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Predictive Big Data Analytics Capability Model to Enhancing Healthcare Organization Performance

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Abstract

Big data analytics capabilities have the potential to help healthcare organizations improve performance and provide high-quality care, and this awareness is growing. However, implementing BDA to optimize healthcare performance is a fundamental challenge for researchers and practitioners alike. This study investigates how big data analytics capabilities can predict the performance of healthcare organizations through five broad categories of BDA capabilities (organizational, technical, analytical, cognitive, and social) with their sub-competencies to improve decision-making and reshape the future of healthcare transmission. These thematic categories were used to develop a prediction model to predict healthcare organization performance accurately. We collect 205 responses from big data analysts and those who work in the hospital's information technology departments through a survey, preprocessing the data, then we use the machine learning and neural networks algorithms to develop and evaluate the model. Insights into the relationship between big data analytics competencies are provided by the results of predictive modelling. The results of the proposed model were good for all capabilities. the model's accuracy at a range 77.6% to 85.4% for all capabilities, these results show that the model has strong and consistent performance, and make it a trustworthy instrument for decision-making in the healthcare industry.

Keywords: *big data analytics, thematic competency, healthcare performance, machine learning, neural networks.*

1 Introduction

Massive amounts of data and information have been produced in many fields due to the recent rapid development of digital and communication technologies, mobile devices,

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and social networks, which has led to the birth of big data. Many institutions and departments must consider, use, and research the challenges and issues raised by the term "Big Data," which was first used in 2005 [1]. More than 5.16 billion people were used the Internet in 2023, up 98 million (1.9 percent) from January 2022, according to the most recent global digital reports. Additionally, more than 4.76 billion people worldwide used social media in 2023, an increase of 137 million (3 percent) from 2022. The use of mobile devices has increased, generating a significant volume of intricate data that requires analysis through the use of novel techniques known as "Big Data Analytics." (BDA) [2].

Given the vast amounts of data that are now available to organizations, advancements in data and analytical capabilities have led to the widespread assumption that Big Data analytics is an IT-driven competency [3]. These capabilities have provided tremendous opportunities to make timely and evidence-based decisions, improving customer services and raising the level of operational performance of organizations. However, there are significant infrastructure challenges associated with Big Data analytics, including data mining, storage, management, analysis, and visualization [4]. However, these problems can be effectively managed through the effective use and exploitation of Big Data, particular organizational resources, and tools that boost the effectiveness of Big Data analytics [3].

The healthcare sector is experiencing explosive growth in the adoption of BDA due to the significant opportunities that these analytics can provide for its improvement [4–6]. In recent years, several studies have shown that the implementation of electronic health systems, especially those incorporating BDA leads to improved health outcomes [7]. One could argue that the healthcare industry produces enormous amounts of biological, administrative, and patient data that are hard to manage with conventional analytics and storage technologies [3]. Owing to the difficulties associated with healthcare data, including its amount, velocity, diversity, and authenticity, the sector must use advanced digital technology to gather, store, and analyze data in order to provide insightful, useful information. Big Data analytics makes sure that data can be sorted, analyzed, and categorized into relevant information that the healthcare organization can utilize to support and enhance its overall performance in decision-making.

Healthcare attempts to exploit Big Data must, however, have a commercial value because using BDA to optimize healthcare performance is a basic problem for researchers and practitioners alike [7]. According to additional research, the adoption of BDA has mostly been facilitated by the notable rise in the degree of digitalization of healthcare systems and the heavy and ongoing reliance on information technology to deliver safe healthcare [8–9].

To evaluate the effect of big data analytics competencies on the performance of healthcare organizations, a number of models and methodologies have been put forth. These models frequently involve the definition of key competencies, assessment of organizational big data analytics readiness, and creation of frameworks or predictive models. As an illustration, a study by Hossain et al. (2018) [10] suggested a model that evaluated organizational readiness for big data analytics and its effect on healthcare performance. The model took data governance, data quality, and analytics capabilities into account. According to a study by Kuo et al. (2020) [11] that looks at the connection between the performance of healthcare institutions and big data analytics capabilities. It examines the competencies necessary for implementing big data analytics effectively as well as their effects on various performance metrics in the healthcare industry, such as clinical quality, patient satisfaction, and financial performance. Regression analysis is used in the research's quantitative methodology to examine the relationship between big data analytics capability and performance outcomes. Data was collected from medical institutions for this study. The study offers empirical proof in supporting the beneficial influence of big data analytics skills on healthcare performance.

From the literature we found a few studies that analyze the effect of big data analytics on the performance of the healthcare sector, Most of these studies used traditional statistical methods (mean, std, ...) to highlight the effect of a single feature or sub-feature on the health care performance [1–6]. To fill this gap, this paper used data mining to build a computational model for predicting the performance of the healthcare organization, with a new combination of the most used dimensions that had the greatest impact on the efficiency of big data analytics which encompasses Organizational, Technical, Analytical, Cognitive, and The Social capability see Fig. 1 No previous literature has been identified that incorporated all these dimensions simultaneously, The development of a prediction model supported by empirical evidence is critical to closing the competency gap and thereby improving the quality and competitiveness of BDA implementation in health services, research, and practice.

