ORIGINAL ARTICLE

A PROTOCOL FOR DEVELOPING A MACHINE LEARNING MODEL TO FORECAST HEALTHCARE TREATMENT RESOURCE UTILIZATION

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ABSTRACT

Despite spending a significant number of resources and years developing a medical system, Patients with underlying comorbidities who have SARS-nCoV-2 carry a heavy financial burden that necessitates significant medical expenditures and resources for patient care. Clinical management cost uncertainty paralyzes the healthcare system and causes deficits in annual national budgets. This research will be focusing the necessary steps in developing the protocol. Overall, this article will include intervention logic mapping, questionnaires, recorded consultations, in-depth interviews, focus group discussions, and contextual data recording will be used as methods. The best effective AI-based technique for medical expense prediction and estimation for COVID-19 patients with comorbidities was identified.Regarding medical perspective and user acceptance, a better grasp of the issues and barriers confronting Malaysia's healthcare system. Deep learning techniques created a CNN-based model for predicting medical costs. Validation of the proposed model using real-world data and demonstration of its capacity to appropriately anticipate expenses. Using a relevant performance indicator such as RMSE, compare the constructed model to existing cost prediction approaches. Insights about the economic impact of COVID-19 on patients with comorbidities and healthcare practitioners in Malaysia. This research on the economic impact of COVID-19 on patients with comorbidities and healthcare practitioners, along with the development of a CNN-based cost prediction model, has significant implications for healthcare management, policy-making, and AI advancement in healthcare. The findings will inform more efficient resource allocation, guide public health policies, and contribute to the ongoing development of AI applications in healthcare.

Keywords: *Artificial Neural Network, Forecasting Model, Resources Forecasting, Pattern Cross-sectional*

INTRODUCTION

Unprecedented black swan events such as the COVID-19 pandemic raised many issues throughout the world [1-7]. The pandemic itself caused widespread disruption across the globe. The pandemic had a significant impact on public health, the global economy, and social norms, and the consequences will be felt for many years. However, the immediate effect of the COVID-19 pandemic is the emergence of healthcare deficiencies and readiness for combating black swan events such as outbreaks and pandemics. The lack of resources [8], medical staff burden [9-11], inadequate communication between medical institutions [12-14], lack of medical access [15], and limited strategies for combating unforeseen events have been contrasting issues since the pandemic lockdown in 2020. Overall, although the problems in the healthcare system are inevitable, the gaps in combating black swans' events could be bridged with emerging technologies and rounds of investment in healthcare sectors. Hence, technological advancements such as telemedicine that include remote medical advice and procedures, Artificial intelligence for numerous medical applications such as automated object detections for radioactive imaging, wearable technologies for data collections and abnormalities detections, 3D printing for surgical and nonsurgical procedures, blockchain for data management and secure financial, and virtual reality for training helps bridging numerous issues in medical sectors. In retrospect, artificial intelligence or machine learning could be leveraged to help stakeholders evaluate medical resources used in all procedures and forecast the increase or decrease in resources needed based on historical or cross-sectional data.

The main issue with forecasting medical resources is the scarcity and/or unreliability of data [16]. Healthcare forecasting has been adopted by health plans and physician groups to predict individual patient outcomes, but there is little evidence regarding how or whether it improves healthcare value. Forecasting is a combination of art and science, as forecasters must consider the cost and trends related to healthcare, as well as factors such as population segments making healthcare decisions [16, 17]. The healthcare system is struggling to manage resources to meet the growing demand for healthcare services. Creating a machine learning model to forecast healthcare treatment resource utilization can assist healthcare providers and policymakers in making informed decisions about how to best allocate resources. Additionally, there are common impediments to providing accurate forecasts, such as ignoring vectors of change or overestimating how quickly changes will occur. At the clinic level, accurately forecasting demand for health products is a significant challenge due to complexities such as seasonality and user preference [18, 19]. Hospitals can manage supply shortages by having visibility into short-term future demand and proactively identifying potential shortages in advance. However, supply forecasting is not a precise science and organizations must address urgent shortages of ventilators, masks, protective gear, and swabs.

