Recommendation of Primary Healthcare Centers through estimating Quality of Services using Momentum Gradient Descent based Multilayer Perceptron

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Momentum Gradient Descent, Multilayer Perceptron,Primary Healthcare Centres and Quality of Services

ABSTRACT:
The prediction of the quality services tends to both service improvement as well as enhanced motivation to visit Primary Healthcare Centres (PHC) for health treatment. There are various estimation tools have been designed to evaluate the quality of the PHC, however, no particular tool is identified in this area. Hence, this research performed to develop as well as estimate the quality assessment tool of PHC. This research proposes the Momentum Gradient Descent based Multilayer Perceptron (MGD-MLP) for the recommendation of PHC and estimating the Quality of Services (QoS) by using SERVQUAL tool. Initially, the data is collected from the medical college hospital, 14 Government taluk hospitals, 75 PHCs, and 252 health sub-centres in Pudukkottai district in the year of 2019 to 2020. The Cronbach alpha technique is utilized for estimating an internal consistency of every model factor. The MGD accelerates the convergence of the optimization process, minimizing the training time to train the model, so it enhances the model performance. The experimental results show that the proposed MGD-MLP approach attains the MSE of 0.119, MAE of 0.205, RMSE of 1.198, and R^2 of 3.893 respectively.

1. INTRODUCTION

The healthcare faces significant challenges of enhancing the expectations, accountability of the providers as well as pressure to improve the quality to meet the generally agreed standards [1]. The quality as well as accessibility of the healthcare facilities plays a significant part solving as well as mitigating the health issues [2]. The Public Healthcare Centers (PHC), plays a vital role in significant-level health service with the aim of managing the public health level [3]. Numerous health services at public health center have been provided with the aim of service standard, comprises of curation, reconstruction, promotion as well as prevention. The aim of this service is anticipated to cover all the level of the societies as well as meet the general requirements of the public health [4][5]. Hospitals are intense on the quantitative as qualitative development, often recruiting well-trained professionals to fill vacant positions. However, service quality practices vary among the healthcare sectors of developing countries [6]. Recently, the service quality has become an important for all the organizations since it drives their marketing as well as financial effectiveness. It has turned as the complex element of the effectiveness as well as acts as a source for attaining the competitive advantage by utilizing service variation [7][8].

Quality healthcare services involve delivering the reliable as well as successful services according to the timely clinical recommendations as well as guidelines [9]. The various tools provide the frameworks for estimating as well as improving the service quality in various contexts [10].Various approaches are developed for estimating the service quality as well as different studies had been performed through utilizing the various estimation tools [11]. Furthermore, it aims to satisfy the patients through contributing the characteristic service elements such as accessibility, affordability, competence as well as timeliness which are performed through the SERVQUAL tool [12]. The SERVQUAL is the most popular utilized tool or scale for estimating the service quality in PHC to assess the perceptions of the patients on the service quality [13]. It is a helpful tool for measuring the services by utilizing five dimensions scales for estimating the quality gaps among the perceptions as well as expectations of the patients. However, the five-dimensions of the SERVQUAL lacks the generalization, so fails to represent some of the service sectors as well as perceived quality should not be effectively measured [14][15]. Hence, this research proposes the Machine Learning (ML) approach for the recommendation of the PHC through estimating the service quality using. The primary contributions of this research are as follows:

- This research aims to propose the framework for recommending PHC for healthcare providers through analysing customers' perceptions as well as expectations with the services.
- The Recursive Feature Elimination (RFE) technique is performed for the estimation of pairwise relations among service quality of the health, trust as well as communication skills. Through eliminating irrelevant or less important features, RFE enhances the predictive accuracy of the model.
- The Momentum Gradient Descent based Multilayer Perceptron (MGD-MLP) algorithm is proposed for the recommendation of PHC.The momentum supports to finding a smoother loss landscape and a better generalization performance.

The rest of the paper is organized as follows: Section 2 presents the literature survey related to an estimation of the quality of services. Section 3 presents the proposed methodology. Section 4 provides the results and discussion and Section 5 concludes the overall research.

2. LITERATURE SURVEY

The existing works related to the estimation and evaluation of the service quality in PHC in rural areas are discussed along with their advantages and limitations.

Pouria Farrokhi*et al.* [16] performed to develop as well as validated a quality estimation tool of the PHC in Iran. Initially, the questionnaires were created and after estimated the different validities like face, content, construct as well as reliability. The Cronbach's alpha as well as Kaiser-Myer-Olkin (KMO) based on the SPSS version 2 were utilized for estimating the questionnaires. The performed approach had effectively identified the weakness in service delivery and evaluated the PHC quality. However, the developed approach had selected the minimum health networks, which restricted the transferability of the outcomes to other PHCs.