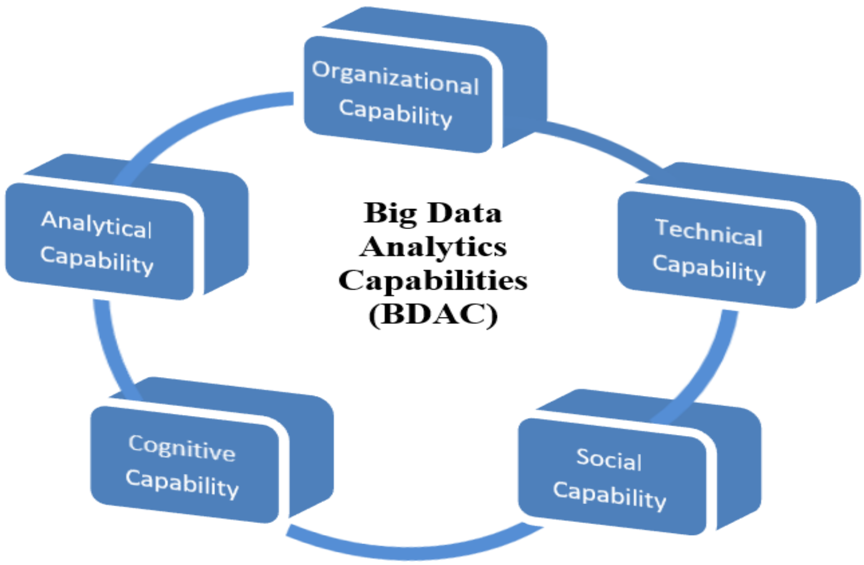

Figure 1: Elements of Big Data analytics competencies.

2 Related Work

Big data analytics effects on healthcare delivery and performance are also examined in the study "Assessing the impact of big data analytics on healthcare delivery: A systematic literature review"[12]. The study examines a wide range of articles to determine the competencies needed for successful big data analytics implementation in healthcare organizations. It examines how these competencies affect clinical outcomes, patient satisfaction, and cost effectiveness in healthcare.

The review offers a thorough understanding of the variables influencing healthcare organization performance by providing insights into the relationship between big data analytics competences and performance outcomes.

Also, a Research: "A framework for evaluating the impact of big data analytics capability on healthcare organization performance" which done by Fosso Wamba et al. [13]; suggests a comprehensive structure for assessing the effect of big data analytics capability on the performance of healthcare organizations. Clinical quality, operational effectiveness, financial performance, and patient satisfaction are just a few of the performance dimensions that are included in the framework. It also takes into account the skills and abilities needed for a successful implementation of big data analytics. The study uses a mixed-methods approach, combining qualitative interviews with healthcare organizations and survey data. The results emphasise the significance of big data analytics skills in achieving performance improvement outcomes in healthcare organizations across a variety of dimensions.

Another study by Maryam and Goran examines the idea of data analytics competency and how it affects the effectiveness and quality of decisions. Through an empirical survey of IT managers and data analysts, the study establishes five dimensions of data analytics competency and validates the idea. The results indicate that decision quality and efficiency are significantly impacted by data analytics competency, with big data assisting as a valuable resource for enhancing decision quality but not decision efficiency. The study concludes by highlighting the significance of data analytics competency for enhancing firm decision-making performance [14].

The 2018 study by Cecilia Adrian examines the advantages of big data analytics implementation for organizations. The theoretical foundation of big data analytics, research methodology, and influencing factors are all covered, and a conceptual model for BDA implementation assessment is also suggested. The paper also provides guidance on how to conduct an organized review of the literature on information systems research. The study's conclusion is that the best method for evaluating big data analytics implementation is a conceptual model. The model assesses the interaction between organizational, human, and technological factors that have an impact on decision-making and BDA implementation evaluation. After a pilot study and an actual study, the proposed conceptual model and questionnaires will be evaluated by specialists from academia and industry. The model will be tested using statistical tools, and the findings will help business leaders plan, maintain, and improve their capacity for data-driven decision-making by evaluating relevant resources [15].

The Ajax Persaud study sheds light on the skills employers look for in big data analytics professionals and the effectiveness of higher education programs in preparing students for the workforce. A literature review, an employer survey, and an examination of job postings are all included in the study. The results imply that employers are looking for a specific combination of personality traits as well as functional, cognitive, and social competencies. In order to better prepare students for the job market, the study also emphasizes the need for higher education institutions to include more practical, hands-on training in their educational programs. Three data sources were used in the methodology of this study: executive interviews, online job postings, and big data programs at universities and colleges. In order to gain insights into the necessary competencies, the study uses text mining analysis guided by a comprehensive competency theoretical framework. To determine the competencies that employers are looking for in big data analytics professions, the authors conducted a literature review, a survey of employers, and an analysis of job postings. A focus group and a Delphi study are also included in the study to elicit opinions from senior executives and data analytics experts. The study's inability to capture workers' perspectives in order to determine how much they believe they possess the necessary competencies is acknowledged by the authors as a study limitation [16].

