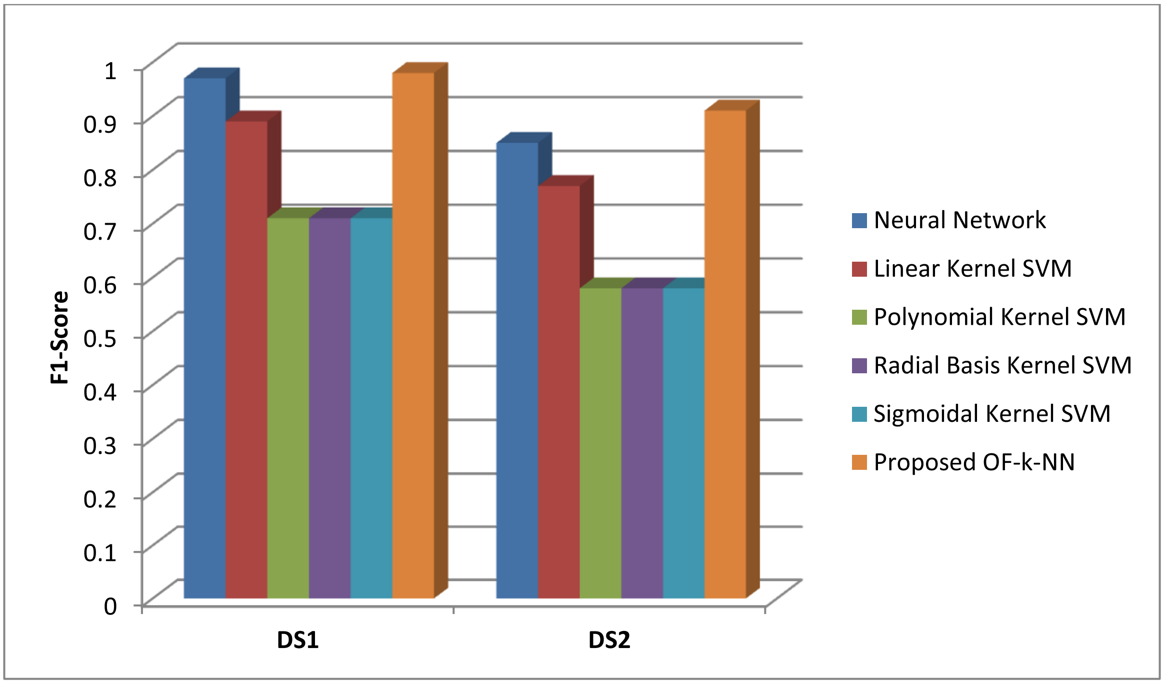

FIGURE 5. F1-score performance of classifiers.

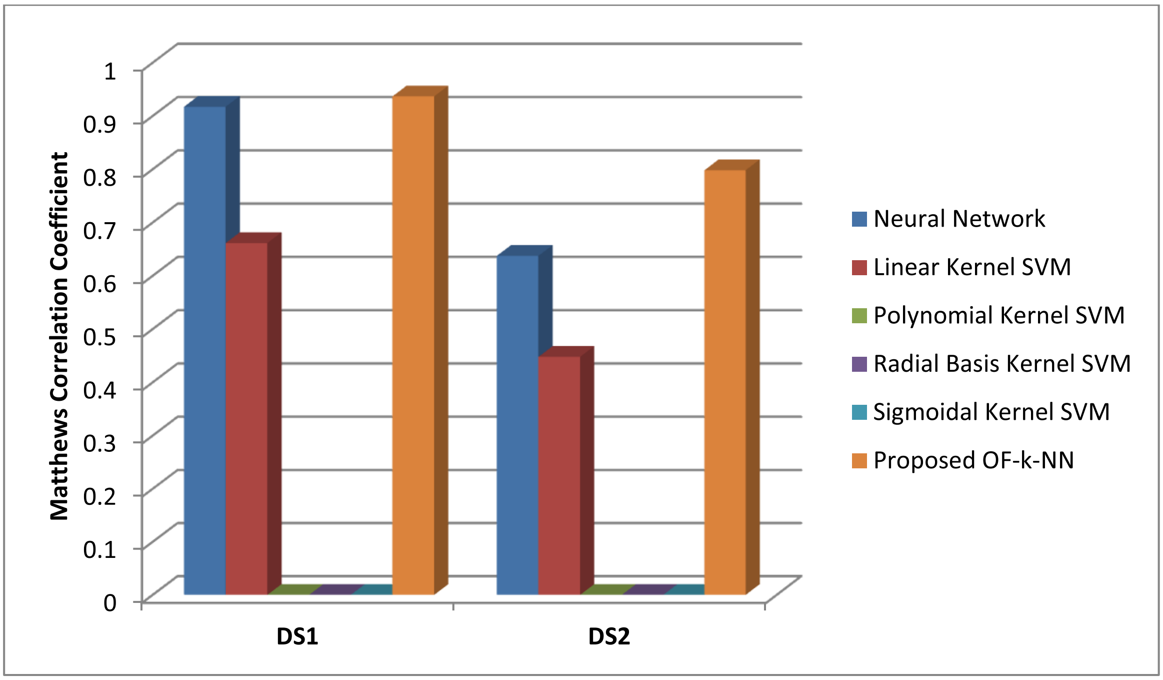

FIGURE 6. Matthews's correlation coefficient performance of classifiers.