KhanMohammadi *et al.* [17] introduced the framework for the evaluation of the Quality of healthcare services through customer's perceptions and service expectations. The quality principles were incorporated to estimate and enhance the service delivery process along with the enhancement of customer satisfaction. The Fuzzy Best-Word Method (BWM) was utilized for the assessment of QoS in hospitals, further making some computations and more consistent comparisons than the Analytic Hierarchy Process (AHP) and Multi-Criteria Decision Making (MCDM) approach. However, the data were collected from experts from 2020 to 2022, extrapolating or generalizing the results beyond this timeframe as external factors such as changes in healthcare policies, influenced the applicability of the findings to future periods.

Shabnam Iezadi*et al.* [18] targeted to evaluates the service quality for the Type 2 Diabetes Mellitus (T2DM) as well as hypertension in PHC setting from an observation of the service users in Iran. The two-phase stratified sampling approach in East Azerbaijan province in Iran were performed. The questionnaires evaluated from the service quality were validated through the one-way ANOVA as well as Multiple Linear Regression (MLR) approaches in STATA-17. MLR provided the accurate estimates of QoS and it enhanced the service quality in PHC. However, the significant results of T2DM as well as hypertension were missed from the medical records as well as does not include in the data analysis.

Gu *et al.* [19] targeted to identified the relationship among communication skills, trust as well as quality of the healthcare service in PHC. The data were gathered from village clinics in rural China and traditional random sampling was carried out for the selection of volunteer village clinics and patients. The quality of the service was significantly facilitated through the relationship among patient's trust as well as communication skills of the patients. Furthermore, the relationship between patients and doctors were examined during revolutionizing of the PHC. However, the causationimplications were not developed among the variables due to their cross-sectional nature of data.

Kabiru Hammanjoda and Arora Gaurav Singh [20] introduced the cross-sectional estimation which effected the service quality dimensions on the patient satisfaction in PHC. The various indices like Chi-square, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) as well as Standardized Root Mean Square Residual (SRMR) were utilized

to estimate the model fitness in preserved data. The introduced approach significantly supported to enhance the service quality and enhanced the user satisfaction level. However, the introduced estimation approach does not consider the demographic impact on the perceived service quality.
From this above analysis, some of the limitations have been identified during the estimation of the service quality in PHC. The limitations like only selected the minimum health networks, lack of including the significant results of T2DM as well as hypertension were missed from the medical records, lack of designing the causality inferences among the variables due to the cross-sectional nature of data and lack of considering the demographic impact on the perceived service quality. Hence, this research aims to solving these problems to estimate the service quality and recommendation of PHC by proposing the novel method of MGD-MLP approach.

3. METHODOLOGY

In this research, the MGD-MLP approach is proposed for the estimation of QoS and recommendation of PHC in Pudukkottai district. It comprises of various sections such as data collection from the Pudukkottai district, participants and sampling method selection by using Cochran's method, service quality estimation and statistical analysis, as discussed in this section.

3.1 Data Collection

In this research, the areas for the QoS estimation of the PHC is considered in Pudukkottai district, Tamil Nadu state. According to the 2011 Census, the Pudukkottai district has a population of 16,18,345 persons, with the rural and urban populations being 13,01,991 and 3,16,354 people, respectively. Pudukkottai district has one medical college hospital, 14 Government taluk hospitals, 75 PHCs, and 252 health sub-centers. Most of the people in this district avail themselves of health care services through health care programs at PHCs. These are the significant reasons for selecting Pudukkottai district for the study. Easy accessibility for data collection also has been a compelling condition for the selection of Pudukkottai district, alongside the researcher residing in this district.This research is based on both primary and secondary data sources. The primary data is collected from the sample respondents who received treatment from local PHCs throughout 2019-2020. This data has been collected by using a pre-structured questionnaire intensive on five dimensions of service quality. Then, the secondary data is collected from various published and unpublished sources, including Directorate of Medical Services Reports, Annual Statistical Abstract of Government of Tamil Nadu, newspapers, articles, journals, and theses, and so on.

3.2Participants and Sampling Method Selection

The study population involves all the patients from the PHC centres of 11 taluks and 13 development blocks involving 498 village panchayats in the Pudukkottai district. Through keeping the 20% as the sample size, this research totally selects the 15 PHC in Pudukkottai district, in which 13 PHCs from the rural areas as well as 2 PHCs from urban areas. These PHC are randomly selected by using the common random sampling approach. The samples are substituted to every PHC centre as well as selected from every centre through the systematic sampling approach. To provide an equal weightage for all the blocks in this district, one PHC from each 13 blocks and one urban PHC from all revenue divisions are selected aimlessly. Afterwards, to determine the sample size of the households, two village panchayats located near the selected PHCs had to be determined. Hence, 30 village panchayats are selected. From every village panchayat, 25 households who had received treatment from the local PHCs were determined and hence, a total sample size of 750 households (30 x 25 = 750) was selected.
In this research, the Cochran's formula [21] is the most popular approach, which is utilized for estimating the statistical sample size from the collected data. The importance level is fixed to 0.05 and the number of samples are N=750. The Cochran's formula is calculated by using the equation (1) as follows: ()^2

$$n = \frac{\frac{z^2pq}{d^2}}{1+\frac{1}{N}\left[\frac{z^2pq}{d^2}-\right]} \qquad (1)$$

