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Research Article

Evaluation of health care systems using supervised and unsupervised machine learning approaches

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ABSTRACT

Both large- and small-scale health system evaluations are crucial. On a larger scale, it facilitates cross-national comparisons, monitors the advancement of global health objectives, aids in the formulation of public health policy, and ensures efficient use of resources. On a smaller scale, it helps countries figure out how well their health programs are working, see health trends, and find areas that need improvement. A health system is made up of a lot of different people and things, like organizations, institutions, resources, patients, and people who might become patients. All of these people and things work together to give health services to a group of people. This research gathered health indicators from 30 OECD (Organization for Economic Cooperation and Development) nations from 2006 to 2020 and evaluated them through both supervised and unsupervised machine learning methodologies. The findings, demonstrating high accuracy in machine learning methods (exceeding 93.3%), indicate that financial models alone are inadequate for evaluating healthcare systems. The complexity and multidimensional nature of these systems necessitate the inclusion of health indicators in the evaluation process. Even with enough money, people may not get the health outcomes they want if there aren't health policies that are based on the basic ideas of fairness, quality of service delivery, and efficiency that can be put into action. This study employs unsupervised machine learning techniques to analyze health indicators. This helps policymakers, researchers, and other people who are interested in healthcare systems learn more about their strengths and weaknesses. These insights can help policymakers make decisions, make it easier to compare medical systems in different countries, and help healthcare systems get better all the time.

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INTRODUCTION

Statistics is a basic tool that helps us draw meaningful conclusions from data, aids in scientific discoveries, helps us make good decisions, and gives us answers to many problems. Health statistics is a specialized subdiscipline that deals with analyzing, interpreting, and summarizing health data [1]. Health statistics are important for figuring out how healthy people and communities are, how common diseases are, how well health services work, and how health policies affect people. These numbers include a variety of quantitative tools used to study health problems, from big epidemiological studies to clinical trials.

When looking into complicated things like health statistics, comparisons and typologies can help you understand them better. Typologies facilitate the simplification of complex empirical realities, thereby enabling systematic analysis of similarities, variations, and the identification of patterns. Machine learning techniques are essential analytical instruments that enable the examination and interpretation of high-dimensional data [2, 3]. There are two main types of machine learning: supervised learning and unsupervised learning. When you use supervised machine learning, you train a model on labeled data that has known outcomes. When you use unsupervised machine learning, you find patterns and relationships in unlabeled data that don't have any known outcomes.

Supervised machine learning is a kind of learning in which the algorithm learns from labeled data, which means that the input data is matched with the right output labels. The goal of supervised learning is to teach the algorithm how to connect inputs to outputs so that it can make accurate predictions or classifications on data it hasn't seen before. In supervised machine learning, classification is a basic idea. It means using algorithms to put input instances into one of several pre-defined groups. Random Forest is a popular supervised machine learning algorithm that is well-known for being good at classification tasks [4].

On the other hand, unsupervised learning is a type of machine learning in which the algorithm looks for patterns, structures, or relationships in the data without any clear labeled output. It finds hidden patterns or structures in the data that is being input. Clustering algorithms are a type of unsupervised machine learning that puts similar data points into groups called clusters. These algorithms help find patterns or groups in a dataset without needing to set class labels ahead of time. K-Means clustering is a common unsupervised machine learning algorithm that divides a dataset into a certain number of groups. It works best when you already know how many clusters there are. K-Means puts each data point in the cluster that is closest to it and then keeps making these assignments better until the sum of the squared distances between data points and their centroids is as small as possible [5].

Standardized indicators are necessary to evaluate the health status of a particular population. These indicators, derived from health records and statistics of individuals and communities, are used to assess current conditions and make predictions about the future. Keeping accurate records and statistics is crucial to seeing things as they are and making wise choices.

Since its founding in 1948, the World Health Organization (WHO) has been a leader in creating health metrics and collecting and analyzing data that can be used to compare different countries [6]. In the 1960s, there was a push to work with other countries around the world and make health indicators and data more consistent. A lot of success has been made by the World Health Organization (WHO) in making rules and standards for gathering and analyzing health data that can be used to compare data from different countries. What are "health indicators"? They were made by the World Health Organization (WHO) and show many different parts of health. Some of these factors are the number of sick people, how well the health system is working, the things that affect health, and the trends in the health of the community. The purpose of these indicators is to help public health officials make choices and decide how to spend their money and time, and to allow people to compare countries. They help countries and international health groups track and rate the success of their health programs, identify health trends, and focus on areas that need work or improvement [7]. These factors are categorized by the World Health Organization (WHO) to help countries make fair decisions:

- **Health Status Indicators:** These show how healthy a person or society is overall by looking at things like the number of diseases, how easy it is to get medical care, and how long people generally live.
- **Risk Factors:** The World Health Organization (WHO) has created a number of signs and tools to help find, track, and protect public health when it comes to health-related risk factors. These things are very important for stopping the spread of diseases and making people healthier.
- **Service Coverage:** The World Health Organization (WHO) has created service coverage indicators to measure how easy it is to get healthcare services and how well they work. These indicators are used to keep an eye on health services and make them work better [7].

The list of health indicators is periodically updated to align with current health priorities. These indicators serve as a crucial tool in assessing the health status of populations, identifying disparities, and guiding evidence-based decision-making at local, national, and international levels. Recent advancements in the field of mathematical analysis have significantly contributed to the development of more accurate and efficient methods for approximating complex functions, which are highly beneficial for evaluating health systems [8-14]. While the literature includes some articles focused on evaluating healthcare systems [15-21], to the best of our knowledge, there are no published works that compare the evaluation performance of supervised and unsupervised machine learning approaches in assessing healthcare indicators of countries. The aim of this study is to evaluate the health systems of 30 OECD countries based on 21 healthcare indicators from 2006 to 2020 using both supervised and unsupervised machine learning approaches.

MATERIAL AND METHODS

The work was done in three main separate steps: i) the healthcare indicators for OECD countries from 2006 to 2020 were gathered, ii) data processing (standardization) was done in Matlab 8.3.0.532 (R2014a) software (MathWorks Inc., Natick, MA, USA), and iii) the evaluation of health care systems was done employing machine learning methodology: the supervised classification and unsupervised clustering. The flowchart in Figure 1 outlines the main steps undertaken in this study. The following sections offer comprehensive explanations of each stage involved in the research process.