Despite the advancement of technology, the development of machine learning models for resource forecasting is a tedious task and involves specialised groups to develop. However, much literature indicates that machine learning could elevate the burden on the healthcare system, especially in repetitive tasks [20] and decision-making [21]. Faghri et al., (2018) anticipate that machine learning models will improve patient counselling, clinical trial design, allocation of healthcare resources and ultimately individualized clinical care [20]. Although scholars share the same perspective on machine learning capability in elevating burden in the healthcare system, the aspiration is only applicable with adequate data handling, valid and reliable model, and adequate clinical applicability with proper handling on modelling and reporting to ensure its rigour [18, 20-22]. Thus, a collaborative effort on a technical team comprising experts in each field of clinical procedure and know-how ability are needed to develop a robust model for clinical applications.

Understanding the need for robust machine learning to elevate the healthcare burden, especially in cost estimation and resource forecasting, this study aims to develop a machine learning model that accurately forecasts healthcare treatment resource utilization. Specifically, this study aims to uncover whether can a machine learning model predict healthcare treatment resource utilization using healthcare data.

METHODS

The development of financial and resource forecasting typically came from historical data. The notion of using previous events to explore future needs or possibilities is well documented in most literature [18-22]. All participants in the cross-sectional data-sensitive detail were excluded to protect patients' or their extended families' confidentiality as noted in Malaysia's ACT 709 (Personal Data Protection Act 2010). Only relevant data such as basic health readings such as weight, age, sex, type of comorbidities, patient admission data, patient medical code, and length of stay were taken into the cross-sectional data for model training and validation purposes.

Study design

Statistical analysis such as causal inferences and effectiveness of treatment analysis will be used and performed in the R Studio and Python software. Some data also will be analysed using neural network structure in Python software and based output will be viewed using the R Shiny extension package in R Studio to address all related parameters in statistical analysis. However, the analysis and parameters for neural network deep learning would be denoted under the pretext that the network's performance will vary greatly depending on how these settings are chosen. Both sorts of hyperparameters have an impact on each other, thus they must be chosen carefully.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a particular sort of neural network. We choose to simplify the presentation of this study by recognizing that it may be divided into two parts: feature extraction and classification. Features selection aims to extract information from the input to help with decision-making. CNN is composed of stacked convolutional blocks that correspond to convolutional layers (denote dγ), an activation function (σ) and one pooling (denote dδ) layer [ON15]. This feature recognition part is plugged into the classification part of n1Fully-Connected (FC) layers (denote dλ). Finally, we denote the softmax layer (or prediction layer) composed of |Z| classes. To sum up, a common convolutional network can be characterized by the following formula:

$$s \,\square\, [\lambda]n_1 \,\square\, [\delta \,\square\, [\sigma \,\square\, \gamma]n_2]n_3 \qquad (1)$$

On aid pattern recognition, the convolutional layer applies a sequence of convolutional operations to its inputs (see Figure 5b). Each input is convoluted with a filter during forward propagation (or kernel). The convolution’s output provides temporal instants that influence classification. Features are the names given to these samples. Some model hyperparameters must be configured before a convolutional layer can be built: kernel length and number, pooling stride, and padding.

1. Filter length– Kernels are created to uncover attributes that could improve classification efficiency. Filters, on the other hand, expose local or global features based on their size. Smaller filters are more likely to recognize local features, whereas larger filters are more likely to find global features. Figure 1 shows an example when the filter length is set to three.