Other studies [17, 18] have used regression analysis, machine learning algorithms, or hybrid models to predict performance outcomes based on big data analytics competencies. These methods shed light on the particular competencies that affect performance.

Also, a competence measurement framework focuses on locating and assessing the precise big data analytics competencies necessary for enhancing performance in healthcare organizations. According to Chae et al. (2020), this strategy entails assessing the organization's capabilities in areas like data management, analytics, and data-driven decision-making. The framework enables an accurate evaluation of competences and the effect they have on performance outcomes [19].

According to Birken et al., the balanced scorecard is a performance measurement framework that takes into account a variety of organizational performance factors, including financial, customer, internal process, learning, and growth perspectives [20].

Healthcare organizations can evaluate how big data analytics competences affect various performance dimensions by incorporating these competences into the balanced scorecard framework.Also, the study "Predictive analytics for healthcare quality improvement: A systematic review of the literature", explained the use of predictive analytics to enhance healthcare quality is the main focus of this comprehensive review. The study looks into how big data analytics skills can be used to predict healthcare performance and raise standards. It examines various predictive modelling approaches used in healthcare, including regression analysis and machine learning algorithms, and evaluates their effects on performance outcomes. The review emphasizes how crucial big data analytics skills are for forecasting healthcare quality indicators and guiding initiatives to improve performance [21].

All the previous studies offer frameworks and empirical evidence for understanding the relationship between competencies and performance outcomes, and they shed valuable light on the influence of big data analytics competencies on the performance of healthcare organizations. By looking at these studies researchers and healthcare professionals can better understand the potential advantages and approaches for leveraging big data analytics capabilities to drive performance improvement in healthcare organizations.

Machine learning is essential for determining how big data analytics will affect healthcare organizations. Based on the gathered data, predictive models can be created using machine learning algorithms. With the help of these models, healthcare organizations can forecast a variety of outcomes, including disease diagnoses, treatment outcomes, patient readmission rates, and the use of healthcare resources [22–24]. Healthcare organizations can benefit from valuable insights that support decision-making and resource allocation by utilizing machine learning [25]. Neural Networks are a key component of deep learning, they are widely used in big data analytics due to their ability to handle complex patterns and large-scale datasets, extract insightful knowledge, and predict outcomes with high accuracy [26].

It was noted that previous studies mainly analyzed the effect of the main big data analytics capabilities on the performance of healthcare institutions [22, 27], this gap was filled by this study which focused on the sub-capabilities for each capabilities mentioned in above.

From the literature, we found a few studies that analyze the effect of big data analytics on the performance of the healthcare sector. Most of these studies used the traditional statistical methods (mean, std …) to highlight the effect of a single feature or sub-feature on the health care performance [3, 15, 16, 27, 28]. To fill this gap, we used machine learning to build a prediction model that complaining the most important five competencies, mentioned above, for predicting the performance of the healthcare organization.

3Methodology

Based on the BDA competencies model Fig. 1, We proposed a conceptual research framework as shown in Fig. 2 The framework represents the capabilities and sub-capabilities that can have an impact on the effective application of Big Data analytics, which in turn entered as input parameters for the feature selection process which used Artificial neural network, then the effective and integrated features used as an input to the prediction model, which holds great potential for predicting the performance of healthcare organizations using artificial neural network(ANN) algorithm.