DATA COLLECTION

Traditionally, the classification of health systems in countries has often relied on economic-based structures in the literature. However, given the unique nature of healthcare services, which differ significantly from other types of services, a focus on fairness-oriented maximum accessibility becomes more crucial than merely ensuring equal distribution. Evaluations based on health indicators—the outputs of provided healthcare services—allow for more valuable and accurate predictions for future assessments. For this study, health status indicators, risk factors, and service coverage indicators from the years 2006 to 2020 for 30 OECD countries were utilized. Health indicator data were collected from the World Data Bank, Eurostat, and WHO databases. To ensure consistency and accuracy, the data were standardized before analysis. This step put all data on the same scale, usually through normalization or z-score standardization, so that differences in measurement units did not affect the results. The dataset covers indicators such as adolescent birth rate, total fertility rate, cancer incidence by type, tuberculosis incidence, cardiovascular death rate, rates of cancer, diabetes, or chronic respiratory diseases in people aged 30 to 70, maternal mortality, death rate from road traffic injuries, under-five mortality, infant mortality, life expectancy at birth, stillbirth rate, and neonatal mortality. The risk factor indicators included in the study are: tobacco use among persons aged 18+ years, total alcohol per capita (age 15+) consumption, prevalence of overweight and obesity in adults, proportion of the population using safely managed sanitation services, air pollution levels in cities, and prevalence of intimate partner violence. The service coverage indicators included were: the coverage rate of vaccination in the national program for vaccines such as diphtheria, tetanus, and pertussis, coverage rate of vaccination for measles, and tuberculosis case detection rate. All the indicators used, along with their codifications and explanations, are detailed in Table 1.

Machine Learning Classification and Evaluation

Machine learning classification trains models to classify data into preset classes. This procedure uses algorithms and statistics to learn patterns and relationships from labeled training data and to predict or label new data. This study classified OECD countries using financial models using decision tree regression (DTR) and support vector regression (SVR) (Fig. 2). Cross-validation tuned the DTR and SVR hyperparameters to optimize model performance. In this study it is selected DTR for its ability to handle complex, nonlinear interactions in the data, and SVR for its ability to handle high-dimensional data and reduce prediction error. These techniques have been successful in effectively

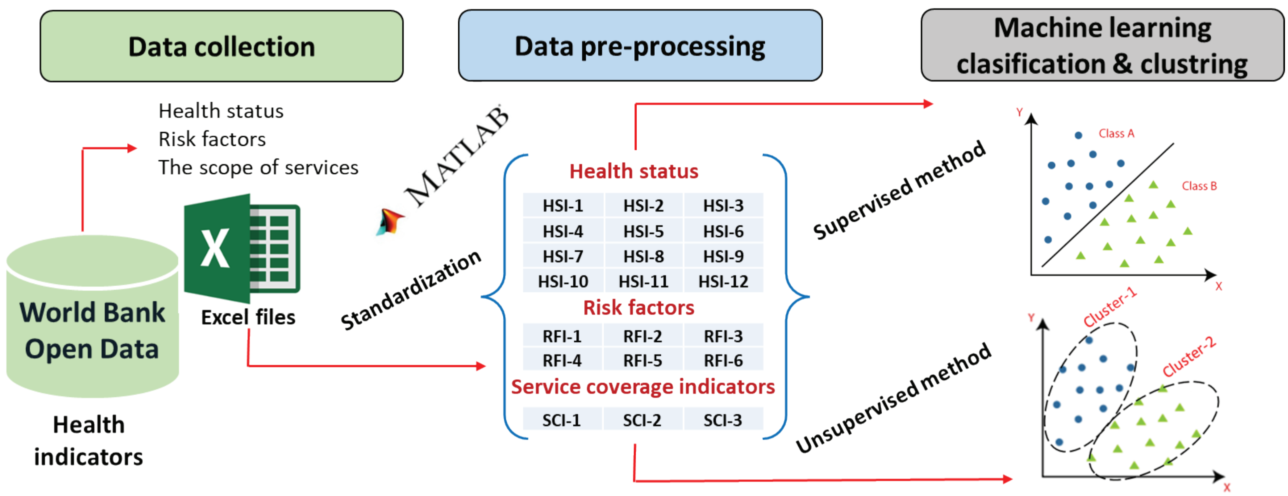

Figure 1. The flow chart outlining the main steps followed in the present study.

Table 1. The used health indicators with their explanations

Code	Health indicators	Explanation
HSI-1	Health status indicators	Adolescent birth rate
HSI-2		Total fertility rate
HSI-3		Cancer incidence rate, by type of cancer
HSI-4		Tuberculosis incidence rate
HSI-5		Rate of cardiovascular deaths, diseases, cancer, diabetes, or chronic respiratory diseases between the ages of 30 and 70
HSI-6		Maternal mortality rate
HSI-7		Death rate due to road traffic injuries
HSI-8		Under-five mortality rate
HSI-9		Infant mortality rate
HSI-10		Life expectancy at birth
HSI-11		Stillbirth rate
HSI-12		Neonatal mortality rate
RFI-1	Risk factors indicators	Tobacco use among persons aged 18+ years
RFI-2		Total alcohol per capita (age 15+) consumption
RFI-3		Overweight and obesity in adults' prevalence
RFI-4		Proportion of population using safely managed sanitation services
RFI-5		Air pollution levels in cities
RFI-6		Intimate partner violence prevalence
SCI-1	Service coverage indicators	Coverage rate of vaccination compared to vaccination for each vaccine (diphtheria, tetanus, pertussis) in the national program
SCI-2		Coverage rate of vaccination compared to vaccination for each vaccine (measles) in the national program
SCI-3		Tuberculosis case detection rate

