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REVIEW ARTICLE

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# Machine Learning in Managing Healthcare Workforce Shortage: Analyzing how Machine Learning can Optimize Workforce Allocation in Response to Fluctuating Healthcare Demands

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## ABSTRACT

This study examines the application of machine learning models in managing healthcare workforce allocation to meet fluctuating demands. Four models—Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine—are evaluated for their accuracy and reliability. The Random Forest model achieves the highest accuracy of 0.98, followed by Decision Tree, Logistic Regression, and Support Vector Machine. The results highlight the models' potential in enhancing operational efficiency and addressing staffing challenges. By utilizing historical and real-time data, these models can predict staffing needs, optimize resource allocation, and improve patient care outcomes. The study emphasizes the importance of adopting machine learning techniques in healthcare workforce management to achieve a more responsive and efficient system.

## ARTICLE HISTORY

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Machine Learning, Random Forest, Decision Tree, Support Vector Machine, Data-Driven Decision Making

## Introduction

The healthcare workforce presents compelling factors that affect the magnifying increase in efficacy as well as quality treatment service delivery. These deficiencies are worse off when subjected to oscillating conditions of healthcare needs, thus creating imbalances in the distribution of the health workforce and added pressure on healthcare service providers. Workforce management enables healthcare organizations to address the patient's needs, deliver quality services, and prevent burnout. The conventional way of managing the workforce entails Guesswork and Fixed staffing which do not change frequently with the fluctuations of demand. As a subfield of artificial intelligence, ML brings in new strategic methods of workforce management and scheduling with the help of big data analysis and forecasting.

## Background

The integration of real-time data into an ML model can then change the workforce based on shifting needs, making sure that healthcare facilities are staffed at all times [1]. This too increases efficiency in the operations of the facility while at the same time being instrumental in improving patient satisfaction due to less wait time for health services. Some of the state-of-the-art applications of ML include the diagnosis and treatment of diseases along with advice on the best treatment regimen for the patients. Extending the application of the ML brings the same beneficial effects at the operational level of the organization and addresses essential staff issues such as staff deficiency and resource management. The adoption of ML in workforce management systems is some sort of a sign of the evolution of the healthcare processes.

## Aim and Objectives

### Aim

The main objective of this study is to determine how machine learning (ML) might be employed in optimizing the distribution of the available healthcare workforce consequent to changing healthcare demands.

### Objectives

- ToI discusses the current situation with healthcare workforce management to establish the background of the issue.
- To examine how machine learning can help in enhancing healthcare services.
- To recognize and assess the machine models that affect the distribution of the workforce.
- To evaluate the effectiveness of the application of the ML model for the workforce distribution on matters of efficiency and improvement of patients' status.

## Literature Review

### Current State of Healthcare Workforce Management

Healthcare workforce management is at the moment experiencing immense pressures arising from rising healthcare delivery demand, an ageing population base, and a scarcity of specialized employees. Such challenges are compounded by the fact that there is an unequal distribution of human health resources which results in a health worker to population density ratio [2]. The classical models of implementing workforce management involve the processes of scheduling and distribution of workforce which are usually static and do not factor in the level of improvisation.

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In most health care facilities there is a heavy dependence on agency staff which is expensive and contributes to inconsistent quality of care.