2. Stride– A step between two convolutional operations is referred to as a stride. When using a tiny stride, an overlap between several filters is generated, whereas a larger stride reduces the output dimension. The stride is set to 1 by default (see Figure 1)

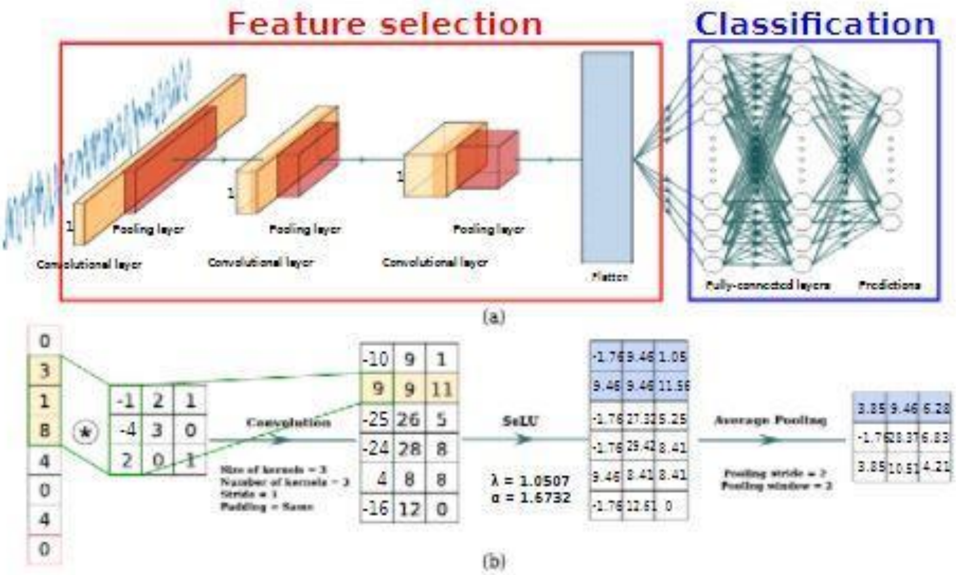

Figure 1. (a) – CNN architecture for side-channel attacks (red area: feature selection part; blue area: classification part). (b) – Operations in convolutional blocks (convolutions, activation, average pooling)

Thus, the layered CNN will focus on developing the algorithm for detecting optimizing parameters based on variables that were utilized in machine learning. In this research, the optimizing output will focus on effective methods in the prediction of handling patients based on symptoms recorded and the cost associated with the particular treatment. Notions on the output should be suggestive in nature and focus on the deep model learning anthology; which means that the output predictions should have a margin of errors to a certain extent but in time of model have sufficient data to run simulations and develop their capability, hopefully, the margin of error will be diminished into an acceptable range.

Comparative Study

To achieve the objective of comparing the effectiveness method of Cost Prediction based on a real data fitted model, the Root means square method will be used to determine the effectiveness of the prediction model of CNN compared to other developed models from previous literature. The root means square error (RMSE) is the residuals' standard deviation (prediction errors). Residuals are a measure of how far the data points are from the regression line; RMSE is a measure of how spread out these residuals are. In other words, it indicates how tightly the data is clustered around the line of best fit. In climatology, forecasting, and regression analysis, root mean square error is widely used to check experimental results. RMSE comparative formulae will be denoted as:

$$Y_{RMSE} = \sqrt{\overline{(f-o)^2}} \qquad (2)$$

Where;
f = forecasts (expected values or unknown results),
o = observed values (known results).
The mean (similar to _x) is the bar above the squared differences. The following, somewhat different, notation can be used to write the same formula.

$$RMSE_{f0} = \left[\sum_{i=1}^{N} \quad (z_{fi} - z_{0i})^2/N\right]^{\frac{1}{2}} \qquad (3)$$

Where;
Σ = summation (“add up”)
(z_fi-z_0i)^2 = differences, squared
N = sample size.
The comparative of the particular predictions result will abide by Table 1.

Patient populations and sample size

All patient data will be de-identified and anonymized to protect patient privacy. The study will adhere to all relevant ethical guidelines and regulations regarding the use of patient data. The study was authorised by the Institutional Review Board (or Ethics Committee) of the Universiti Malaya Medical Centre (UMMC) (protocol code MRECID: 202133-9908) and carried out by the Declaration of Helsinki (RSCH-ID-2200441-K3T).