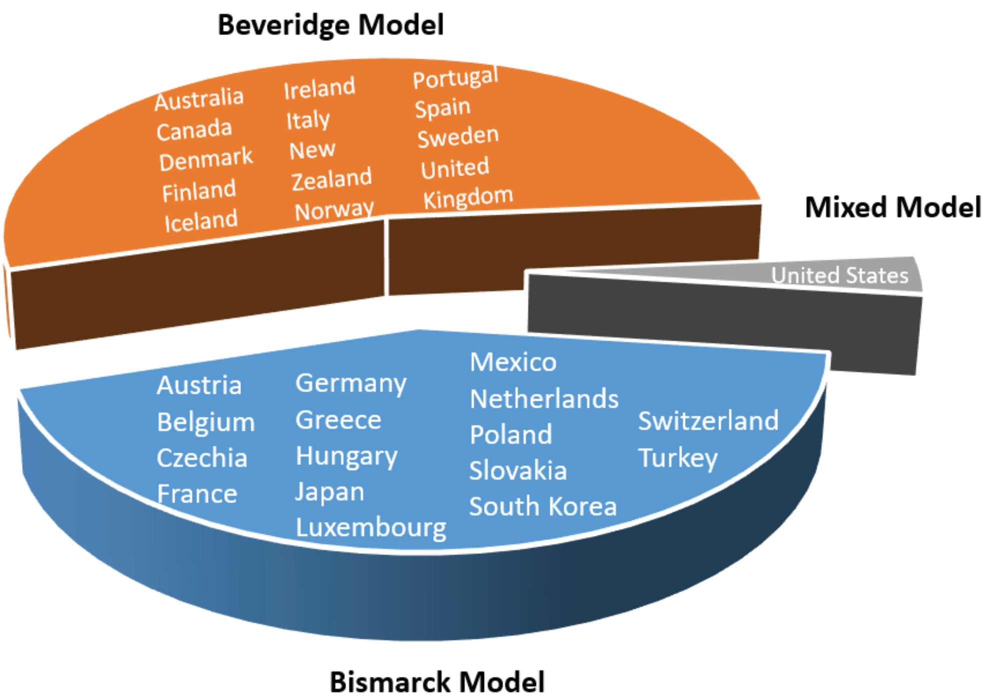

Figure 2. Classification of health care systems based on financial models.

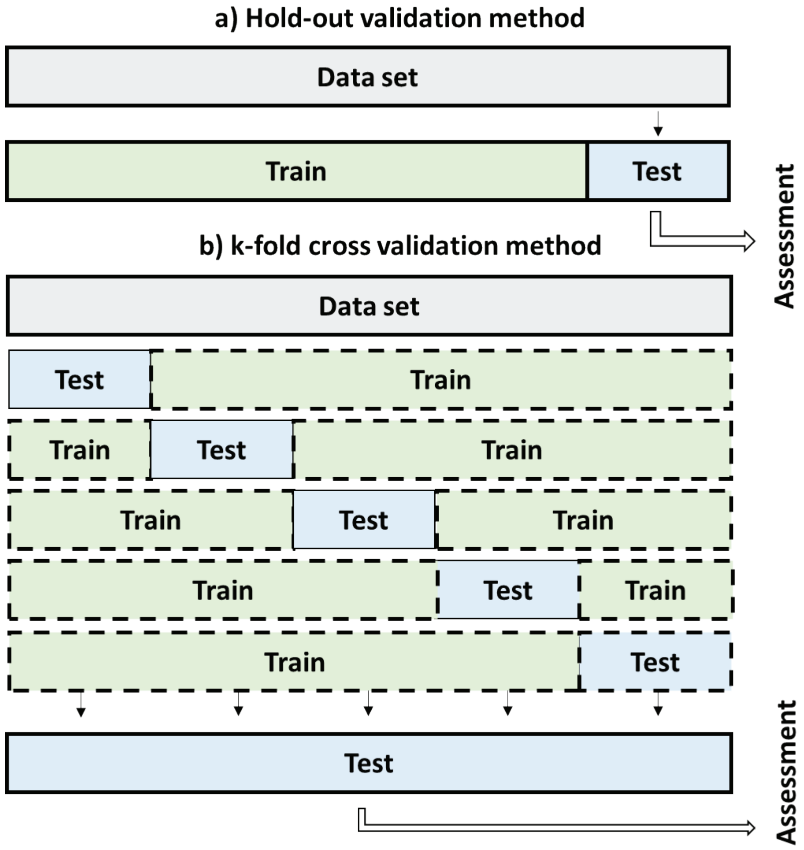

Figure 3. The schematic illustration of validation methods of a) hold-out validation and b) k-fold validation.

capturing the complex dynamics of financial data in healthcare systems.

Hold-out validation and k-fold cross-validation are two validation methods that are often used in machine learning. The dataset is split into two parts for hold-out validation: a training set and a test set [22–24]. The model is trained on the training set, and its performance is then evaluated on the test set. The dataset is split into k equal parts for k-fold cross-validation. One part is used for testing and the other parts are used for training in each iteration. To see how well the model works on the whole dataset, the results from all iterations are put together. Cross-validation is generally considered more unbiased, as it uses multiple partitions for testing, whereas hold-out validation can introduce bias due to random splitting. This study utilized a 10-fold cross-validation method, as illustrated in Figure 3.

By using a confusion matrix, which comprehensively divides the model's predictions into true positives, true negatives, false positives, and false negatives, the effectiveness of the proposed model on classification problems can be evaluated [18–20]. The confusion matrix facilitates the calculation of multiple performance metrics, such as sensitivity, recall, F1 score, and specificity, each providing insight into different aspects of the model's accuracy. Additionally, the average accuracy—which is determined by dividing the number of correctly categorized cases by the total number of examples—can be used to characterize the classifier's overall performance. This is represented mathematically by Equation (1) [25]:

$$Average\ accuracy = \frac{\left(\sum_{i=1}^{l} \frac{tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i}\right)}{l} \quad (1)$$

where tp_i is the number true positive class, tn_i is the number true negative class, fp_i is the number false positive class, fn_i is the number false negative class, l is the number of evaluated classes.

RESULTS AND DISCUSSION

In this study, the burn images were trained using the deep learning algorithms GoogleNet, ResNet-50, and Inception-v3, which consist of 22, 50, and 48 layers, respectively, within the Matlab software environment. The training dataset comprised a total of 1294 burn images, broken down into 561 first-degree, 275 second-degree, and 458 third-degree burn images [26, 27].

For societies, resources are limited while needs are unlimited. The ability to meet maximum needs with these limited resources relies on accurate current situation analysis and future predictions. The situation is no different in healthcare services. Both the human resources capable of providing healthcare services and the medical equipment used in healthcare are constrained, and theories are generated to determine how to achieve maximum benefit, forming the foundation of healthcare systems [28].

The proper and logical interpretation of health indica-tors, which are tangible outputs of the healthcare systems used by countries, enhances the success of future healthcare policies by optimizing the use of limited resources allocated to healthcare services [29]. This allows for the optimal utilization of scarce resources. In this study, classification and interpretation are intended to be carried out based on health indica-tors from 2006 to 2020 for 30 OECD countries.