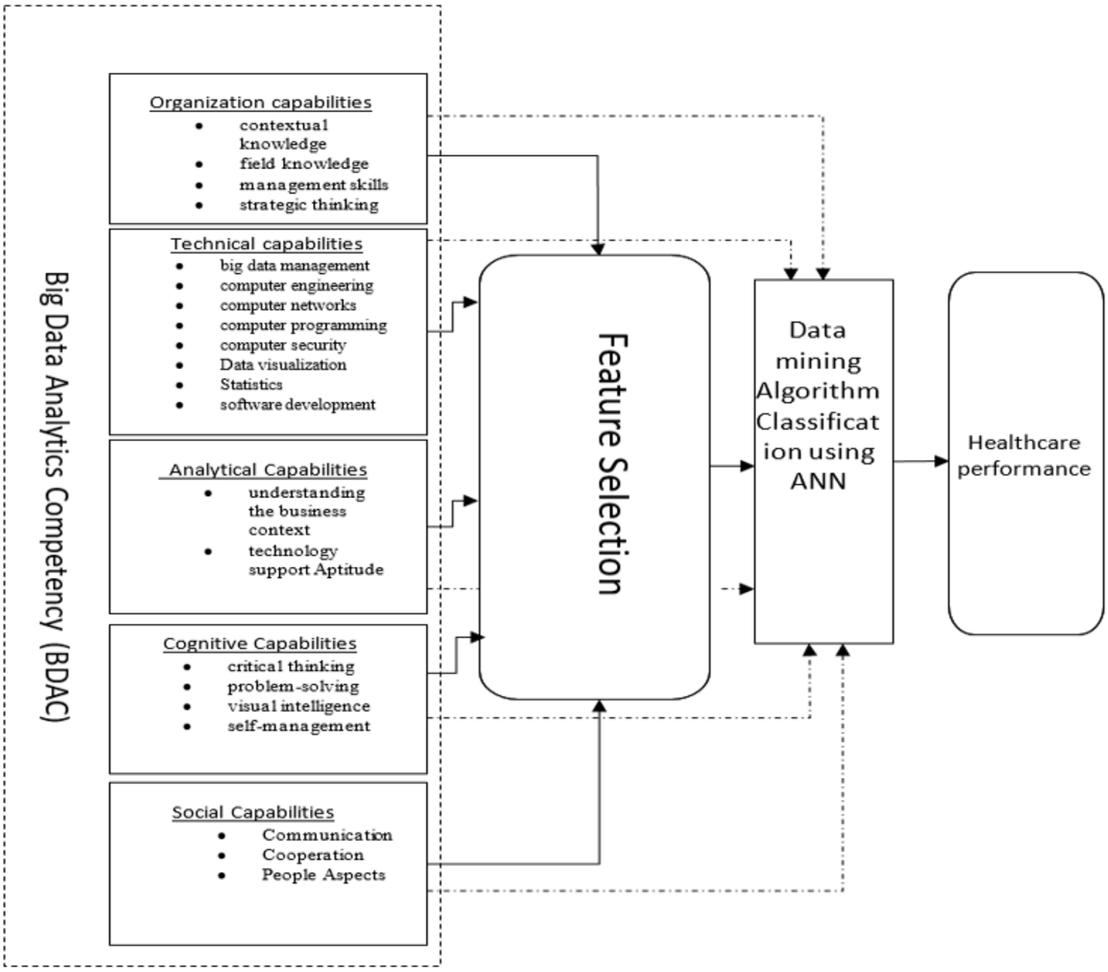

Figure 2: Research framework.

Thus, the proposed model offers the potential to enhance the prediction of healthcare organization performance. Its comprehensive framework recognizes the interconnected nature of healthcare capabilities and their impact on organizational outcomes, while ANN's computational power provides cutting-edge insights into performance dynamics. However, the effectiveness of this approach depends on data quality, accuracy of feature engineering, and selection of appropriate model architecture, each of which requires careful attention.

3.1 Data mining

Data mining methods have the capability to forecast and extract information from vast datasets, so they have become extensively employed in the design of big data analytics systems. Within data mining, Machine Learning (ML) techniques are particularly popular for constructing BDAC (Big Data Analytics competency) systems, especially for tasks like classification and clustering [20, 25]. In this paper, the methodology consists of four key elements: Raw Data Pre-Processing, Feature Selection (FS), Data mining technique(s) for classification, and Evaluation Fig. 3.

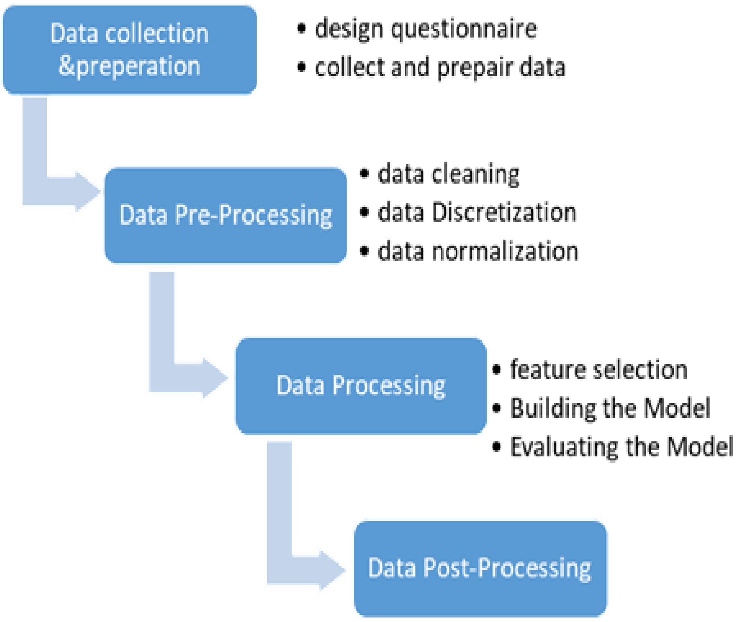

Figure 3: The BDAC prediction approaches elements.