This study's patient population consists of people who had comorbidities before contracting COVID-19 and were admitted to the University Malaya Medical Centre (UMMC) in Malaysia for treatment. Patients admitted to UMMC between 2019 and 2022 during the COVID-19 pandemic were included in the study. Comorbidities are pre-existing medical conditions that can exacerbate COVID-19 symptoms and complications. UMMC is a tertiary hospital in Malaysia that offers specialised medical care to patients, and it was chosen for this study because of its expertise in treating COVID-19 patients. Because of the inclusion criteria, which narrow the pool of eligible patients, the sample size for this study is expected to be relatively small where the total number, inclusion, and exclusion categories are as mentioned in Table 2.

Certain demographic or clinical characteristics of the patient population may limit the generalizability of the findings to other populations. This includes the gender, age, socio-demographic background, lifestyle, and severity history of comorbidities. This study, on the other hand, is significant because it focuses on a high-risk population that requires specialised medical attention and may provide useful insights into the management of COVID-19 in patients with comorbidities.

Table 1: Efficiency result for RMSE comparative test.

RMSE Output	Indication
0.00* - 0.19	The simulation model could predict data accurately.
0.20 – 0.49	The simulation model could relatively predict data accurately.
≥ 0.50**	Model poor ability to accurately predict or simulate real data.

** Result output statistically should not be 0.*
*** Results of simulation exceeding 0.5 could be used however the simulation with lower RMSE was considered to be better forecasting values with a higher degree of accuracy, efficiency and precision*

Table 2: Inclusion and Exclusion criteria for patients in cross-sectional data

Characteristic	Inclusion	Exclusion
Date	Admission starting in 2019 to 2022	Admission prior 2019
Patients	Patients with comorbidities histories before contacting COVID-19	Patients didn't suffer comorbidities before contracting COVID-19 or were detected with comorbidities after COVID-19 treatment.
Location	The patient was admitted to UMMC only	Patient outside UMMC
Medical record	Complete medical record	No or incomplete medical record to detect any comorbidities before contact with COVID-19

RESULTS

The expected results presented in this protocol will consist of data acquisition, data analysis and data presentation. This study will use a retrospective cross-sectional design. We will develop and evaluate a machine learning model using electronic health record (EHR) data obtained from a large academic medical centre.

The model will be designed to forecast the number of hospital beds, ventilators, and other resources that will be needed for a specific period. Sample size determination is n ≥ 1,000. The total number of data is 2,500 divided into 1,000 for model training and 1,500 for model validation. The study will use cross-sectional data obtained from the medical centre's (UMMC) database for the period of 2019 to 2022. The data will be cleaned and pre-processed to ensure data quality. The features used to develop the model will include demographics, diagnosis codes, medication orders, lab results, and vital signs. The data will be divided into a training set and a test set. The model will be trained using machine learning algorithms such as logistic regression, decision trees, and neural networks. The performance of the model will be evaluated using metrics such as accuracy, precision, recall, and F1 score. The data processing process is illustrated in Figure 2 below.