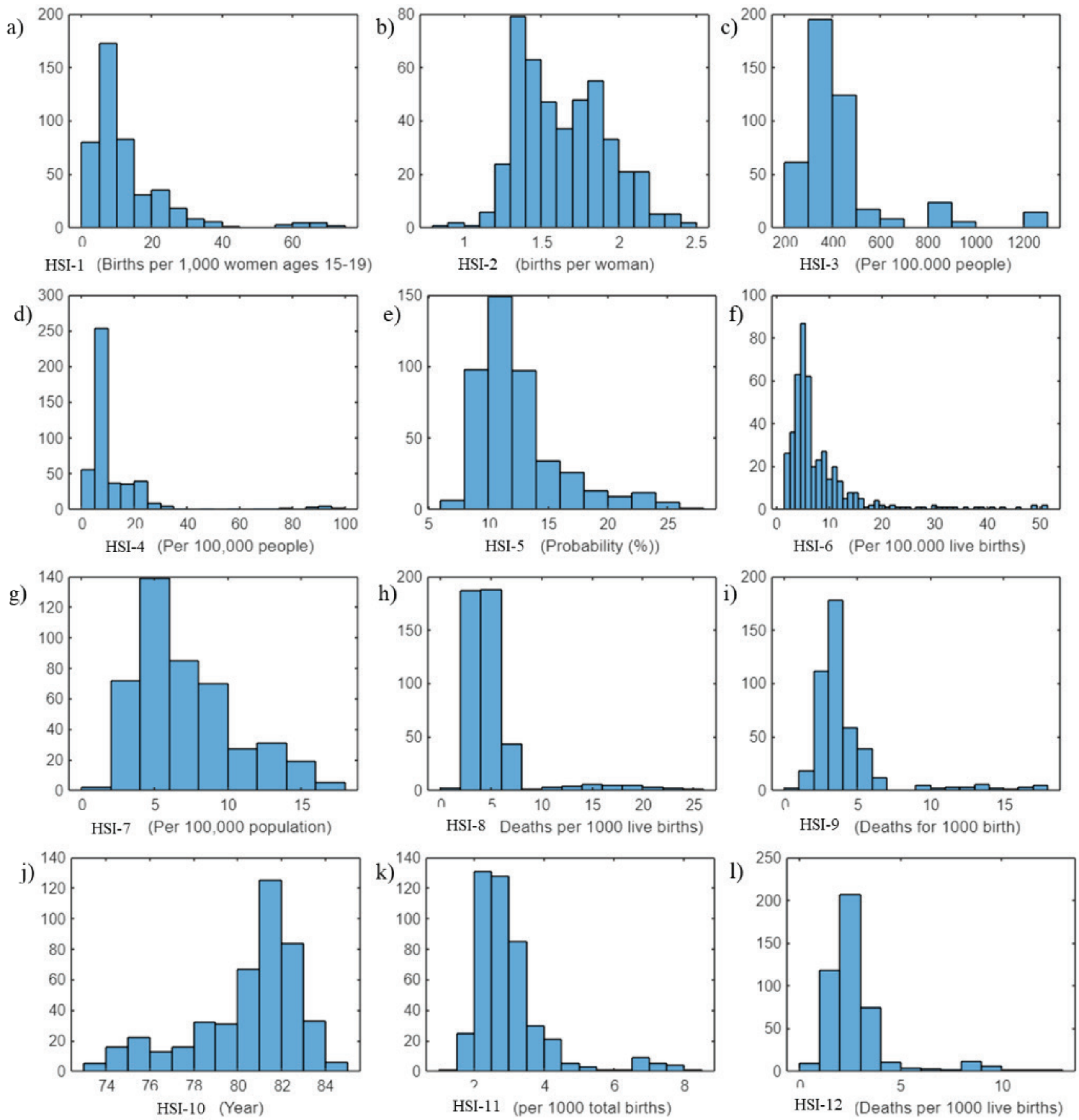

Figure 4. Histograms depicting the variables are shown for: a) HIS-1, b) HIS-2, c) HIS-3, d) HIS-4, e) HIS-5, f) HIS-6, g) HIS-7, h) HIS-8, j) HIS-9, j) HIS-10, k) HIS-11and l) HIS-12.

From the basic health indicators, statistics on birth (adolescent birth rate, total fertility rate), diseases (cancer incidence rate by type of cancer, tuberculosis incidence rate), causes of death (rate of cardiovascular deaths, deaths due to cancer, diabetes, or chronic respiratory diseases between the ages of 30 and 70, maternal mortality rate, death rate due to road traffic injuries), and age and gender-specific mortality (under-five mortality rate, infant mortality rate, life expectancy at birth, stillbirth rate, neonatal mortality rate) have been used as health status indicators (Fig. 4).

In the study, from the basic health indicators; non-communicable diseases (tobacco use among persons aged 18+ years, total alcohol per capita (age 15+) consumption, overweight and obesity in adults' prevalence), environmental risk factors (proportion of population using safely managed sanitation services, air pollution levels in cities), injuries (intimate partner violence prevalence) statistics were used as risk factor indicators (Fig. 5).

The study utilized basic health indicators, specifically focusing on vaccination coverage rates for each vaccine included in the national program, such as diphtheria, tetanus, pertussis, and measles. Additionally, the tuberculosis case detection rate was employed as a service coverage indicator, as illustrated in Figure 6.

Decision trees are adaptable and widely used categorization techniques. They work by iteratively splitting data into subsets based on the values of input features. These splits are determined by the algorithm's parameters to optimize information gain or Gini impurity. Decision trees are understandable and facilitate a simple depiction of the