3.2 Data collection

We collect 205 responses from big data analysts and those who work in the hospital's information technology departments through a structured questionnaire comprising five distinct fields: Big Data Analytics capabilities, each capability includes sub-capabilities, the overall sub-capabilities (consisting of 65 features), and Healthcare Organization Performance Questionnaire (including 5 features).

3.3Data preprocessing

3.3.1 Data cleaning and preparation

The collected data underwent a rigorous cleaning and preparation process to ensure its quality and reliability. Unwanted data, missing values, redundant rows, and irrelevant columns were removed. Duplicate values were also eliminated, and appropriate data type conversions were performed to enhance consistency and uniformity.

As part of the preprocessing phase, the linguistic data obtained from the questionnaires was transformed into numerical values, assigning values within the range of 1 to 5. Additionally, data scaling and normalization techniques were applied to minimize the influence of large value discrepancies. This involved scaling the values to a standardized range of 0 to 1. Moreover, a binary classification approach was implemented, labeling values equal to or greater than 3 as "good" (assigned the value 1) and those below 3 as "bad" (assigned the value 0). This transformation aimed to expedite the processing within the neural network.

3.3.2 Data normalization

This is a data scaling process where the data is scaled down from [1.0 5.0] to the range [0.0 1.0], or from a large scale to a small scale. The goal of normalization is to speed up the classification process for many classifiers. Additionally, normalization makes the effects of a large range of attributes similar to those of a small range of attributes and prevents outweighing for data mining methods that use a measure of distance [30]. Min-Max Normalization method were used as Eq. 1 [29]:

$$X' = ((X - mina) / (maxa - mina)) * (new\_maxa - new\_mina) + new\_mina \quad (1)$$

Where X', are normalized value of X, old range, respectively.

3.4Feature selection

In this study, we applied a feature selection algorithm to improve the accuracy of the healthcare institution performance prediction model. To ensure an accurate and efficient feature selection process, we individually test all selected features within the selected capabilities. We used a Multilayer Feed Forward Neural Network (MFFNN) to analyze each capability and its sub-features independently. To identify the most effective and predictive features, model performance was evaluated by comparing the accuracy results generated by each set of features. This process aims to identify the most predictive features with high accuracy.

3.4.1 Multilayer Feed Forward Neural Network (MFFNN)

In this section of the methodology, we used a multi-layer forward neural network, where the network contains one input layer, a hidden layer, and a neuron for the output layer. The Scaled Conjugate gradient back propagation (SCGBP) algorithm was used to train the network, in addition to using the logistic function as an activation function to activate neurons in the network. The difficult challenge here is to optimize the number of hidden neurons in the network. Two problems arise: The first problem lies if the number of hidden neurons is too small, which leads to what is called underfitting. The second problem is if an excessive number of hidden neurons are selected, which leads to the problem of overfitting. To address these issues, this study optimized the number of hidden neurons in the network using an empirical approach.

In this study, to find the best number of hidden neurons we investigated different network architectures with different numbers of neurons in the hidden layer. After that, we chose the network with the highest accuracy. Through experimentation.

3.4.2 Neural Network Architecture:

The architecture of the designed Neural Network for predicting healthcare organization performance involves several key components and design choices. Based on all five capabilities Table 1 displays the structure of all neural networks through the number of input features, the number of hidden neurons that give the best accuracy, the activation function used, and finally the output layer which consists of one neuron for healthcare organization performance.

Table 1: The Structure of Neural Networks

Feature	**# of Inputs**	**# of Hidden Neurons**	**Activation function**	**Output**
Organizational	13	10	Log Sigmoid Function for all Networks	Healthcare Organization Performance (HOP)
Technical	11	12		
Analytical	13	9		
Cognitive	12	10		
Social	16	11		

3.5 Classification and Evaluation

Depending on the feature selection process, we used the integrated and effective features as inputs to a multi-layer feed-forward neural network (MFFNN) supervised classifier to evaluate how the big data analytics capabilities (big data analytics competency model) affected the accuracy of the classification. To obtain efficient model training and evaluation of the model, we divide the data set into three subsets, as shown in Fig. 4. 70% of the data set is designated to represent the training set; this is equivalent to 143 cases of data, which enabled it to extract insights from data patterns and relationships. 15% of the data was then allocated to the validation set, equivalent to 30 instances of data, which played a critical role in avoiding overfitting by helping to fine-tune the model and validate its performance throughout the training phase. Finally, the test set, which also makes up 15% (30 instances) of the data, serves as an independent evaluation dataset after training, making it easier to evaluate the trained model's accuracy and generalization capabilities.