Where, n represents required sample size; N denotes the population size; z depicts the number of standard deviations from the mean respective to the anticipated confidence level; p represents the evaluated proportion of the population; q represents the proportion of the population which does not requires the attribute of the interest and d denotes the anticipated precision level. In 60 days, 300 questionnaires are circulated to the PHC, in which 280 questionnaires are aggregated through patients when they leave PHCs. Hence, only the entities who had involves the all types of services with the doctor's appointment are involved in this research.

3.3 Healthcare Institutions in Tamil Nadu

The primary objective of the government of Tamil Nadu is to provide affordable, accessible, equitable, affordable and health care quality, marginalized and vulnerable sections of the population. The private sector with the support of Government efforts is also furnishing to the provision of Health Care Services (GoT, 2011-12 to 2013-14). As on March 31st, 2020, 8713 Sub Centres, 1884 PHCs, 400 Community Health Centres(CHCs), 278 Sub Divisional Hospitals(SDHs) and 32 District Hospitals(DHs) were functioning in the government of Tamil Nadu. In the total health care institutions, 8713 sub-centers, 1420 PHCs, and 385 CHCs were functioning in the rural areas (GOI, 2019-2020). Table 1 depicts the District-wise Healthcare Institutions in Tamil Nadu.

Table 1: District-Wise Health Care Institutions in Tamil Nadu*(As on March 31st, 2020)*

Sl. No.	**Name of the District**	**Number of Functional**				
		Sub Centres	**PHC's**	**CHC's**	**Sub-division Hospital**	**District's Hospital**
1	Ariyalur	117	32	6	3	1
2	Chennai	0	144	15	3	1
3	Cuddalore	319	58	13	9	1
4	Coimbatore	328	77	12	12	1
5	Dindigul	311	59	14	12	1
6	Dharmapuri	218	43	8	3	1
7	Erode	311	62	14	7	1
8	Kancheepuram	364	64	13	9	1
9	Karur	168	29	8	6	1
10	Kanniyakumari	267	38	9	8	1
11	Krishnagiri	239	51	10	6	1
12	Madurai	314	75	13	6	1
13	Namakkal	240	48	15	8	1
14	Nagapattinam	258	47	11	11	1
15	Nilgiris	194	33	4	3	1
16	Pudukkottai	242	62	13	9	1
17	Perambalur	90	25	4	12	1
18	Ramanathapuram	244	48	11	11	1
19	Sivaganga	275	40	12	13	1
20	Salem	398	87	20	16	1
21	Theni	162	33	8	5	1
22	Thanjavur	309	63	14	5	1
23	Thiruvarur	195	40	10	9	1
24	Thiruvallur	303	54	14	8	1
25	Tirunelveli	379	85	19	9	1
26	Tiruchirappalli	307	70	14	16	1
27	Tiruvanamalai	410	81	18	9	1
28	Tirupur	242	54	13	10	1
29	Toothukudi	253	48	12	7	1
30	Viluppuram	557	88	22	11	1
31	Vellore	454	99	20	12	1
32	Virudhunagar	245	47	11	10	1
Total		**8,713**	**1,884**	**400**	**278**	**32**

Source: Rural Health Statistics 2019-2020, MHFW, New Delhi, Government of India

In the present study, among the various vital health variables, 4 health variables namely, life expectancy at birth, Crude Birth Rate (CBR), Crude Death Rate (CDR) and Infant Mortality Rate (IMR) were taken for finding the levels of status of health of the population in Tamil Nadu.Figure 1 shows the trends in health indicators of Tamil Nadu for the period 1995 to 2019. Such a decline in the indicators of CBR, CDR and IMR and increase in life expectation at birth could be attributed to better health status of Tamil Nadu, technology and its adoption of health care delivery and its utilization and health awareness and attitudes of the people. The increase in life expectation at birth shows the efficiency of health delivery system in the Tamil Nadu state.