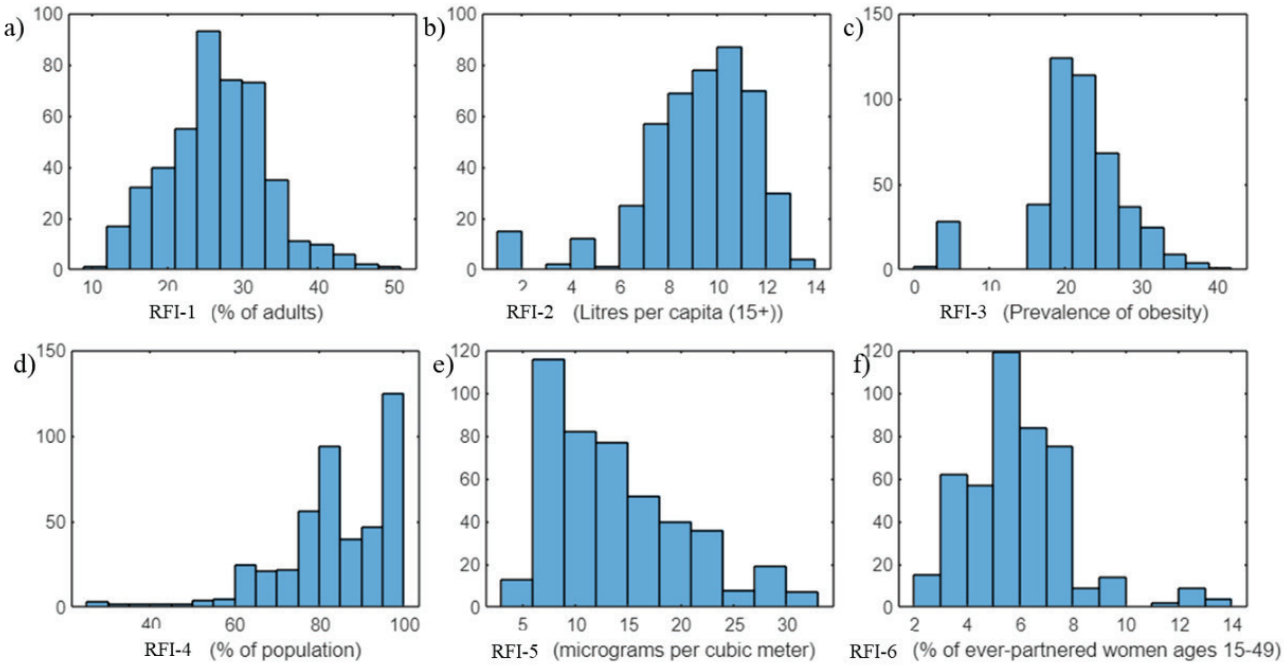

Figure 5. Histograms depicting the variables are shown for: a) RFI-1, b) RFI-2, c) RFI-3, d) RFI-4, e) RFI-5 and f) RFI-6.

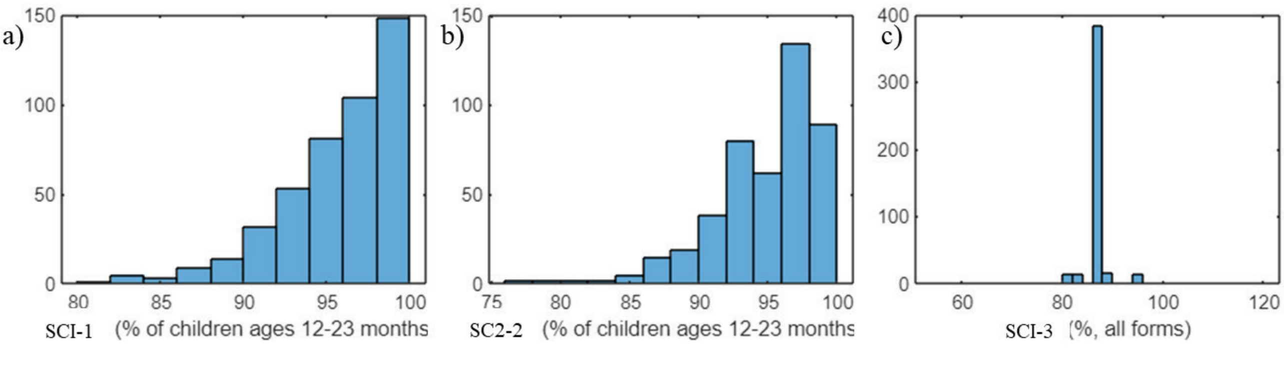

Figure 6. Histograms depicting the variables are shown for: a) SCI-1, b) SCI-2 and c) SCI-3.

decision-making process. Their ability to handle both qualitative and numerical data makes them suitable for many applications.

Support Vector Regression is an effective method used for classification and regression applications. It is highly effective for regression tasks that aim to predict continuous values. SVR aims to identify a hyperplane that best accommodates the data while reducing the margin of error. It determines the support vectors, which are the data points closest to the hyperplane. SVR uses a kernel function to map the data to a higher-dimensional space, enabling the identification of nonlinear correlations between variables.

Findings obtained from the supervised machine learning analysis results; when a classification is made based on health indicators, a similar result to the classification in the literature known as the beveridge, bismarck, and mixed model classification is obtained (Fig. 7). However, when the trends of countries under this classification are examined, changes in classifications are observed parallel to other developments in the OECD countries [30, 31].

As seen in Figure 7, the financial-based models (Beveridge, Bismarck, and mixed) used for classifying the healthcare systems of OECD countries can be simulated with an accuracy of 93.3% using the support vector machine algorithm and 96.7% using the decision tree algorithm. While these high accuracies highlight the importance of financial models in understanding and classifying healthcare systems, they are insufficient to capture the full complexity of these systems. Health systems are influenced by a wide range of stakeholders, including government agencies, private institutions, healthcare providers, and patients, and are characterized by services that cannot be delayed or replaced. Therefore, combining health indicator-based models with financial-based models provides a more comprehensive assessment. Health systems are multidimensional and shaped by economic, social, cultural, technological, and human factors. Financial models offer valuable insights into resource allocation and economic sustainability, but they fail to account for critical factors such as health outcomes, quality of care, equity, and patient satisfaction. Therefore, health policies and system designs must adopt a multidisciplinary approach that integrates financial analysis with public health, sociology, technology, and ethics to develop strategies that ensure health systems are economically sustainable and can provide high-quality, equitable, and accessible care to all.

While classifying countries' healthcare systems according to financing-based approaches might provide a high level of accuracy [32], to reveal the interconnections among these complex and multidimensional healthcare services,

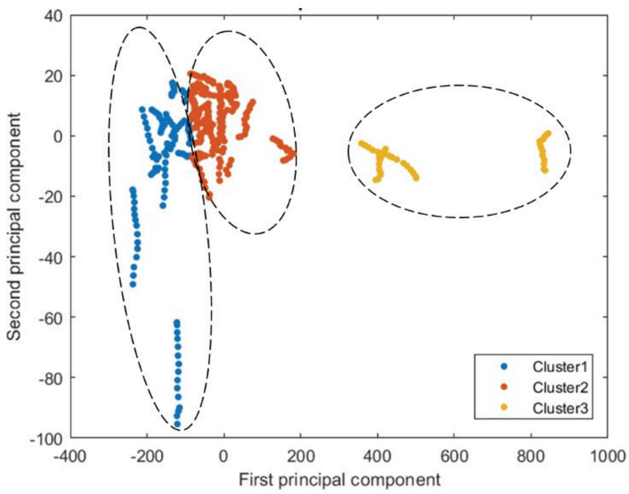

Figure 8. Cluster analysis of healthcare systems depending on the first two principal components using k-means clustering method.