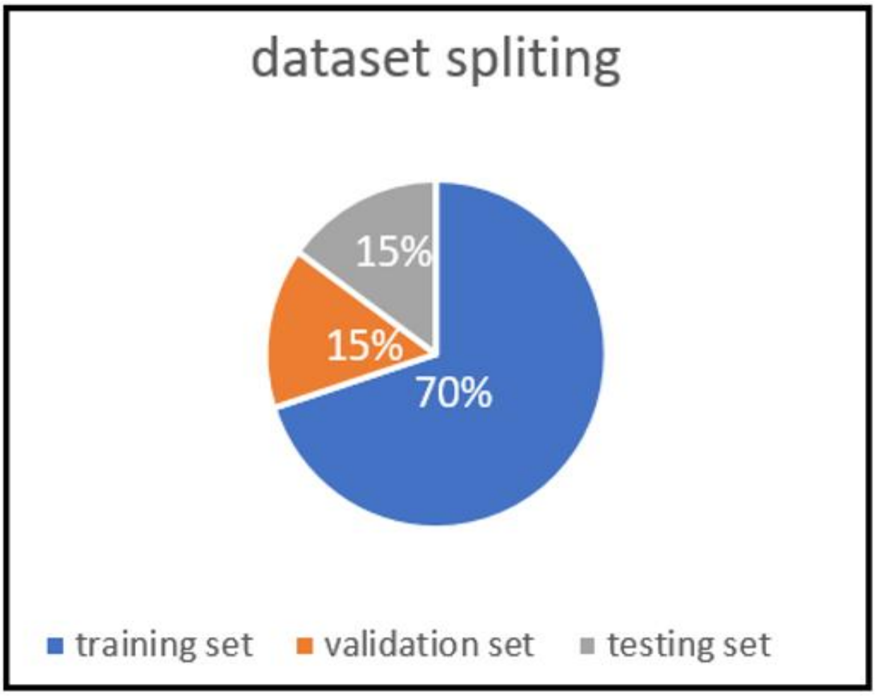

Figure 4: The dataset sets

4 Results, Analysis and Discussions

4.1 Model Evaluation

We use a confusion matrix for model evaluation and refinement process, including predicting healthcare organization performance. A confusion matrix provides a comprehensive overview of how the model's predictions align with the actual outcomes, allowing us to assess various performance metrics and refine our model accordingly.
As with most previously built prediction systems, this research will use tests of overall accuracy, sensitivity, specificity, false positive rate, and false negative rate. Whereas the accuracy of the model signifies the rate of correctly predicted instances out of the total instances, the sensitivity of the model also referred to as the true positive rate, represents the rate of actual positive instances that the model correctly identifies, Conversely, the specificity of the model, synonymous with the true negative rate, signifies the model's ability to identify negative instances correctly, Additionally, the false positive (FP) rate, denoting the rate of instances that are negative but are misclassified as positive by the model, Lastly, the false negative (FN) rate, which reveals the rate of instances that are truly positive but are misclassified as negative by the model.

4.2 Confusion Matrix for all Capabilities

Based on the Confusion Matrices in Fig. 5, we calculated metrics which offer a comprehensive assessment of the model, shedding light on its accuracy, sensitivity, specificity, false positive (FP) rate, and false negative (FN) rate. These metrics encapsulate the model's performance characteristics across different aspects. While the accuracy and sensitivity demonstrate notable strengths in overall correctness and positive instance identification, the specificity, FP rate, and FN rate offer insights into areas that might require further refinement in order to optimize the model's predictive powerness and achieve a more balanced performance.