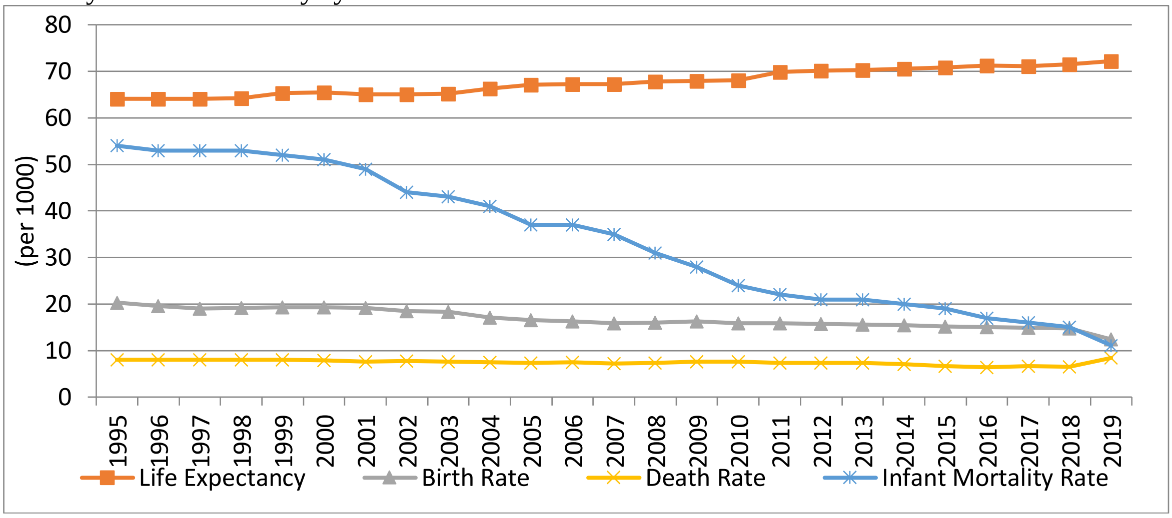

Figure 1: Trends in Health Indicators of Tamil Nadu for the period between 1995 to 2019 *(per thousand)*

Source: (i) Handbook of Statistics on Indian States 2015-16 & 2020-21, Reserve Bank of India, Mumbai. (ii) Directorate of Medical and Rural Services, Chennai. (iii) 1991, 2001 & 2011 Census of India. (vi) Various issues of Statistical Handbook, Department of Economics and Statistics, Government of Tamil Nadu.

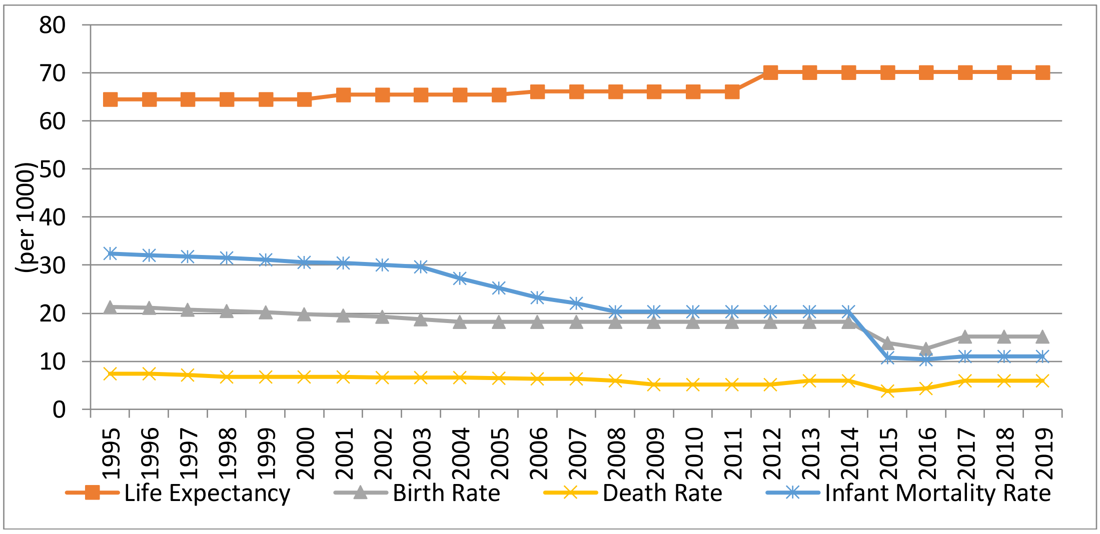

Figure 2: Trends in Health Indicators of Pudukkottai District in the period of 1995 to 2019 *(per thousand)*

Figure 2 shows the trends in the health indicators of Pudukkottai district in the period 1995 to 2019. Life expectancy at birth in the district was 64.5 in 1995 and it had risen to 65.5 and 66.2 in 2001 and 2006 respectively. Since 2012, the life expectancy at birth in the district had risen to 70.2. During the study period, the BR had decreased from 21.3 per 1000 to 15.2 per 1000; the death rate had decreased from 7.4 per 1000 to 7.30 per 1000 and the infant mortality rate had fallen from 32.4 per 1000 to 11.0 per 1000.