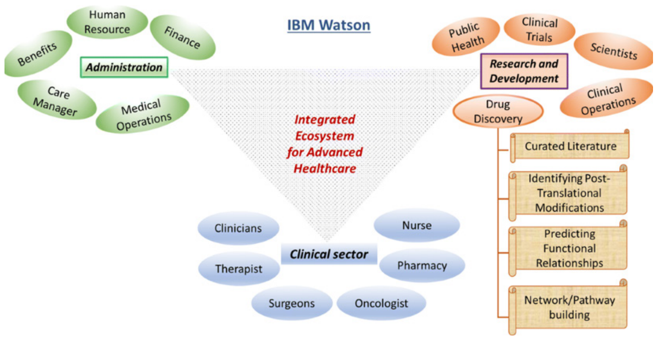


**Figure 1:** Current State of Healthcare Workforce Management

The fact that organizations have full-time, part-time, and contract employees has been viewed to increase the pressure on administrative capacity. However, the introduction of new technologies and Electronic Health Records has imposed other requests on those practicing in the healthcare setting, thus resulting in burnout and dissatisfaction with their job. However, the management of the workforce in healthcare is compounded by such factors as regulations, time and financial budget, and general models of continuing healthcare [3]. These account for challenges in staffing a sufficient workforce, especially in different specialty areas and shifts, causing burnout among healthcare practitioners as well as compromising the quality of patient care. ML also presents a prospect in healthcare workforce administration by creating the chance to use predictive models with actual-time decision support systems. It must be extremely beneficial if using the powerful function of the 'Big Data', the sophisticated ML algorithms can examine numerous samples of historical data and forecast specific activity levels concerning the admission rates of patients, implement the number of ER visits, and the fluctuating dynamism in the healthcare industry throughout different seasons.

This predictive capability makes it possible for an organization to make anticipative adjustments on the number of people that need to be hired and the skills they should possess so that the right people are in the right place at the right time [4]. Moreover, through the adoption of ML-based workforce management systems, scheduling tasks can be handled automatically considering the staff's preference, availability, and specialization together with legal requirements. This minimizes administrative hassles that affect health care managers and brings efficiency in the performance of tasks hence the available resources are channeled towards training and attending to the patients.

## Role of Machine Learning in Healthcare

The medical data input into the ML algorithms consists of records of the patient's medical history, imaging studies, and even genetic data, and the ML algorithm then targets the data looks for patterns, and makes accurate predictions based on the data fed into it [5]. These effective models help the healthcare givers to diagnose these illnesses early, save the patients, and possibly cut on the costs of managing these diseases. Furthermore, ML helps in the application of the concept of precision medicine, where therapies to be administered can be chosen accordingly depending on the patient's information. In operational management, the implementation of ML leads to overall resource management, effective organization of hospitals' processes, and the working processes of managers.

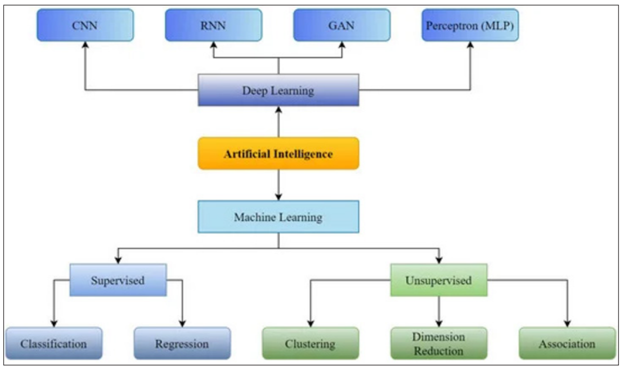


**Figure 2:** Role of Machine Learning in Healthcare

In addition, machine learning also helps in drug discovery by pointing out possible compounds and their effectiveness levels before these are unveiled in the market, expediting drug development [6]. The research has also indicated that the incorporation of ML in telemedicine has helped improve access to health care, especially for patients located in remote or hard-to-reach areas.

Machine learning (ML) is transforming healthcare through providing effective approaches to diagnose diseases, create treatment plans, enhance the functioning of producing organizations, and increase patients' quality of life. Its role spans across various critical areas within the healthcare sector:

## Personalized Medicine

Some of the applications of Machine Learning are as follows: Large-scale patient data analysis involves the collection of data such as patient's genetics, medical history, and other lifestyle parameters using variations from which treatment plans can be developed concerning the patient [7]. Such an individualized approach improves the result of the therapy, reduces side effects, and properly expends resources.

## Predictive Analytics

Using big patient data, the ML models can identify diseases, risk of readmission, and other tendencies of the healthcare facility. This predictive ability helps healthcare facilities in the distribution of resources, staff scheduling, and possible early action to be initiated rather than waiting for a mishappening in terms of health [8].