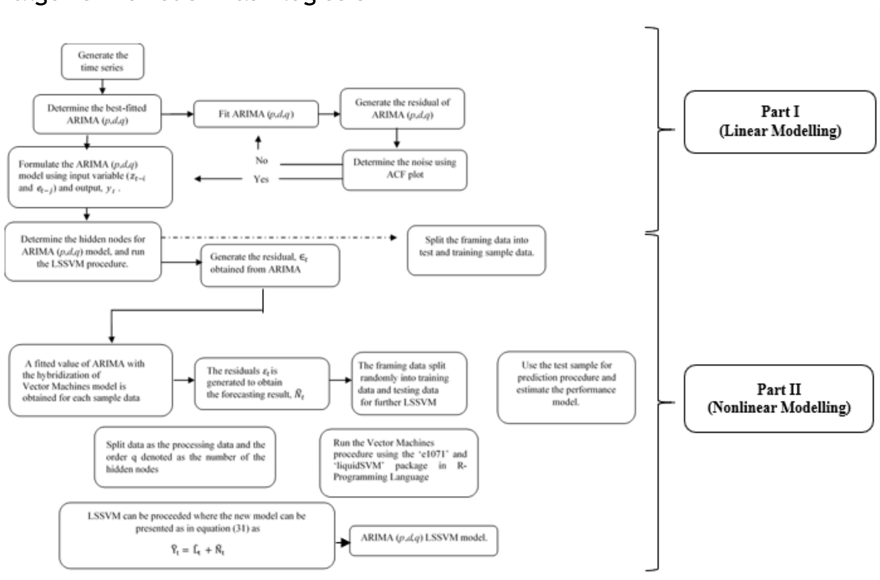

Figure 2. Data processing flowchart

The results of the study will be shared with the medical centre's administrators and policymakers to inform decisions on resource allocation. This will be accomplished through a thorough review of the literature on the subject, including both published and unpublished studies. Also, in-depth interviews and focus group discussions with relevant stakeholders such as health practitioners, policymakers, and patients.

The outcome will entail the creation of a model based on patient-level data from Malaysian hospitals. The model will be created in Python or R Shiny and trained with deep learning techniques. The developed model will be tested on data from Malaysian hospitals, specifically for patients with comorbidities who have been treated for COVID-19. The developed model's performance will be compared to existing models using a commonly used metric, root mean square error (RMSE). These anticipated outcomes will add to the body of knowledge on the economic impact of COVID-19 on comorbid patients and health practitioners in Malaysia. They will also provide insights into the challenges and barriers confronting Malaysia's healthcare system, as well as inform the development of a deep learning-based cost prediction system. The expected data analysis output is shown in Tables 3 to 6 below.

Table 3: Summary of systematic literature review

Author/Year	Research Area	Independent Variable	Parameter Used	Data Frequency	Performance analysis and findings

Table 4: Meta-analysis

Literature	Intervention n/N	Control n/N	Odd Ratio M-H, Random, 95% CI	Weight	Odd Ratio M-H, Random, 95% CI

Table 5: Comorbidity rank based on data (hypothetical)

Comorbidity	Count	Percentage
Hypertension		
Diabetes		
Heart disease		
Chronic obstructive pulmonary disease (COPD)		
Cancer		
Renal disease		
Immunocompromised		
Other		
Non-related		
	N=	**100.00%**

Table 6. Correlation matrices based on data analysis output (hypothetical)

	Age	**Gender**	**Ethnicity**	**Comorbidity**	**Comorbidity Type**	**COVID-19 Severity**	**Length of Stay**	**Outcome**	**ICU Admission**	**Ventilation**
Age	**1**									
Gender	**-0.02**	**1**								
Ethnicity	**-0.04**	**-0.01**	**1**							
COM	**0.28**	**-0.03**	**-0.06**	**1**						
COM Type	**0.29**	**-0.04**	**-0.07**	**0.99**	**1**					
C Severity	**0.19**	**-0.01**	**-0.05**	**0.16**	**0**	**1**				
LOS	**0.33**	**0.04**	**-0.08**	**0.18**	**0.17**	**0.55**	**1**			
Outcome	**-0.12**	**-0.02**	**0.03**	**-0.09**	**0.19**	**-0.37**	**-0.21**	**1**		
ICU	**0.16**	**-0.01**	**-0.05**	**0.14**	**-0.1**	**0.49**	**0.39**	**-0.34**	**1**	
Ventilation	**0.15**	**-0.01**	**-0.05**	**0.13**	**0.15**	**0.48**	**0.38**	**-0.33**	**0.99**	**1**

DISCUSSION

Addressing gaps in understanding the financial burdens faced by comorbid patients and healthcare practitioners during the COVID-19 pandemic, especially in Malaysia, is of utmost importance. This comprehensive exploration seeks to highlight the various economic challenges encountered by these groups, offering a detailed analysis of the financial strains they endure. The pandemic has exacerbated existing vulnerabilities, leading to increased medical expenses, loss of income [23], and heightened stress levels among patients and healthcare providers alike [24]. These challenges underscore the urgent need for targeted interventions.