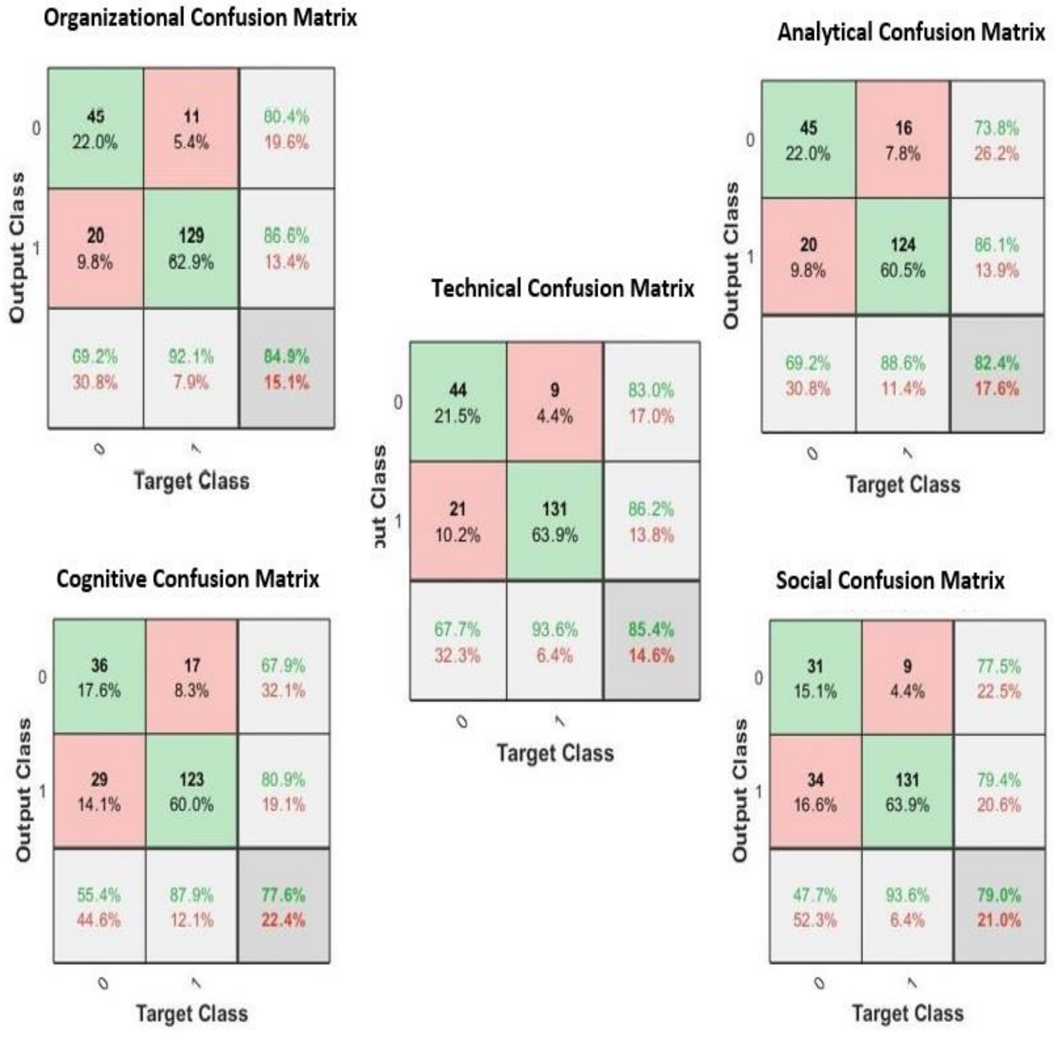

Figure 5: Confusion Matrices for all Capabilities.

Based on the confusion Matrix above, we analyze the data and calculate the values of all mentioned measures as shown in Table 2.

Table 2: Comparison between Results of all Capabilities

Feature	Accuracy	sensitivity	specificity	FP rate	FN rate
Organizational	84.9%	86.6%	80.4%	19.6%	13.4%
Technical	85.4%	86.2%	83.0%	17.0%	13.8%
Analytical	82.4%	86.1%	73.8%	26.2%	13.9%
Cognitive	77.6%	80.9%	67.9%	32.1%	19.1%
Social	79.0%	79.4%	77.5%	22.5%	20.6%

Depending on the result of all measures, Organizational and technical capabilities showed the highest accuracy rates, with accuracy reaching 84.9% and 85.4%, respectively. These two capabilities also achieved high sensitivity and specificity rates (86.6% and 80.4% for organizational capability, and 86.2% and 83.0% for technical capabilities). These results indicate that organizational and technical capabilities play an important role in improving the performance of healthcare institutions.
On the other hand, the analytical capability showed an accuracy of 82.4%, sensitivity of 86.1%, and specificity of 73.8%. Although this capability showed high sensitivity, specificity was lower compared to organizational and technical capabilities. Regarding cognitive capability, the accuracy was 77.6%, with a sensitivity of 80.9% and a specificity of 67.9%. These results reflect that cognitive capability is the least accurate and has the least impact on the performance of healthcare institutions among the five capabilities. As for social capability, it achieved an accuracy of 79.0%, a sensitivity of 79.4%, and a specificity of 77.5%.

4.3 Comparison between Capabilities

A comparison was made between the results of all capabilities, the analysis showed that the accuracy value was close among all features as shown in Fig. 6, indicating that each feature had a similar effect on the model performance. Based on this observation, all mentioned features has a strong impact on predicting healthcare institution performance.