Source: (i) DANIDA, Tamil Nadu Area Health Care Project - Phase III, Health & Family Welfare Department, Government of Tamil Nadu. (ii) Various issues of District Statistical Handbook, Pudukkottai. (iii) Various issues of Statistical Handbook, Department of Economics & Statistics, Government of Tamil Nadu.

3.4Questionnaire Development

Various instruments are selected based on designing the questionnaire such as HEALTHQUAL, a modified form of the SERVQUAL questionnaire for estimating the quality of the services in PHC. The primary care assessment toolestimates the primary care as well as focusses on accessibility, availability as well as referral system. The data involves 22 samples which evaluates the service qualityof the health by using five dimensions. Every sample is scored from 1 to 5, where 1 represents the extremely poor and 5 represents the extremely good. This information is further exploited to minimize inequality and enhance the response rate and service quality. The five dimensions are formulated and applied to service organization. The five dimensions are listed as follows:

1. *Tangibles:*The clients pay attention to physical facilities, equipment, materials, employees, and communication channels while attending a service firm.
2. *Reliability:*The clients are persuaded to have confidence in that the organizations can consistently and effectively provide the services they expected.
3. *Responsiveness:*It is an organization, which is interested in offeringappropriate services and supporting clients to obtain best services.
4. *Assurance:*The ability and familiarity of assistants attract the client's trust to persuade them to revisit in future.
5. *Empathy:*Tendency to support clients and customers trying to provide better services for them.

The instruments are surveyed are extracting theappropriate items as well as features for measuring the quality of the services in PHC. Related items are combined as well as duplicate items are eliminated. The questionnaires are estimated based on the 5-point Likert scale such as 5 denotes strongly agree, 4 represents agree, 3 represents not sure, 2 represents disagree as well as 1 represents strongly disagree.Table 2 depicts the dimensions of the services quality in its most recent conceptualization, service quality is described as an estimation of perceived expectations (E) and perceived performance (P) of a service, yielding equation $SQ = P - E$. The service quality is judged as low when the expectations are greater than the perceptions of the customer. The quality of the service is large when the perceptions are greater than the customer's expectations.

Table 2 Dimensions of the Service Quality

Items	Service Quality Dimensions	Mean (E)	Mean (P)	Quality Gap (P-E)	Score
	Tangibility	**4.8**	**4.4**	**-0.4**	**5**
1	The presence of physical facilities	4.6	4.6	0.0	
2	The presence of service provider	4.8	4.5	-0.3	
3	Availability of modern equipment's	4.7	4.0	-0.7	
4	Communication materials accessibility	5.0	4.5	-0.5	
	Reliability	**4.3**	**3.3**	**-1.0**	**3**
5	Maintenance of assured appointment schedules	4.3	3.2	-1.1	
6	Shows genuine interest in diagnosing the issues	4.2	3.8	-0.4	
7	Provision of excellent service on the first visit	4.3	3.0	-1.3	
8	Error-free treatment with sufficient records	4.2	3.2	-1.0	
9	Providing the assured service without	4.1	3.1	-1.0	

	compromise				
	Responsiveness	**4.5**	**3.2**	**-1.3**	**1**
10	Providing the service without redundant delay	5.0	3.2	-1.8	
11	Ready to provide accurate data on time	4.5	3.2	-1.3	
12	Ready to assist at any time	4.3	3.4	-0.9	
13	Speedy handling of criticisms and investigations	4.2	3.2	-1.0	
	Assurance	**4.5**	**3.3**	**-1.2**	**2**
14	Trustworthiness	3.8	2.7	-1.1	
15	Providing the secure and safe services	4.5	3.2	-1.3	
16	Capability of service provider	5.0	3.8	-1.2	
17	Staff consideration	4.6	3.3	-1.3	
	Empathy	**3.9**	**3.4**	**-0.5**	**4**
18	Accessibility and contact comfort	4.2	4.2	0.0	
19	Listening to customers and their problems	4.0	2.8	-1.2	
20	Understanding the customer	3.5	3.0	-0.5	
21	Providing attention and treatment	3.0	2.6	-0.4	
22	Expedient business hours	4.7	4.5	-0.2	

In Table 2, the dimensions of SERVQUAL, Responsiveness and Assurance has the maximum quality gap are discussed. The Responsiveness dimension receives negative scores, indicating that the majority of customers are unsatisfied with those characteristics. Assurance is the next-lowest scored dimension when compared to responsiveness. The majority of the customers want the service provider to assure them that they will receive safe and secure treatment from PHC. In terms of reliability, the expectations of the customers are lesser than their perceived service delivery. However, there is some dissatisfaction with interruptions in referring doctors and getting the diagnostic test, while the majority of the customers are willing to admit it to be a normal occurrence. Customers are satisfied with the tangible aspects of PHCs, and in specific cases, they are unconcerned with the structure or the modern-looking equipment The majority of customer's expectations on the empathy dimension are lesser than their perceived service. This is due to the majority of the frequent visitors are above 50 years old and female population from the rural areas.

