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Forecasting of the Dental Workforce with Machine Learning Models

Diş Hekimliği İşgücünün Makine Öğrenmesi Modelleri ile Tahmin Edilmesi

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ABSTRACT

This study aimed to predict dentists employed in Turkey with ML (ML) models. The predicted results were obtained by applying ML methods; namely, generalized linear model (GLM), deep learning (DL), decision tree (DT), random forest (RF), gradient boosted trees (GBT), and support vector machine (SVM) were compared. The RF model, which has a high correlation value (R2=0.998) with the lowest error rate (RMSE=656.6, AE=393.1, RE=0.025, SE=496115.7), provided the best estimation result. The SVM model provided the worst estimate data based on the values of the performance measurement criteria. This study is the most comprehensive in terms of the dental workforce, which is among the health resources such as physicians, nurses, medical technicians, etc. Finally, we present an example of future applications for ML models that will significantly impact dental healthcare management.

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ÖZET

Bu çalışma, Türkiye'de çalışan diş hekimlerinin makine öğrenmesi (ML) modelleri ile tahmin edilmesini amaçlamıştır. ML yöntemleri olan genelleştirilmiş lineer model (GLM), derin öğrenme (DL), karar ağacı (DT), rastgele orman (RF), gradyan artırılmış ağaçlar (GBT) ve destek vektör makinesi (SVM) uygulanarak tahmin edilen sonuçlar karşılaştırıldı. En yüksek korelasyon değerine (R2=0.998) ve en düşük hata oranına (RMSE=656.6, AE=393.1, RE=0.025, SE=496115.7) sahip olan RF modeli, en iyi tahmin sonucunu sağlamıştır. SVM modeli, performans ölçüm kriterlerinin değerlerine göre en kötü tahmin verilerini sağlamıştır. Bu çalışma hekim, hemşire, tıp teknisyeni vb. sağlık kaynakları arasında yer alan diş hekimliği işgücü açısından en kapsamlı çalışmadır. Son olarak diş sağlığı yönetimini önemli ölçüde etkileyecek ML modelleri için gelecekteki uygulamalara bir örnek sunuyoruz.

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1. INTRODUCTION

Machnine Learning (ML) models, are types of artificial intelligence (AI) that discover patterns specific to the data and query multiple datasets to determine the relationships of parameters [1]. ML is an AI method that focuses on building systems that learn or improve performance based on observed data. ML models are known as the process of training and predicting a certain amount of data by learning a data set in detail [2]. In particular, ML models play a significant role in estimating complex data sets by analyzing them quickly and efficiently [3]. Researchers prefer the ML method to overcome the complex structure created by the data of healthcare systems [4]–[7]. However, machine learning, which is preferred in the field of health, is used in the detection, diagnosis, and prevention, and monitoring of disease progression [8]–[10].

The most important feature that distinguishes this study from other studies is that ML models are not directly related to a medical issue but are related to health management and informatics [11]. The paper proposes that the ML perspective should be used to contribute to the development of data analysis in healthcare management [12]. Measurement criteria values were calculated to compare the performance of the results of the artificial intelligence models used [13]. For this reason, it is possible to compare the forecast data by using multiple forecasting models, and the results of the model with the best performance are preferred [14]. In this study, six different ML models named GLM, DT, DL, RF, GBT, and SVM were run to estimate the number of dentists employed. The performance measurement criteria values of these models were compared for the present paper. This study is motivated to demonstrate the need to use ML models to predict the number of dentists employed in terms of healthcare management in Turkey.

2. LITERATURE REVIEW

ML, has been widely used in the field of health, generally in studies related to disease diagnosis, prevention, and treatment process [15], [16]. Researchers emphasize the importance of using a ML approach for rapid and accurate medical diagnosis and successful treatment of diseases [17], [18].