## Operational Efficiency

The application of ML helps to enhance the performance of health systems by automating minor functions like appointment booking, handling EHRs, and payment procedures. This automation leads to a reduction in the workload of the numerous administrative personnel and, an increase in the efficiency of operations and thus the health care services. It speeds up research and development, makes them cheaper, and introduces new treatments into the market

## Machine Learning Models for Workforce Allocation

Machine learning algorithms can help healthcare organizations streamline staffing, reduce costs, and improve patient care by predicting workforce needs and optimizing resource allocation. It is appreciated and widely used because of its 'human readability', taking both categorical and numerical data, which in addition can be used in more complicated staffing problems. Deep learning specifically, is a form of NNs that has shown the ability to optimally analyze and map through data, thus allowing accurate predictions of the demand for the workforce as informed by data. The use of reinforcement learning models which are the models that learn the best strategy in every simulation and usually involve a great number of trials is effective if the staffing requirements are constantly shifting. Another model is called support vector machines, which are also widely used for classification; for example, to estimate staff shortages, it is possible to design various features related to labor.

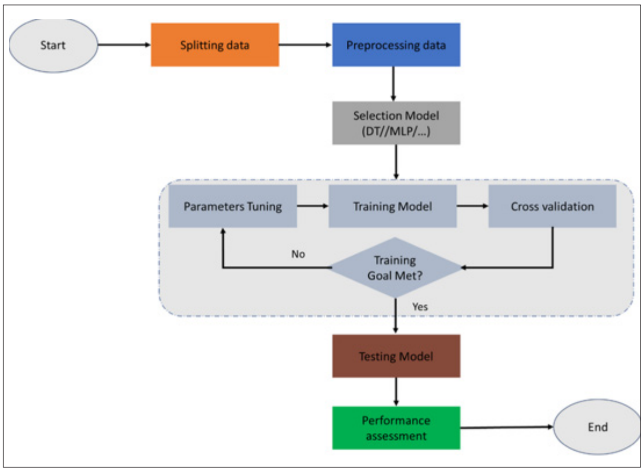


**Figure 3:** Machine Learning Models for Workforce Allocation

Thus, the use of the ML models regarding force distribution in healthcare facilities is of great importance because it defines the staffing levels, contributes to enhancing the overall effectiveness of a particular environment, and increases the quality of patient care [9]. Here are several key ML models and their applications in workforce allocation: Here are several key ML models and their applications in workforce allocation:

### Predictive Staffing Models

These apply past patient records, time-related trends, and other factors to calculate future healthcare needs. For example, time series forecasting includes the use of ARIMA (Auto Regressive Integrated Moving Average) or more complex such as LSTM (Long Short-Term Memory) deep learning model for predicting future patient admissions, emergency room visits, or outpatient clinic requirements [10]. Such predictions facilitate the forecast of the demand for staffing and enable healthcare managers to alter staffing levels in anticipation of the changes.

### Optimization Algorithms

Machine Learning-based optimization algorithms, for example, linear optimization or genetic algorithms, then optimally deploy the healthcare staff according to the staff's availability, based on the forecasted demand. Such algorithms take factors such as staffing regulation, employees' preferences and skills, and other factors to produce efficient staffing schedules [11]. For instance, a genetic algorithm can produce schedules that distribute workload among healthcare personnel with a view of keeping the costs of the service low/ and at the same time ensuring that the targets set for the various shifts are met.

Natural Language Processing (NLP) for Demand Analysis: Several natural language processing methods are applied to unstructured sources such as patient notes, orders of a physician, or discharge summaries to derive conclusions about the consumption of healthcare services. Subsequently, patient acuity, special needs, and fluctuations due to the time of the year contribute to refining the demand forecasting process and better workforce distribution plans using NLP-powered models.

### Reinforcement Learning (RL)

RL models acquire the best strategies for staffing with interaction with the healthcare environment. For example, RL algorithms may be assigned the flexibility of changing the number of staff in shifts according to real-time admission and discharge data plus other healthcare workers' responses [12]. This process makes it possible to always have and improve the best staffing solutions as per changes in patient requirements and work circumstances.

### Impact on Workforce Efficiency and Patient Outcomes

This is because through workforce allocation such improvements in efficiency are made in light of the recommended workforce based on statistical analysis. Using historical data and inputs derived from real-time data collection, the number of patients likely to flow into a given healthcare facility at a given time can be estimated, and thus human resources can be hm adjusted accordingly [13]. It eliminates exposure to situations in which you have too few employees during busy hours and too many employees during less busy hours to guarantee the efficient utilization of resources. An increase in efficiency is directly proportional to the decrease in employees' stress levels and the overall ease at which they perform their duties in an environment with healthy working conditions. Therefore, it preserves and increases healthcare providers' job satisfaction and productivity. Besides enhancing the performance rates of the workforce, the application of machine learning models contributes back to the improvement of patients' status.