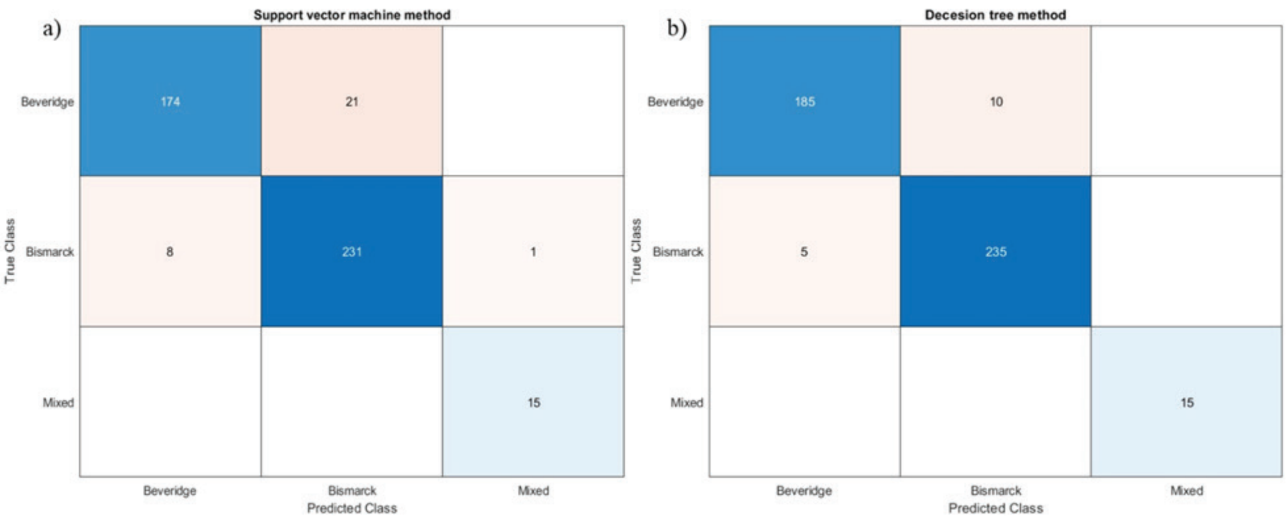

Figure 7. Classifying healthcare systems depending on a) support vector machine algorithm, b) decision tree algorithm.

the healthcare systems of OECD countries have been categorized into three clusters using the K-means method, an unsupervised machine learning technique, by utilizing the outputs of 21 key health indicators (Fig. 8).

Based on the unsupervised machine learning results observed in Figure 8, the representation of OECD countries divided into three clusters in the world map is presented with different colours for Cluster 1, Cluster 2, and Cluster 3. According to the results of cluster analysis, the world map displays that in Cluster 1; Austria, Japan, Mexico, Poland, Portugal, South Korea, Turkey, Spain, and Hungary countries are located; in Cluster 2; Belgium, Canada, Czechia, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Slovakia, Sweden, Switzerland, and the United Kingdom countries are situated; and in Cluster 3, the United States, Australia, and New Zealand countries are included (Fig. 9).

The machine learning analysis indicates that the classification of OECD nations according to health metrics diverges from conventional classifications in the literature. Germany, traditionally linked to the Bismarck model, is included with the United Kingdom, recognized for the Beveridge model, in the classification based on health indicators (Group 2). The reclassification post-2013 can be ascribed to both nations embodying the social state paradigm, wherein healthcare services are funded through public resources such as taxes, indicating a transition towards a more universal healthcare model. Belgium has been classified with Group 2 countries since 2013, presumably because to its progressive healthcare policies that prioritize social fairness and extensive coverage. Slovakia demonstrates a notable reclassification in the post-2007 period, consistently aligning with Group 2 countries and demonstrating reforms focused on improving accessibility, quality, and equity in healthcare. These findings highlight the dynamic nature of healthcare systems, suggesting that traditional classifications may not adequately reflect the complexities and evolving characteristics of contemporary healthcare systems and require a more nuanced approach that integrates a variety of health indicators for a precise assessment.

The findings indicate that the United States, classified as a mixed model, also falls under Group 3 in the health indicators-based classification. New Zealand and Australia, categorized under the Beveridge model, are placed in Group 3, alongside the United States, based on a 15-year analysis of health indicators. Consequently, it can be asserted that evaluations based on health indicator outputs yield different outcomes than those derived from economic-based classifications in healthcare systems.

In the literature, among OECD countries; Czech Republic, Luxembourg, France, Greece, Netherlands, and Switzerland are classified under the Bismarck model group. However, in the obtained findings, when the 15-year health indicator data of these countries are evaluated, it can be seen that they are among the group 2 countries where Germany and the United Kingdom are located.

Among OECD countries, Spain and Hungary are classified under the Beveridge model when evaluating the healthcare system. However, in the analysis results of the data of both countries, it is possible to say that they are

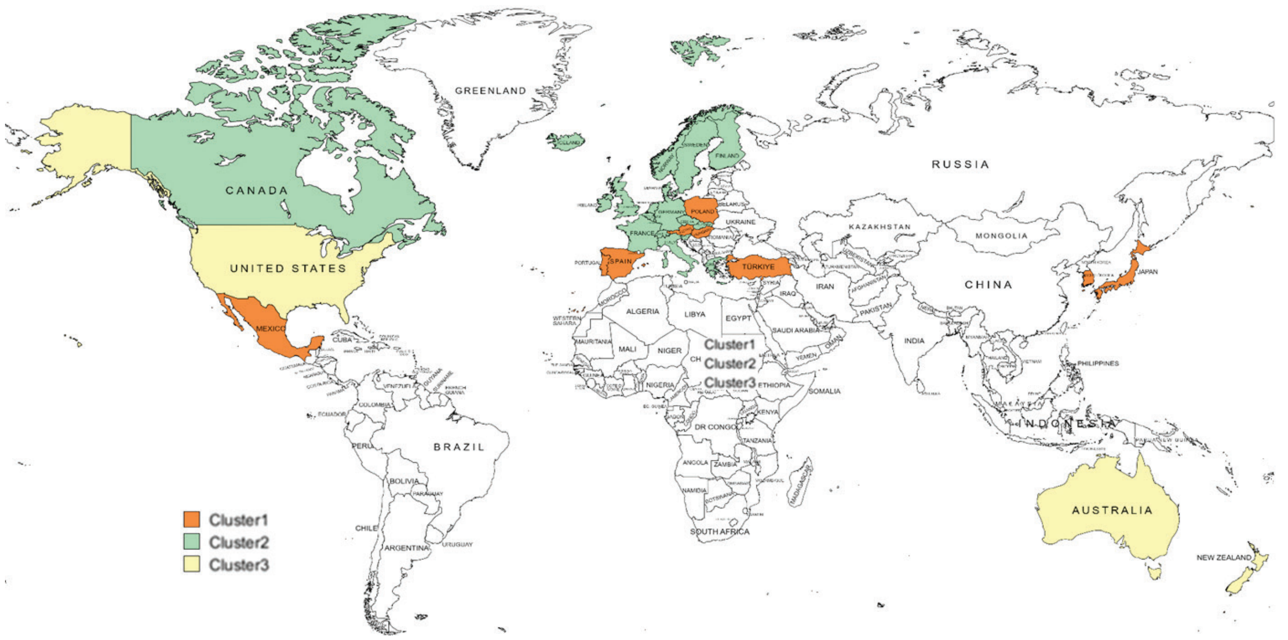

Figure 9. The illustration of OECD countries on world map depending on the cluster analysis of healthcare systems depending.

in the Group 1 category after 2016 when a health indicator-based classification is made.