3.5 Face, content and Construct Validity

The expert's involvement in content validity is basic. The couple of rounds of the Delphi method is utilized through the residentspecialists to perform satisfied validation of the questionnaires. The questionnaires are provided to 8 experts in an area of service quality to scorethe items with respect to complexity, grade of fitting among the items as well as stated dimensions, an ambiguity stage as well as misapprehensions in an explanation of the items on the three types of scales like relevant, moderate as well as irrelevant. The questionnaires are altered based on the recommendations of the experts. Based on the content validation, the requirement of the questions as well as their suitable designs are confirmed through utilizing the Content Validity Ratio (CVR) as well as Content Validity Index (CVI).To perform the construct validity as well as identified the dimension as well as items by utilizing the Exploratory Factor Analysis (EFA). It is basic approach used for retaining the most complex factors as well as eliminate items with minimum correlations. Furthermore, the scree plot is utilized for identifying the various types of factors in EFA. A Kaiser-Meyer-Olkin (KMO) is utilized for make sure the competence of the selected samples in EFA. It verifies whether a correlation matrix is an identity matrix through testing the null hypothesis or not.

3.6Statistical Analysis

In the statistical analysis, the following steps are employed to determine the relationship among patient's perception of communication skills of the doctors and the patient's trust in the doctors. The expressive analysis and normal distribution tests are used to comprehend the overall characteristics of the sample and to establish the model.

3.6.1 Recursive Feature Elimination

The RFE [22] falls under the filtering type utilizing a proxy measure to estimate the feature subset. Various filtering approach provides the feature ranking with the cross-validation utilized to identify the cutoff point of the ranking. In this research, the features are considered as the life expentency, BR, DR, IMR. The RFE is the most significant approach which keeps only the best key features through measuring the weights of every feature for the provided output. Therefore, the model complexity obtains much minimized as well as execute effectively through training on the optimized feature sets. The weighted voting approach is formulated in equation (2) as follows;

$$D(x) = w.(x - \mu) \tag{2}$$

Where, $D(x)$ represents the decision function; w denotes the weight vector as well as μ denotes the mean vector overall training patterns. The ranking is identified through utilizing the equation (3) as follows:

$$DJ(i) = \frac{1}{2}\frac{d^2 J}{dw_i^2}(DW_i)^2 \tag{3}$$

Where, J represents cost function.By using the RFE, the 6 significant features of gender, age, social group, type of house, sources of drinking water, and sanitation facility are selected. Then, these selected features from RFE are provided for the healthcare prediction process based on the user ratings.

3.6.2 Momentum Gradient Descent based Multilayer Perceptron

In this research, the MGD-MLP approach is proposed for the recommendation of PHC through estimation the services quality. The MLP uses the supervised learning approach, which is known as backpropagation during the training stage. Basically, the MLP involves the various layers such as input, hidden layers as well as output layer. The hidden as well as output layers in the neurons are the computational units in MLP. In training phase, an input data is initially weighted as well as summed with bias constraint. After that, the summed value is moved to an activation function and finally the result is acquired. As for a weight updating as well as error function, the gradient descent approach as well as cross-entropy are basically used, which is related to the features of an object data. The multiple layers in the MLP approach provides the increased input-desired result mapping capability. The respective weights associating an input and hidden layer, as well as the weights associating a hidden as well as output layer are designed by ω_{ij}^1 and ω_{jn}^2, while $C_j$denotes a hidden node threshold. The network learns the relationship among the input data as well as predicted the output feedback through different weights as well as bias values. Simultaneously, the MLP network predicted output to jth neurons with the kth node is formulated in equation (4) as follows:

$$\hat{y}_n = \sum_{j=1}^{k_h} \omega_j^2 F\left(\sum \omega_{ij}^1 g_i(t) + c_j\right) \tag{4}$$

For $1 \leq n \prec m, 1 \leq j \prec k_h, \left(\omega_j, j = 0,1, \ldots, k_h\right), \left(\omega_{ij}, i = 0,1, \ldots, m; j = 0,1, \ldots, k_h\right)$

Where, m, h and k_h denotes an input node number, hidden node as well as hidden node number; $i$denotes the input i to j hidden layer neuron. Asigmoid activation function is the significant function, which is utilized in the MLP network. The sigmoid activation function is formulated in equation (5) as follows:

$$F(a) = \frac{1}{1+e^{-a}} \tag{5}$$

Where, $F(a)$ denotes the set of actualnumbers. The weights ω_{ij}^1 and ω_{jn}^2, with the threshold c_j are unfamiliar as well as it is selected to update as well as minimize the error during prediction. The prediction error is formulated in equation (6) as follows:

$$\varepsilon_n = \frac{1}{2}\sum_{n=1}(y_n - \hat{y}_n)^2 \tag{6}$$

Where, y_n and $\hat{y}_n$ denotes the target data as well as their predicted output; $n = 1, \ldots, N$ with N denotes the number oforiginal data samples. In MLP training, an error for measuring the network learning enhancement related to the convergence speed is the comprehensivecombined error values. It is continuously estimated by utilizing Mean Square Error (MSE).