Such findings will provide actionable insights into the barriers hindering effective healthcare delivery during the pandemic, guiding future policy and healthcare system improvements. By thoroughly understanding these financial hurdles, stakeholders can develop targeted strategies to alleviate the economic pressure on both patients and healthcare providers [24]. For instance, implementing financial support programs, subsidizing medical costs, and ensuring timely payment of healthcare professionals can significantly reduce their economic burden. Additionally, these strategies can enhance the overall well-being and morale of healthcare workers, enabling them to deliver better patient care.

Ultimately, these efforts will enhance the overall healthcare response during ongoing and future health crises. Policymakers and healthcare administrators can use this knowledge to create more resilient healthcare systems that are better equipped to handle the financial implications of pandemics. By addressing these economic challenges proactively, we can ensure a more equitable and effective healthcare delivery system for all, particularly during times of crisis. Moreover, such proactive measures can lead to long-term improvements in healthcare infrastructure and resource management.

The study will produce a validated, cutting-edge AI model that can accurately predict medical costs for COVID-19 patients with comorbidities, potentially transforming resource allocation in hospitals. By comparing the new model with existing ones, the study will advance the field of AI in healthcare, offering a new approach to medical cost prediction that could be adapted for other diseases and contexts. This AI model will not only enhance the precision of medical cost forecasting but also provide a robust framework for understanding the economic dynamics associated with various health conditions. The innovative nature of this model could set new standards in predictive analytics within the healthcare sector.

The results of this study will have far-reaching implications. They will directly inform healthcare policy and hospital management, leading to more efficient and equitable resource distribution during and after the pandemic [25]. Policymakers will be able to use these findings to devise strategies that ensure optimal allocation of funds and resources, thereby improving patient care and outcomes. Hospital administrators will benefit from the ability to make data-driven decisions that enhance operational efficiency and reduce financial waste. Additionally, the study's insights can help in designing better financial management practices within healthcare institutions.

Moreover, the study will set a precedent for future research in AI-driven medical cost prediction. By demonstrating the effectiveness of the new model, it will pave the way for further innovations and applications in healthcare. Researchers and practitioners can build upon this foundation to address other complex medical and economic challenges [25, 26].The study aims to contribute to the creation of a more resilient and responsive healthcare system, better equipped to handle the financial implications of pandemics and other health crises. This contribution will not only benefit the current healthcare landscape but also equip future generations with the tools needed to combat similar challenges effectively.

Implications and Future Directions

The research on the economic impact of COVID-19 on patients with comorbidities and healthcare practitioners, alongside the development of an AI-based cost prediction model, has several critical implications across healthcare management, policy-making, technology adoption, and future research.

In healthcare management and resource allocation, the insights from this study will empower healthcare administrators to make data-driven decisions regarding resource allocation [27]. With a validated cost prediction model, hospitals can better anticipate the financial resources needed to manage patients with multiple comorbidities, leading to more efficient budgeting and resource distribution during health crises. Additionally, the study highlights the significant economic burden associated with treating COVID-19 patients with comorbidities. This can lead to the development of targeted interventions to prioritize high-risk patients, potentially improving outcomes and reducing overall healthcare costs. In policy-making and public health planning, the findings can inform policymakers on the economic strains of pandemics, particularly on vulnerable groups like patients with comorbidities. This can influence the creation of more robust public health policies that ensure better preparedness and equitable access to healthcare during future pandemics. By understanding the economic impact, policymakers can devise better insurance frameworks and financial support mechanisms for patients, especially those who are economically disadvantaged and suffer from multiple health conditions.