in smart phones at the consumer layer. This live captures of voice data is sent to the Amazon web service platform deployed in cloud layer to analyse the symptoms using voice data analysis. Further, the proposed OF-k-NN classifier model is used to classify the disease severity according to the different stages of Parkinson disease. Finally, the classifier will predict whether the given voice sample is affected by Parkinson disease or not and notify the same to the consumer layer. The automated care service negotiation system will then negotiate with multiple care services available on the market and suggest the best optimal care service to the consumer. Based on payment, online Tele monitoring and diagnosis will be supplied to patients and physical therapy exercises given through a smart virtual care environment.

To evaluate the performance of the proposed OF-k-NN classifier model used in DTHS, two benchmarking datasets were used to achieve an effective comparative analysis with existing classifier models.

B. DATASET DESCRIPTION

Two real-time voice sample datasets were collected from source x and y: DS1 and DS2. DS1 was collected from different patients, and they consulted at the Cerrahpasa Faculty of Medicine, Istanbul University [16]. This benchmarking dataset consisted of training and testing data files as per the specifications of the University of California-Irvine (UCI) data repository. Here, the training dataset consisted of different sets of sound recordings of 195 voice samples, of which 147 samples had Parkinson disease and 48 samples did not. These voice samples were collected from 31 subjects (8 healthy and 23 Parkinson affected subjects). For the sake of the experimental purposes, 23 features related to linear and time frequency-based parameters were extracted from each voice sample. In DS2, source of samples were collected from the University of Oxford, consisting of voice samples collected from 195 subjects [17]. Here, 147 subjects were affected and 48 subjects were not affected by Parkinson disease. Based on the voice sample of each subject, 22 major features were extracted from voice that were considered to be the most preferable characteristics of Parkinson disease such as pitch, amplitude and frequency. The complete dataset count is illustrated in the Table 2. One label was included in the dataset to indicate '0' for Parkinson affected or '1' for Parkinson not affected status information. In the next section, experimental validation was conducted to test the performance of the proposed OF-k-NN classifier model over existing models such as the Neural Network, Linear Kernel SVM, Polynomial Kernel SVM, Radial Basis Kernel SVM and Sigmoidal Kernel SVM. These classifiers were first trained well with the help of the training dataset. Following by this training, the classifier models were evaluated using the testing dataset to predict whether the given subject data were affected or not by Parkinson.

C. RESULTS AND DISCUSSIONS

The proposed OF-k-NN classifier model for identification and diagnosis of Parkinson disease are compared with existing classifier models such as the Neural Network, Linear Kernel SVM, Polynomial Kernel SVM, Radial Basis Kernel SVM and Sigmoidal Kernel SVM. These classifier models were implemented over the proposed DTHS and the observed results are shown in Table 3.

The scientific results were compared with respect to evaluation parameters such as prediction time, prediction accuracy, F1-Score and Matthews's correlation coefficient by varying the benchmarking datasets (DS1 and DS2). In the resulting graph, the proposed OF-k-NN classifier model clearly outperformed the existing classifier models in aspects of both datasets used in the experiments as shown in Figure 3, 4, 5, and 6 respectively. In the future, DTHS can be enhanced with a broker-based negotiation framework to choose the appropriate services on the Tele-health care market after negotiating with multiple healthcare service providers [17]. This type of cloud-based negotiation broker will be the future trend of the Tele-health care service access mechanism. In addition, the performance of the proposed OF-k-NN classifier of DTHS can be improved, by introducing novel dimensionality reduction and feature selection methods such as Correlation-based Feature Selection, Wrapper and Principal Component Analysis. Further improvement of the classifier model can be achieved using probabilistic approximation of the classification and forecast prediction.

V. CONCLUSION AND FUTURE ENHANCEMENTS

The major objective of this research was to design the proposed DTHS using the OF-k-NN classifier model, which predicts the Parkinson disease more accurately using voice features. This type of prediction based on non-clinical parameters will facilitate remote patient monitoring and diagnosis using voice features extracted from remote patients. To further improve the classification results of Prediction Time, Prediction Accuracy, F1-Score and Matthews Correlation Coefficient were used. The benchmark data set was used to test whether the feature selection methods showed any significant improvements in prediction compared with all six classifier models. Moreover, a comparative study was performed among the classifier models, which showed that the proposed OF-k-NN classifier model outperformed the existing Neural Network, Linear Kernel SVM, Polynomial Kernel SVM, Radial Basis Kernel SVM and Sigmoidal Kernel SVM in terms of Prediction Time, Prediction Accuracy, F1-Score and Matthews Correlation Coefficient. The results of the proposed OF-k-NN classifier model are more encouraging, and the development of DTHS using such a classifier will greatly benefit remote patients with economic monitoring and diagnosis. Further, this research work can be extended using probabilistic methods with more voice data to differentiate other disease that can also cause a voice disorder.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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