During MLP training, a significant task is to identify the parameters among the adjacent layers, comprises of the connected weights as well as biases. Based on estimating the parameters in an optimization issue, the gradient descent is the significant solution to solve this problem. Particularly, all the parameters are randomly initialized and then it can be trained iteratively and it continuously estimating the gradient as well as updating the parameters until the certain constraint is met. However, the gradient descent approach is widely utilized in parameter optimization, still there are various complexities involving it needs to be solved. Every update operation of the conventional descent approach in MLP training procedure is depends on the current position, decelerating the convergence speed. Hence, the MGD as a type of stochastic gradient descent approach is improved in the MLP approach. Combining the MGD in MLP is formulated in equations (7) to (9) as follows:

$$v_{\nabla\omega}^{k+1} = \beta . v_{\nabla\omega}^{k} + (1-\beta).\nabla\omega^{k} \quad (7)$$

$$v_{\nabla b}^{k+1} = \beta . v_{\nabla b}^{k} + (1-\beta).\nabla b^{k} \quad (8)$$

$$\omega^{k+1} = \omega^{k} - \alpha . v_{\nabla\omega}^{k+1}, b^{k+1} = b^{k} - . v_{\nabla b}^{k+1} \quad (9)$$

Where, α represents a learning rate; β denotes a momentum coefficient and its default value is constantly fixed to 0.9; v denotes a momentum utilized to maintain the convergence speed. The QoS in PHC is effectively recommended through the SERVQUAL, which further manages the complex data relationships and tends to efficient PHC recommendation. Hence, the obtained results are provided in the further section to estimate the effectiveness of the proposed MGD-MLP approach.

4. RESULTS AND DISCUSSION

In this section, data analysis and statistical analysis are performed by using SERVQUAL tool. In this section, the effectiveness of the proposed SGD-FL approach is implemented on the Python 3.8 platform with the system configuration Windows 10 OS, Intel Core i7 processor, and 8GB RAM. The effectiveness of the proposed approach is estimated on various performance metrics like Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE and R-square (R^2). The mathematical expressions of these metrics are formulated in equations (10-13).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \quad (10)$$

$$MAE = \sqrt{\frac{1}{m}\sum_{i=1}^{n}|y_i - \hat{y}_i|} \quad (11)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (12)$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2} \quad (13)$$

Where, $n$is the number of points, $y_i$is the predicted value obtained from the neural network, $\hat{y}_i$ is the real value, and $\bar{y}$is the mean of the real value.

4.1 Data Analysis

To describe the reference point features of the respondents, basicexpressive statistics like frequency as well as percentage are developed.Cross tabulation is used to identify the percentage of effectiveness for committee members according to their demographic features. Socioeconomic status is a crucial factor whichtakes a significant deal of weight in health-related research. One's socio-economic standing reflects their patient's behaviour as well as arrogancesover one's perception. Table 3depicts the general profile of the sample households in the selected area.

Table 3. General profile of the sample household

Characteristics	Number of respondents	Percentage (%)
Gender		
Male	268	35.7
Female	482	64.3
Age		
21 - 30	374	49.9
31 - 40	238	31.7
41 - 50	102	13.6
51 - 60	24	3.2
Above 61	12	1.6
House Type		
Tiled	404	53.9

Terrace	312	41.6
Thatched	34	4.5
Social Group		
SC/ST	380	50.7
Backward	312	41.6
Forward	58	7.7
Sanitation Facility		
Yes	132	17.6
No	618	82.4
Drinking Water Sources		
Well	24	3.2
Bore well	122	16.3
Tape	589	78.5
Others	15	2.0

In this analysis, a total of 750 respondents are considered; In that, the female respondents participate more (64.3%) than male participants (35.7%). Based on the age, a large number of respondents such as 49.9% between the ages of 21 and 30 are participated. The minimum number of respondents participated are between the ages of 51 to 60, and above 61, constituting up to 3.2% and 1.6%, respectively. In comparison to the participants aged between 51 and 60, those of the age above 61 relatively obtain lesser percentage. Whereas, the participants aged between 31 and 40 constitute 31.7%, while those between the ages 41 and 50 constitute 13.6%. The majority of 50.7% of respondents belong to scheduled caste followed by the backward community of 41.6% and forward community of 7.7%, respectively. Furthermore, 78.5% of the respondents depended on public tape for safe drinking water. Likewise, 16.3% depended on bore well followed by 3.2% and 2% who depended on wells and other sources, respectively. 82.4% of the sample respondents do not have sanitation facilities and merely 17.6% have sanitation facilities in their homes.