This study highlights the importance of clustering healthcare systems as a mechanism for facilitating informed decision-making, policy formulation, and constructive dialogue among stakeholders. Utilizing machine learning methodologies renders the classification of healthcare systems more objective, data-driven, and adept at managing extensive datasets and intricate relationships characteristic of healthcare data. This study effectively used machine learning to classify the health indices of 30 OECD countries with high accuracy. This achievement demonstrates the significant potential of machine learning to provide valuable insights into the characteristics and effectiveness of health systems, thereby improving understanding of how other countries manage and deliver health care.

Health indicators are very important for both national and international levels because they provide critical information for assessing people's health status. Because health problems often create significant positive externalities and impact global public health, there is an urgent need for objective and accurate methodologies for classifying health systems. The primary goal of addressing global health challenges is to improve population health, which necessitates data-driven and objective methodologies for understanding and evaluating the effectiveness of health systems. Policymakers, researchers, and stakeholders can significantly benefit from these findings, as they establish a basis for continuous endeavors to optimize healthcare systems and, consequently, boost global health outcomes. Moreover, clustering according to health indicators can substantially aid in the development of health policy recommendations designed to improve community well-being and health [33-35]. This approach enables multiple essential processes: i) Objective Evaluation of Healthcare Systems: Clustering based on health indicators facilitates an impartial comparison of various healthcare systems, providing a greater insight into the performance of different countries regarding health outcomes and healthcare delivery. ii) Identifying Strengths and Weaknesses: By categorizing countries with similar health indicators, this approach facilitates a clearer distinction between the strengths and weaknesses inherent in each health system. This, in turn, facilitates the development of a more focused strategy to address areas requiring improvement. iii) Disseminating Effective Policy Strategies: When countries have similar health concerns and needs, clustering helps identify successful policy strategies. These practices can then be disseminated to other countries facing similar challenges, fostering a collaborative strategy to address common health concerns. iv) Identifying Best Practices: Analyzing the experiences of countries with similar health indicators facilitates the identification of best practices and can result in improved resource allocation and implementation methods among countries facing similar health challenges. v) Facilitating Collaboration: Clustering based on health indicators fosters collaboration and the sharing of experience among countries with similar health profiles. This collaboration may yield more cohesive and united strategies for addressing global health concerns. vi) Improved Health Policy Formulation and Execution: By elucidating the correlations between health indicators and healthcare system efficacy, clustering enhances the formulation and execution of health policies. This results in more informed decisions and more precisely focused actions that cater to the distinct needs of various populations.

Clustering based on health measures not only helps with objectively putting healthcare systems into groups and judging them, but it also plays a key role in making health policies that are more likely to improve people's health and well-being. The insights gained from this method could lead to positive changes in healthcare around the world. This makes it an essential tool for lawmakers, researchers, and other people who want to improve public health.

CONCLUSION

This study presents an innovative methodology employing a Deep Convolutional Neural Network (DCNN) model designed for the accurate detection and classification of skin burn severity using images sourced from medical atlases and textbooks. The model utilizes these images to identify key features, which are subsequently processed through a fully connected feedforward neural network. The purpose of this network is to categorize burns into three categories according to severity: first-degree, second-degree, and third-degree burns. The DCNN model described in this work is designed to significantly support medical professionals and healthcare providers by offering a swift and reliable approach for assessing the severity of skin burns, thereby facilitating prompt and appropriate treatment decisions. This DCNN-based model has applications extending beyond traditional clinical settings. This approach holds significant potential to enhance telemedicine, particularly in rural regions or underdeveloped nations where the scarcity of healthcare professionals is prevalent. This method is particularly advantageous in healthcare environments with limited resources, as it enables these facilities to determine burn severity more swiftly and precisely. This innovative technology employs deep learning to assess the severity of a burn. It will improve the treatment process by providing physicians with a method to quickly, fairly, and accurately assess burn severity. These assessment interfaces, which utilize deep learning techniques, can process comprehensive datasets to efficiently categorize burn injuries, thereby improving patient management. These digital platforms support healthcare professionals by providing access to educational resources and guidance. They also facilitate data collection and analysis for epidemiological research and enable remote consultations and assessments. This technology will significantly impact the management of burn injuries, a significant public health problem. It facilitates the prevention of burns and enhances the efficacy of treatments, resulting in enhanced patient outcomes. Future extensions of this research may include the incorporation of authentic patient photographs to improve the model's ability to differentiate between superficial-partial and deep-partial thickness burns, as well as the development of algorithms to accurately estimate the Total Body Surface Area (TBSA%) affected. This enhancement would increase the clinical tool's utility in assessing and managing burn patients, thereby further advancing patient care and treatment strategies.

The outcomes of this study demonstrate that financial models alone are insufficient to fully explain the functioning of healthcare systems. This stems from the complexity of healthcare systems, which encompass numerous factors that influence their efficiency and outcomes. While financial models are essential for resource allocation, ensuring system sustainability, and assessing profitability, they do not comprehensively capture the complex dynamics of healthcare delivery, service quality, patient outcomes, social determinants of health, technological innovations, and cultural influences. It is challenging to compare healthcare with other industries due to its encompassing various domains such as ethics, technology, society, and culture. To better understand health systems, it's essential to examine them holistically, not just from a financial perspective. To achieve a comprehensive understanding, this approach must incorporate economic principles, as well as sociopolitical insights, cultural nuances, and technological advancements. This study highlights the importance of integrating health data with financial models to achieve a more detail understanding of health systems. This combination allows us to examine how factors such as resource allocation, service delivery, patient outcomes, and equity influence the overall quality, efficacy, and efficiency of healthcare services in a more comprehensive manner. For this approach to be effective, it is essential that both long-term financial sustainability and societal impacts are considered, and that individual health and well-being are not compromised by financial hardship. These findings suggest that policymakers and other stakeholders should adopt a multidisciplinary approach when formulating health policies. Value-based healthcare models and other strategies that consider health outcomes in financial decision-making can assist policymakers in promoting high-quality, patient-centered care. Real-time health data analytics can also facilitate informed decision-making grounded in factual information, thereby promoting more efficient resource utilization and reducing disparities in healthcare access and outcomes. In the future, additional research should emphasize the integration of concepts from diverse disciplines, such as economics, behavioral science, data science, and public health, to develop more effective models for evaluating healthcare systems. Additionally, exploring advanced technologies such as artificial intelligence and machine learning will enhance healthcare efficiency, facilitate trend prediction, and support policymakers in decision-making. These tools have important potential to increase the sensitivity and responsiveness of health systems, enabling more effective interventions. By advancing research in these areas, it can make sure that future health policies are more sustainable, equitable, and deliver high-quality services that meet the varying needs of diverse populations and improve overall health outcomes.