Table 1. Studies on the dental workforce

Purpose of the Study	Factors	Methods	Ref.
Compare the frequency and duration of career breaks taken by the dental surgeons and evaluate the impact of these and changes in working hours on human resource planning	Age, the proportion of hygienists, the duration of career breaks, GDPs of dental surgeons	Questionnaire survey, statistical analysis	[25]
Forecasting the supply and demand of dental operations in the UK	Staff type, staff cost, treatment hours, treatment type,	Operational research (OR) techniques-linear programming	[26]
Establishing a forecasting model of demand and supply for dentists for workforce planning in dentistry	The age structure of the population, the dentate and edentulous subpopulations of adults,	Forecasting models, statistical analysis	[27]
Literature review on factors influencing oral health workforce planning and management in developing countries (DCs)	Lack of data, the restorative and preventive care, the number of dental schools, the dentistry students, privatization of dental care services, skill mix, the scope of practice, workforce management	Literature review	[28]
Identifying data sources from countries concerned with the selection of oral health indicators in a sample of FDI member countries;	Children oral health care, Behaviors and coverage, Oral health economics, Oral health equality of life	A cross-sectional survey- Mann–Whitney U-tests, statistical analysis	[29]
Develop and operationalize a workforce planning simulation tool based on oral health needs	Gender, age, number of natural teeth, the problem with food/pain, level of service, type of service, frequency of service	Simulation models	[30]
Identify trends in the dental workforce in Oman from 1990 to the present and compare the dental workforce with medical counterparts in Oman and other countries, and assess the future dental workforce in Oman	Dentist workforce, dentist-to-population ratios	Basic integrated model, statistical analysis	[31]
estimating patient and service ratios for oral health therapists (OHTs), dental hygienists (DHs), and dental therapists (DTs)	Age, sector of practice, practice type, length of service, number of dentists, % of child patients, locations,	self-report questionnaire, statistical analysis	[32]
Identifying factors affecting the dental workforce and predicting the optimum dentist	Economic, population, literacy rate, the life of expectancy, dentist workforce	ML Models, SVM, RF, GLM, GB	This Study

FDI: World Dental Federation

ML, which is widely used in general medical issues, has also been used in the field of dental treatment in recent years. The prediction data was obtained using ML for a national health database of data from the National Health and Nutrition Examination Survey to develop recommendations for dental treatment [19]. Another study used ML models to predict the clinical effects of dental diseases, periodontal diseases, trauma and neuralgias, cysts and tumors, glandular, and dental and orofacial diseases, and compared the results [20]. The bayesian algorithm from ML models was used for genomic analysis of head and neck squamous cell carcinomas of oral oncology [21]. Data from a total of 125 patients were compared using ML models to predict the occurrence of BRONJ associated with dental extractions [22]. Using Medicaid data from 24233 pediatric patients over nine years, ML methods were used to group and estimate patients' early childhood by cumulative dental cost curves [23]. Detection and diagnostic predictions of dental caries on periapical radiographs were performed using 3000 periapical radiographic image datasets utilizing the Deep convolutional neural networks (CNNs) algorithm, one of the ML models [24]. Studies conducted within the scope of dental employment are discussed in Table 1.
Some studies reveal predictive data using ML models individually or using multiple algorithms [33], [34]. In this study, we have used six models of machine learning, namely GLM, DL, DT, RF, GBT, and SVM, that are most suitable for the dataset. These models include a wide range of ML techniques that are suitable for capturing the complexity of various features and relationships. The complexity and structural features of the dataset support the use of various models such as GLM, DL, DT, RF, GBT and SVM.This research is a pioneering study since there is no direct study covering the field of health management with a ML approach, and there are very few studies indirectly. However, some studies suggest a ML approach to overcome the extreme complexity and variability of healthcare processes to provide high service quality and cost-effectiveness in health systems [35]. We can assume that ML algorithms have an important role in decision-making in the light of the data obtained in health management, just like in medical issues.

3. METHODOLOGY

3.1. Data Preparation

In this study, data on dependent and independent variables were obtained and run in ML algorithms. For the training and testing phases of ML algorithms, data was shared at 80% and 20% rates. Prediction data was obtained without normalization operations for the data in the data sets. The data of this study was obtained from open access data by Turkish Statistical Institute (TÜİK) [36]. The dependent variable was defined as the number of dentists employed in Turkey between 1960 and 2018 in this study. Fig. 1 shows the number of dentists employed during the selected period. The number of dentists considered includes only those employed in government institutions. The average of the 59-year data was calculated as 11373, while the number of dentists employed in 2018 was 30615. The number of dentists per 1000 people was computed as 0.429 for 2018.