4.2 Performance Analysis

In this section, the performance analysis of the proposed MLP approach is validated and tested based on the collected data. The effectiveness of the proposed MLP method is estimated based on the performance metrics like MSE, MAE, RMSE and R^2. Table 4displays the performance analysis of the prediction results of LGBM.

Table 4. Performance analysis of prediction results of LGBM

Methods	MSE	MAE	RMSE	R^2
DT	1.782	0.928	2.293	6.281
RF	0.683	0.893	1.494	5.782
ANN	0.472	0.493	1.303	5.293
MLP	0.221	0.381	1.292	4.043
MGD-MLP	0.119	0.205	1.198	3.893

In Table 4, prediction results of LGBM in terms of various error metrics are analysed. The existing methods like Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN), and MLP are compared and estimated with the proposed MGD-MLP approach. Through incorporating momentum, the optimizer moves more swiftly in the direction of persistent gradients, making the training process faster and more efficient. The proposed MGD-MLP approach attains the MSE of 0.119, MAE of 0.205, RMSE of 1.198, and R^2 of 3.893 respectively.In the study movements of health indicators and in the case of Tamil Nadu, Pudukkottai district. Table 5 shows the result of trends in selected health indicators in the government of Tamil Nadu in the period 1995 to 2019. Life expectancy at birth over the period has the increasing growth rate of 0.3649 per year.

Table 5: Result of Health Indicators trends in Tamil Nadu for period between 1995 to 2019

Sl. No.	Health Indicator's	Coefficiency		R^2
		'a'	'b'	
1.	Life expectancy by birth	62.9392	0.3649* (27.02813)	0.9695
2.	Birth rate (BR)	20.197	-0.2579 (-15.4065)	0.9117
3.	Death rate (DR)	8.065	-0.0435 (-4.2289)	0.4374
4.	Infant Mortality Rate (IMR)	59.382	-1.9614 (-31.6353)	0.9775

Table 6 shows the result of trends and the yearly rate of change in selected health indicators in Pudukkottai district for the period 1995 to 2019. Life expectancy at birth over the period has the increasing growth rate of 0.2945 per year which shows a positive indicator. The CBR, DR and IMR has shown a declining trend with the yearly rates of change being -0.2655, -0.0916 and -0.9991 respectively. IMR has declined largely by -0.9991 in the district. Both the BR and DR had declined but yearly rate of the decline in BR (-0.2655) was higher than the decline in DR (-0.0916).

Table 6: Result of Health Indicators trends in Pudukkottai District between 1995 to 2019

Sl. No.	Health Indicators	Coefficients		R^2
		'a'	'b'	
1.	Life expectancy at birth	63.103	0.2945* (10.9545)	0.8392
2.	Birth Rate (BR)	21.6059	-0.2655 (-8.888)	0.7745
3.	Death Rate (DR)	7.3188	-0.0916 (-5.5859)	0.5757
4.	Infant mortality Rate (IMR)	35.9632	-0.9991 (-16.8014)	0.9247

4.3 Discussion

In this section, the achievement of the proposed approach is discussed along with their advantage. The existing works have the limitation such as KMO [16] approach had selected the minimum health networks, which restricted the transferability of the outcomes to other PHCs.In BWM [17], the data were collected from experts from 2020 to 2022, extrapolating or generalizing the results beyond this timeframe as external factors such as changes in healthcare policies, influenced the applicability of the findings to future periods. the significant results of T2DM [18] as well as hypertension were missed from the medical records as well as does not include in the data analysis.The causationimplications were not made among the variables due to the cross-sectional nature of data and lack of considering the demographic impact on the perceived service quality.

5. CONCLUSION

The significant challenge when estimating the QoS in hospitals in the uncertainty as well as fuzziness is involved in measuring the performance criteria. This research proposes the MGD-MLP approach for the recommendation of PHC through estimation the QoS by using SERVQUAL tool. The momentum supports to finding a smoother loss landscape and a better generalization performance. For QoS estimation in PHCs, this means more accurate and reliable predictions on unseen data, leading to better decision-making and resource allocation.The significant service quality gap is determined in the Responsiveness and Assurance dimension. Hence, the discoveries of this research are utilized to enhance the service quality and behavioural loyalty of the patients, thereby leading to minimizing the patient's visits in a number of hospitals. The experimental results show that the proposed MGD-MLP approach attains the MSE of 0.119, MAE of 0.205, RMSE of 1.198, and R^2 of 3.893 respectively. In the future, the Deep Learning (DL) approaches can be considered to further better prediction results in PHC.

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