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

During the preparation of this work, the authors used Chatgpt to improve the writing and English of some sections.

REFERENCES

[1] Ocaña-Riola R. The use of statistics in health sciences: situation analysis and perspective. Stat Biosci 2016;8:204–219. [CrossRef]

[2] Aldape-Pérez M, Alarcón-Paredes A, Yáñez-Márquez C, López-Yáñez I, Camacho-Nieto O. An associative memory approach to healthcare monitoring and decision making. Sensors 2018;18:2690. [CrossRef]

[3] Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, et al. A guide to deep learning in healthcare. Nat Med 2019;25:24–29. [CrossRef]

[4] Jiang T, Gradus JL, Rosellini AJ. Supervised machine learning: a brief primer. Behav Ther 2020;51:675–687. [CrossRef]
[5] Eckhardt CM, Madjarova SJ, Williams RJ, Ollivier M, Karlsson J, Pareek A, et al. Unsupervised machine learning methods and emerging applications in healthcare. Knee Surg Sports Traumatol Arthrosc 2023;31:376–381. [CrossRef]
[6] Clift C. The role of the World Health Organization in the international system. Burns 2013;39:291–299. [CrossRef]
[7] World Health Organization. Health in sustainable development planning: the role of indicators. No. WHO/HDE/HID/02.11. World Health Organization; 2002.
[8] Wendt C. Mapping European healthcare systems: a comparative analysis of financing, service provision and access to healthcare. J Eur Soc Policy 2009;19:432–445. [CrossRef]
[9] Wendt C, Frisina L, Rothgang H. Healthcare system types: a conceptual framework for comparison. Soc Policy Adm 2009;43:70–90. [CrossRef]
[10] Freeman R, Frisina L. Health care systems and the problem of classification. J Compar Policy Anal 2010;12:163–178. [CrossRef]
[11] Ferreira PL, Tavares AI, Quintal C, Santana P. EU health systems classification: a new proposal from EURO-HEALTHY. BMC Health Serv Res 2018;18:1–11. [CrossRef]
[12] Lee S, Kim C. Estimation of association between healthcare system efficiency and policy factors for public health. Appl Sci 2018;8:2674. [CrossRef]
[13] Espinosa-González AB, Delaney BC, Marti J, Darzi A. The role of the state in financing and regulating primary care in Europe: a taxonomy. Health Policy 2021;125:168–176. [CrossRef]
[14] Klumpp M, Loske D, Bicciato S. COVID-19 health policy evaluation: integrating health and economic perspectives with a data envelopment analysis approach. Eur J Health Econ 2022;23:1263–1285. [CrossRef]
[15] Rajawat RS, Singh KK, Mishra VN. Approximation by modified Bernstein polynomials based on real parameters. Math Found Comput 2024;7:297–309. [CrossRef]
[16] Mishra VN, Rajawat RS, Sharma V. On generalized quantum Bernstein polynomials. Adv Pure Appl Algebr 2023;27:149–160. [CrossRef]
[17] Raiz M, Rajawat RS, Mishra VN. α-Schurer Durrmeyer operators and their approximation properties. Ann Univ Craiova Math Comput Sci Ser 2023;50:189–204. [CrossRef]
[18] Pandey S, Rajawat RS, Mishra VN. Approximation properties of modified Jain-Gamma operators preserving linear function. Palestine J Math 2023;12:169–182.
[19] Raiz M, Rajawat RS, Mishra LN, Mishra VN. Approximation on bivariate of Durrmeyer operators based on beta function. J Analysis 2023. [CrossRef]
[20] Bulut C, Sönal T, Kolca D, Tarlak F. Evaluation of COVID-19 mortality using machine learning regression methods based on health system indicators. Sigma J Eng Nat Sci 2024;42(6):1797–1805. [CrossRef]
[21] Bulut C, Kolca D, Tarlak F. Development of a software for detecting burn severity using convolutional neural network-based approach. Sigma J Eng Nat Sci 2024;43:598–606. [CrossRef]
[22] Anguita D, Ghio A, Ridella S, Sterpi D. K-Fold cross validation for error rate estimate in support vector machines. In: DMIN; 2009:291–297.
[23] Wong TT, Yang NY. Dependency analysis of accuracy estimates in k-fold cross validation. IEEE Trans Knowl Data Eng 2017;29:2417–2427. [CrossRef]
[24] Mengash HA, Mahmoud HH. Brain cancer tumor classification from motion-corrected MRI images using convolutional neural network. Comput Mater Continua 2021;68:1551–1563. [CrossRef]
[25] Sokolova M, Lapalme G. A systematic analysis of performance measures for classification tasks. Inf Process Manag 2009;45:427–437. [CrossRef]
[26] Deng X, Liu Q, Deng Y, Mahadevan S. An improved method to construct basic probability assignment based on the confusion matrix for classification problem. Inf Sci 2016;340:250–261. [CrossRef]
[27] De Diego IM, Redondo AR, Fernández RR, Navarro J, Moguerza JM. General performance score for classification problems. Appl Intell 2022;52:12049–12063. [CrossRef]
[28] Toth F. Classification of healthcare systems: Can we go further? Health Policy 2016;120:535–543. [CrossRef]
[29] Jacques O, Noël A. The politics of public health investments. Soc Sci Med 2022;309:115272. [CrossRef]
[30] Böhm K, Schmid A, Götze R, Landwehr C, Rothgang H. Five types of OECD healthcare systems: empirical results of a deductive classification. Health Policy 2013;113:258–269. [CrossRef]
[31] Ariaans M, Linden P, Wendt C. Worlds of long-term care: A typology of OECD countries. Health Policy 2021;125:609–617. [CrossRef]
[32] Benoît C. The regulatory path to healthcare systems' financialization. J Eur Soc Policy 2023;09589287231176776. [CrossRef]
[33] Bertin G, Carrino L, Pantalone M. Do standard classifications still represent European welfare typologies? Novel evidence from studies on health and social care. Soc Sci Med 2021;281:114086. [CrossRef]
[34] Capano G, Toth F. Health policy under the microscope: a micro policy design perspective. Front Public Health 2023;11:1180836. [CrossRef]
[35] De Carvalho G, Schmid A, Fischer J. Classifications of health care systems: Do existing typologies reflect the particularities of the Global South? Glob Soc Policy 2021;21:278–300. [CrossRef]