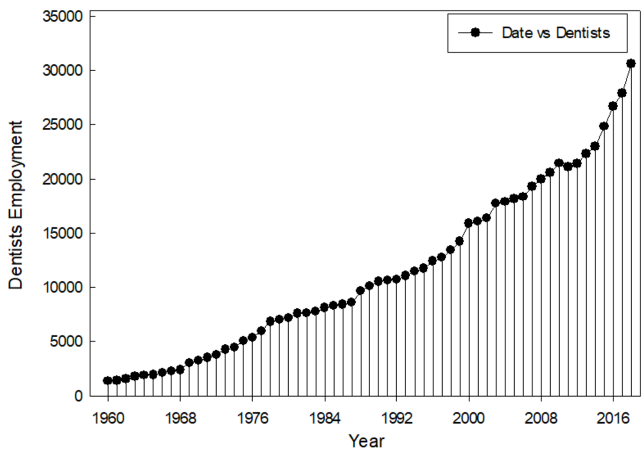

Fig. 1. The dentists employed between 1960-2018.

Country population, gross domestic product per capita (GDP PC), life expectancy, and literacy rate (considered as education factor) that affected the dependent variable were defined as independent or input variables. The changes in the input factors during the considered period were shown in Fig. 2. These factors were preferred to establish the link between the increase in the rate of patients applying to dental clinics and the number of employed dentists. In addition to being directly related to the increase in the country's population and the dental workforce, the desire of people to live for a long time also plays an important role in this relationship. Due to little or no government support for dental treatment in most countries, people have to pay for these treatments out of pocket. In this case, we have taken this factor into account in this study to question the link between people's income rate and dental treatment. With the last input parameter of the study, people's literacy rate data were taken to analyze the importance that educated people attach to dental treatment. There are two cases in the data used for this factor. The data used belong to the literacy rates of people aged 15 and over. The other case consists of annual data between 2004-2018 and five-year data between 1960 and 2004. The data for the years in which literacy rates could not be reached were formed by taking the average values of the differences between the two years.