Regarding technology adoption in healthcare, the development and validation of a CNN-based cost prediction model represent a significant advancement in the use of AI in healthcare. This research will demonstrate the potential of AI to improve cost estimation and resource management, paving the way for broader adoption of AI technologies in various aspects of healthcare. The model developed in this research can serve as a prototype for similar AI applications in other healthcare settings, both within and outside of Malaysia. The adaptability of the model could lead to its customization for other diseases or different healthcare systems, broadening its impact. For healthcare practitioners, the research sheds light on the economic pressures faced during a pandemic, particularly those treating patients with comorbidities. Understanding these challenges can help in workforce planning and the provision of support to healthcare workers, ensuring their well-being and sustainability of care delivery during prolonged health emergencies.

Building on the findings and implications of this study, several avenues for future research can be identified. Expanding the scope beyond COVID-19 includes applying the cost prediction model to other diseases that require intensive care and management of comorbidities, such as cancer or chronic kidney disease. This would validate the model's applicability across various medical conditions and healthcare environments. Expanding the research to compare the economic impacts and healthcare system responses in different regions or countries could provide valuable insights into how different healthcare systems cope with pandemics and other large-scale health crises. Longitudinal studies on economic impact could track the economic impact on patients with comorbidities over a more extended period, even beyond the pandemic [28]. This would provide a deeper understanding of the long-term financial burden and recovery processes for both patients and healthcare systems. Future research could also explore the socioeconomic disparities in the economic impact, analyzing how different income groups are affected and how this influences health outcomes and access to care.

Enhancing the AI model could involve incorporating additional variables, such as social determinants of health, patient behaviour, and healthcare access, to improve its predictive accuracy. Exploring the integration of the AI model into real-time healthcare management systems could be another future direction. This would involve developing models that can predict costs dynamically as patient data is updated, providing healthcare providers with immediate financial insights during treatment. Exploration of ethical and social implications could include delving into the ethical implications of using AI in healthcare cost prediction, particularly concerning equity [9, 28]. Research could explore how these technologies might be used to ensure equitable care for all patients, including marginalized and underserved populations. Another direction could involve investigating the acceptance and trust of AI models among patients and healthcare practitioners. Understanding their perspectives on AI-driven decision-making tools could inform better design and implementation strategies that enhance user trust and engagement.

Collaboration and interdisciplinary research could involve the integration of interdisciplinary approaches, combining AI, economics, healthcare, and public health, to lead to more comprehensive and innovative solutions. Future research could involve collaborations between data scientists, healthcare professionals, and policymakers to create models and systems that are both technically robust and practically applicable. Collaborating with international researchers and institutions could help validate the models in diverse healthcare environments, enhancing the global relevance and impact of the findings.

Strength and limitation

Understanding the limitations and strengths of this research is crucial for developing any clinically sound system. To date, there has been a lack of efforts in developing artificial intelligence applications for healthcare cost forecasting in Malaysia. Thus, we understand that this project is a novel initiative that could provide valuable insights and significantly contribute to existing literature if Malaysia decides to advance its healthcare system into the Industrial Revolution 4.0 domain.

While studies on machine learning technology have developed tremendously worldwide, data sharing is still limited within respective organizations. Some data are considered too sensitive to share, especially on an international level. However, developing forecasting strategies and accumulating data could drive collaboration between organizations nationally. Though some limitations exist, the potential benefits of this research could outweigh these challenges. By fostering national-level collaborations and creating frameworks for secure data sharing, we can pave the way for more robust and comprehensive AI applications in healthcare cost forecasting.

CONCLUSIONS

In summary, this study aims to develop a sophisticated machine-learning model to forecast healthcare treatment resource utilization using Electronic Health Records (EHR) data. It will employ a retrospective cross-sectional design alongside advanced machine learning algorithms to both develop and thoroughly evaluate the model. The results of this study will have significant implications for healthcare providers and policymakers, particularly in making informed resource allocation decisions.

Competing interests

There are no competing interests to declare.

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