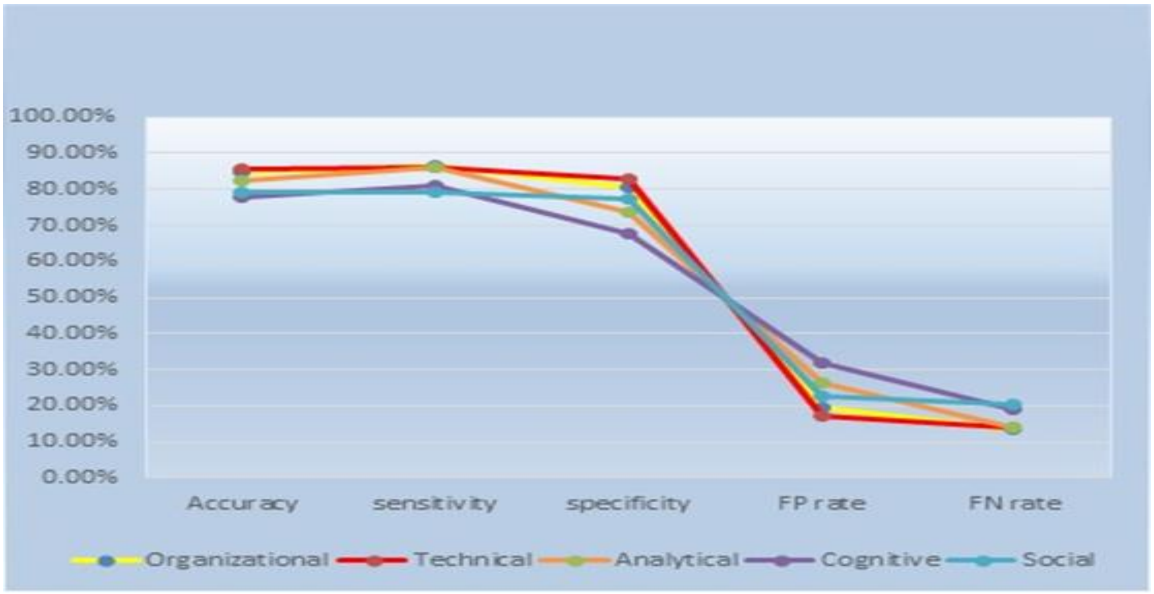

Figure 6: Comparison between Measures for all Capabilities.

Depending on these comparisons and the closeness between capabilities results, 65 data features were selected to effectively represent these capabilities and used as input to a predictive model designed using the artificial neural network algorithm to predict the performance of healthcare institutions.

4.4 Healthcare Organization Performance Prediction Results

The results showed in Table 3, that the model achieved an accuracy of 0.70, which means that the model has a correct prediction ability of 70%. This is a relatively good result, indicating that the model can predict the performance of healthcare organizations in most cases. However, the context of healthcare applications typically requires higher accuracy due to the importance of decisions based on these predictions.

Table 1 Result of Healthcare Organization Performance Model

Input Features	Classifier	Output	Accuracy	Sensitivity	Specificity	AUC
65 Integrated Features of Big Data Analytics Capabilities	Artificial Neural Network (ANN)	Healthcare Organization Performance (HOP)	70.0%	60.0%	100%	0.90

In addition, the sensitivity value was 0.6, which means that the model can detect 60% of actual positive cases. This result reflects the need for the model to improve its ability to detect all positive cases more efficiently, especially in a healthcare context where identifying all positive cases is crucial.

On the other hand, the Specificity value reached 1.0, which means that the model achieves 100% accuracy in correctly identifying negative cases. This result is excellent, as it shows that the model completely avoids false positives, which enhances its reliability in ensuring that the negative cases it identifies are indeed incompetent.

In addition to the results of accuracy, sensitivity, and specificity, the model's performance was measured using the value of the area under the receiver operating characteristic curve (AUC - Area under the Curve), which for this model was 0.9. This value is a strong indicator of the predictive model's performance, as it reflects the model's ability to effectively distinguish between positive and negative cases.

5 Conclusion

The study results indicate that big data analytics plays a vital role in improving the efficiency and quality of healthcare, as it allows organizations to analyze large amounts of data to extract useful insights that support decision-making. The maximum benefit from these analyses depends on enhancing five main capabilities: organizational, technical, analytical, cognitive, and social. Organizational and technical capabilities have proven to be the most influential, as they provide the infrastructure and tools necessary to collect and analyze data effectively. Analytical and cognitive capabilities contribute to understanding data and extracting insights, while social capabilities enhance collaboration and coordination between multidisciplinary teams. Through an integrated approach that enhances these capabilities, healthcare organizations can achieve significant improvements in the performance and quality of services provided, leading to better healthcare delivery and superior outcomes.

It is believed that the development of this prediction model, supported by empirical evidence is critical to closing the competency gap by indicating which big data analytics capabilities have a significant impact on predicting Healthcare institution performance, thereby improving the quality and competitiveness of BDA adoption in both healthcare research and practice.

Additionally, we can conclude that using all features rather than reducing or excluding some of them led to building a more comprehensive and robust model in the future, capable of providing more accurate and reliable predictive results. This approach enhances the effectiveness of the model in providing accurate assessments of the performance of healthcare institutions and thus contributes to improving decision-making processes in the healthcare field.

As big data analytics becomes increasingly important in improving the quality and efficiency of healthcare services, several possible research opportunities emerge for future studies. It is possible to expand the scope of the studied capabilities by exploring the impact of additional capabilities, such as financial and economic capabilities, legal and regulatory capabilities, and environmental capabilities, on the efficiency of healthcare institutions. In addition, future research can improve the predictive model using advanced techniques such as deep learning, advanced neural network analysis, and using different classifiers. These technologies can provide higher predictive accuracy and provide deeper insights into the factors influencing the performance of healthcare organizations.

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