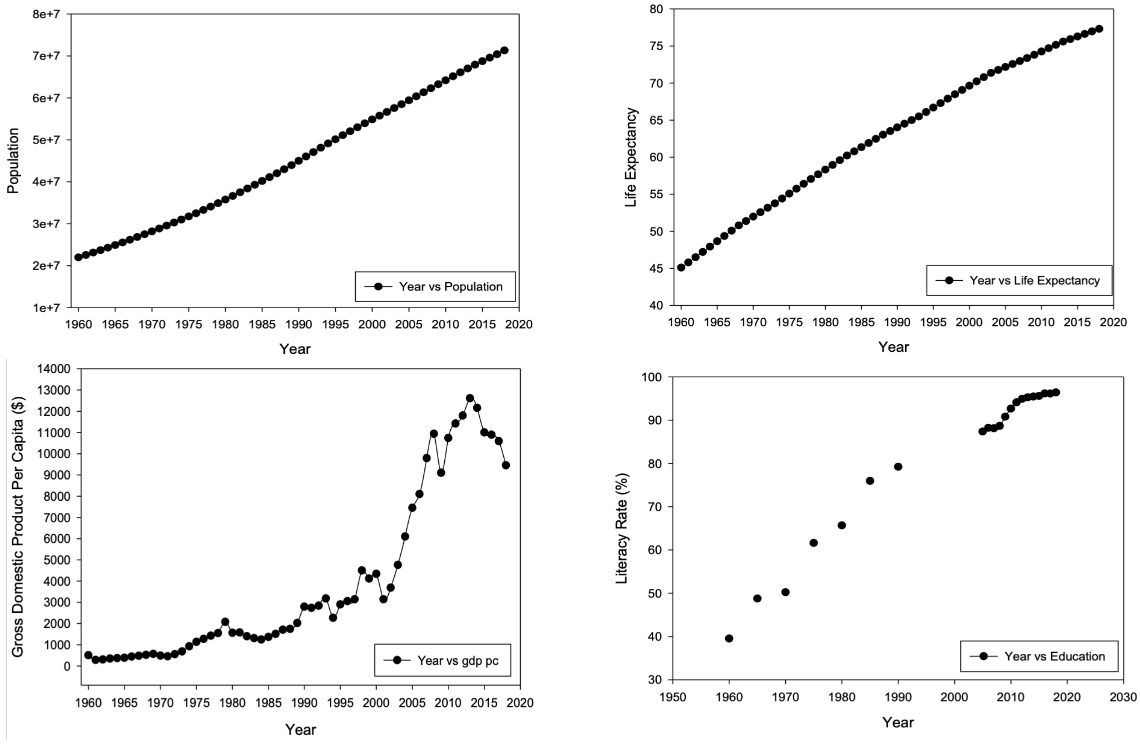

Fig. 2. The input parameters between 1960-2018.

3.2. ML Algorithms

The number of dentists employed annually was estimated using ML models in the second stage of the study. Among the ML models, generalized linear model (GLM), deep learning (DL), decision tree (DT), random forest (RF), gradient boosted trees (GBT), and support vector machine (SVM), which are the most used by researchers, were preferred in this study. Each model tries to predict the response function with different algorithms. The GLM model works with the logic of regression analysis. The DL approach is an algorithm that uses representative data from the previous layer to explore complex systems and predict expected data at each layer of a machine. The DT model minimizes errors by classifying them as decision trees to increase the prediction accuracy of complex structures. The RF prediction model predicts data by classifying test data such as DT and working with a culture of regression analysis similar to the GLM model. GBT model is a ML technique based on the gradient-assisted tree algorithm. The SVM model has an algorithm developed by classifying (at least two classifications) the data in the data set for the prediction data. In creating a subset of the clusters created in the ML models dataset, some newly created feature selection is required. A feature set has a different number of complexities, achieving an error rate. For this reason, as in Table 2, each model selects features to provide the most consistent results for itself.

Table 2. The feature selection information of ML models

Model	Selected Feature Numbers	Population	Life Expectancy	GDP PC	Literacy Rate	Evaluated Feature	Generated Future
GLM	3.00	✓	✓	✓		1376.0	111.0
DL	2.00		✓	✓		460.00	63.00
DT	1.00				✓	3628.0	166.0
RF	3.00	✓	✓		✓	2589.0	178.0
GBT	3.00	✓	✓		✓	143.00	21.00
SVM	2.00		✓	✓		1817.0	95.00

Nearly 59 data of all data (80 %) were used for the training phase, while the remaining data (20 %) were used for the testing phase [24]. Rapid Miner 9.1 software was used to obtain predicted results of ML models in this study. Estimating the number of dentists employed was provided using six different ML models in the present study. In order to make a comparison between these models, some performance criteria need to be calculated. These criteria are included in ML as Relative error (RE), root mean square error (RMSE), mean absolute error (MAE), mean squared error (MSE), and the coefficient of correlation (R^2), respectively. The equations used for performance measurement are given below:

$$\in = y_i - \tilde{y}_i \tag{3}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i) \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \tilde{y}_i| \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \tilde{y}_i| * 100 \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2}{n}} \tag{7}$$

$$R^2 = \sum_{i=1}^{n}\left[\frac{\tilde{y}_i - y_i}{y_i - \bar{y}_i}\right]^2 \tag{8}$$

where y_i, $\bar{y}_i$, and $\tilde{y}_i$ represent the actual value in the data set, the average value of the data set in the data, and the predictive values generated by ML models, respectively. n is the number of samples in a dataset. The margin of error $\in$ value computes between the actual data and the forecast data. MSE, MAE, RE, and MAPE are the performance measurement tools that minimize empirical predictive values in ML models. The value of R^2 takes a number between 0.00-1.00. In ML models, the option of determining the variables that will give the best result for which model by applying feature selection is widely used.

4. RESULTS OF THE STUDY

In most studies, the results are compared using one or more of the ML models. In this study, a comparison was made using six models of the ML method. Interpretations of the results are provided by considering many parameters for the comparison of the models. This error rate is considered the training error rate. The test error verified in the data set is higher than the training error. When creating feature sets, it is desirable to have low complexity and low error rates. Especially in small-scale data, prediction data with low error in predictive data is derived by feature selection. However, it is not possible to both reduce the error rate and minimize the complexity. However, using fewer features allows ML models to train faster and have fewer errors than predictive values.
The statistical results of the performance measurement criteria of ML models were discussed in Tables 3-7 in detail. The software used to ensure that the estimated results are ready provides more than 1000 points per second for the real-time scoring method, making it balanced in the estimated data. For models whose input parameters correspond to uncontrollable parameters, results are provided quickly. The time used for the estimation data obtained for the solution in these tables is based on seconds. The correlation values, one of the performance criteria, express the connection between the estimated results obtained by the models and the actual results. The RF model showed the best performance with a correlation value of 0.998. As a result of comparing the models with RMSE, AE, RE, and SE data, RF has a low margin of errors with values of 656.6, 393.1, 0.025, and 496115.7, respectively. The RF ML model has the best prediction results compared to other models in terms of all these results.

Table 3. The statistical results of the performance measurement criteria of ML models

Model	Correlation	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
GLM	0.996	0.0005	101548.0	127.1	0.0
DL	0.996	0.0012	103729.0	711.9	0.0
DT	0.991	0.0054	35598.0	0.0	0.0
RF	0.998	0.0019	94435.0	84.7	106.4
GBT	0.989	0.0077	113857.0	1745.8	42.6
SVM	0.975	0.0215	21122.0	59.3	21.3

Table 4. The RMSE values of the models

Model	RMSE	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
GLM	763.2	103.20	101548.0	127.1	0.0
DL	809.8	68.700	103729.0	711.9	0.0
DT	1403.6	529.00	35598.0	0.0	0.0
RF	656.6	285.00	94435.0	84.7	106.4
GBT	1437.1	751.20	113857.0	1745.8	42.6
SVM	3012.3	1623.0	21122.0	59.3	21.3

As a result of statistical data of other models, GLM, DL, DT, GBT, and SVM correlation values were calculated as 0.996, 0.996, 0.991, 0.989, and 0.975, respectively. GLM and DT models have data of consistent estimation results with high correlation values among the five models. The RSME values of GLM, DL, DT, GBT, and SVM

Table 5. The AE values of the models

Model	AE	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
GLM	571.7	59.80	101548.0	127.1	0.0
DL	563.0	40.00	103729.0	711.9	0.0
DT	732.5	211.8	35598.0	0.0	0.0
RF	393.1	144.1	94435.0	84.7	106.4
GBT	721.1	339.1	113857.0	1745.8	42.6
SVM	1847.5	947.8	21122.0	59.3	21.3

Table 6. The RE values of the models

Model	RE	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
GLM	0.049	0.0058	101548.0	127.1	0.0
DL	0.045	0.0050	103729.0	711.9	0.0
DT	0.041	0.0084	35598.0	0.0	0.0
RF	0.025	0.0069	94435.0	84.7	106.4
GBT	0.043	0.0155	113857.0	1745.8	42.6
SVM	0.097	0.0299	21122.0	59.3	21.3

Table 7. The SE values of the models

Model	SE	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
GLM	591024.7	157469.400	101548.0	127.1	0.0
DL	659570.6	108376.400	103729.0	711.9	0.0
DT	2193889.0	1192405.30	35598.0	0.0	0.0
RF	496115.7	337975.200	94435.0	84.7	106.4
GBT	2516592.0	2038691.30	113857.0	1745.8	42.6
SVM	11180992.9	10754187.8	21122.0	59.3	21.3

were calculated as 763.2, 809.8, 1403.6, 1437.1, and 3012.3, respectively. Likewise, GLM and DT have low errors compared to the RMSE values of the models. The AE values of GLM, DL, DT, GBT, and SVM were computed as 571.7, 563.0, 732.5, 721.1, and 1847.5, respectively. The RE values of GLM, DL, DT, GBT, and SVM were estimated as 0.049, 0.045, 0.041, 0.043, and 0.097, respectively. DT and GBT models have data of consistent estimation results with low RE values. The SE values of GLM, DL, DT, GBT, and SVM were computed as 591024.7, 659570.6, 2193889.0, 2516592.0, and 11180992.9, respectively. GLM and DT models have lower SE values than other models in this performance criterion and the values of RMSE and AE. According to the values of the performance measurement criteria, RF provides the best estimate of the most response variable, while SVM provides the worst estimate data.

The comparison between the estimated the dental workforce and the actual number according to the RF algorithm that exhibits the best performance from the ML models was shown in Fig.3. Approximately 12 data were estimated since about 80% of all data was used for the training (or education) phase and the remaining 20% for the testing phase. It is understood that there is considerable consistency between the forecast data and the actual data. We observed that only the 7th (-1164), 9th (2015), and 12th (2135) testing data differ from the estimated data and the actual data. The most negligible difference value between the actual data and the prediction data was obtained in the 4th test data (38). The RF model has shown that early estimation of dental workforce is key to the possibility of advance planning in healthcare management for Turkey.

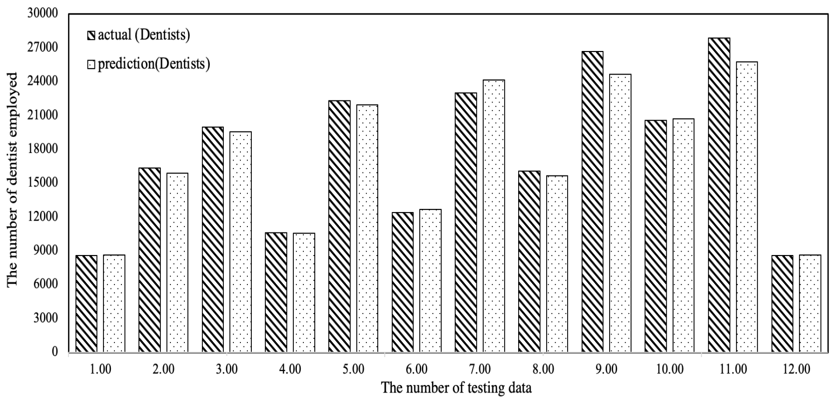

Fig. 3. Estimated and actual values of the number of dentists employed by the RF model.

This study has some limitations. The analysis is limited to four input factors, eliminating factors that cannot accommodate long-term data. Therefore, the effects of variables with other demographic characteristics on the dental workforce could not be analyzed. A second limitation is the literacy rate data selected among the

independent parameters to reflect the education level in the country. Otherwise, this study does not directly include the education level factor when there is no long-term data on education level. We have wanted to underline that the data obtained in this study were taken into account by four independent factors. Another limitation is that the dental workforce is limited only to those working in government-supported institutions. Since there is no official data on the dental workforce in private dental clinics, they were not included in the study.
Health expenditure rates in countries are increasing day by day [37]. One of the biggest shares in health expenditures is health resources. Using alternative resource allocation techniques in dental health care, more information about the economic impact can be provided to decision-makers, namely policymakers [38]. Inefficient resource management negatively affects health systems in terms of cost and time [19]. For this reason, it is inevitable to use the ML method, which is one of the most up-to-date methods of today. This study offers a solution to the resource management problem in health management with the machine learning.

5. CONCLUSIONS AND PERSPECTIVE

By running ML models, namely, GLM, DT, DL, RF, GBT, and SVM, performance measurement criteria values were compared to show the consistency of the estimated data on the dental workforce. Among the ML models, the model with the best performance was defined as RF, while the model with the worst prediction data was determined as SVM. To conclude, ML models provide the opportunity to know the problems that may occur by obtaining predictive data and sensitivity analyses in many areas. The potential of ML in overcoming the complexity of various data and the difficulties encountered in healthcare management has been revealed in this study. The most crucial reason for consistent data in healthcare management is the human factor. In order to minimize the cost of human resources in healthcare, ML models must be needed to overcome the data of this complex system. ML models are generally used in medical diagnosis in the field of healthcare. This paper showed using algorithms that allow ML to be developed for predictive data to enable more data-driven health informatics and management solutions. We have emphasized that ML models should be used in healthcare and non-medical issues and issues related to healthcare management. The implications for health management research are that there is no doubt that health system management will become more dependent on ML models of complex data such as health resources, health economics, patient rights, patient's and health professional's satisfaction, and so on. Finally, we present an example of future applications for ML models that will significantly impact healthcare system management.

Author Contributions

Each author has contributed equally to the work.

Conflict of interest

The author declares that there is no conflict of interest.

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