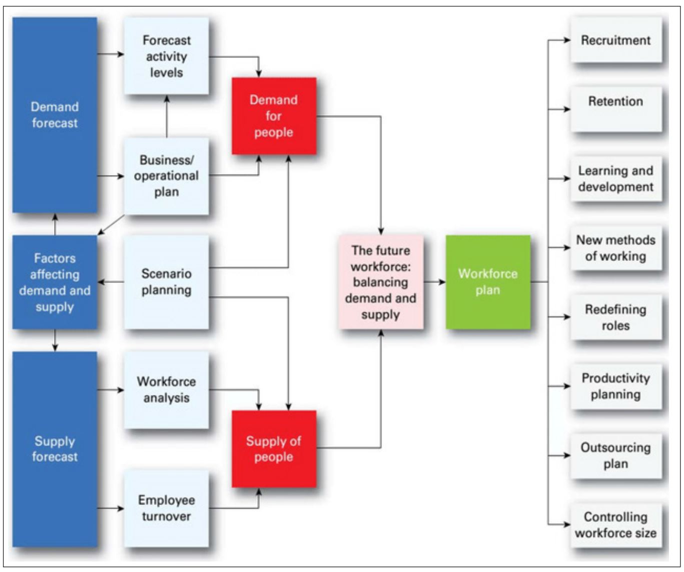


**Figure 4:** Impact on Workforce Efficiency and Patient Outcomes

### Workforce Efficiency

The application of ML models in staffing activities includes reduced time for staff planning by using predictive analysis of patients' traffic, schedule design, and other routine tasks. In predictive staffing models, certain times of the day are assumed and the operating staff is coordinated to ensure less over-staffing and cases of under-staffing. Computation-based models manage resources using the performance data received, and the right staff with the required skills is engaged when required [14]. This efficiency reduces costs in operation, increases productivity, and also eliminates cases of high turnover among healthcare professionals.

### Patient Outcomes

The application of ML in managing the workforce most clearly enhances patient care since patients receive proper and timely attention from care providers. Predictive analytics make it possible for healthcare providers to prepare for their patients hence increasing their ability to attend to their patients and improving their access to healthcare services [15]. Appropriate staffing ensures the patient gets close attention from the caregivers and receives care specific to his condition and need hence compliance to the treatment and general wellbeing is enhanced. Outsourcing of certain administrative activities improves the doctor- or nurse-patient ratio due to a reduction of time doctors and nurses spend on paperwork.

### Literature Gap

Prior literature on ML implementation in healthcare WM is largely centered on predictive and subsequent improvements to patients' statuses with limited attention paid to the complexity of the dynamic WM process [16]. It is also crucial to discuss that there is no extensive literature that combines dynamic scheduling, demand forecasting, and workforce management within a single framework. Also, the effects of these integrated solutions on the level of staff satisfaction and, as a result, their turnover have not been analyzed enough.

### Methodology

### Data Collection and Preprocessing

The data collection process consisted of acquiring large datasets from various healthcare organizations' staffing schedules, patients' intake records, and historical demand [17]. These datasets offered the source of understanding patterns in the distribution of the workforce, and the changes in healthcare demands which are critical in training and testing its models. The first phase that takes place in the preprocessing stage is the data cleaning stage, which deals with the issues of missing values, outliers, and inconsistencies.

### Demand Forecasting

y^=N1i=1∑Ny^i

### Mean Absolute Error (MAE)

MAE=n1i=1∑nIyi−y^iI

This has been followed by feature selection to determine which of the variables chiefly affect the workforce distribution and demand estimation process. Lastly, the dataset has been divided into training, validation, and testing as this lets models develop from different and consecutive subsets of data [18]. To achieve this, the process of data collection and data preprocessing followed a systematic approach in a bid to enhance the machine learning models' accuracy and generalizability of the models.

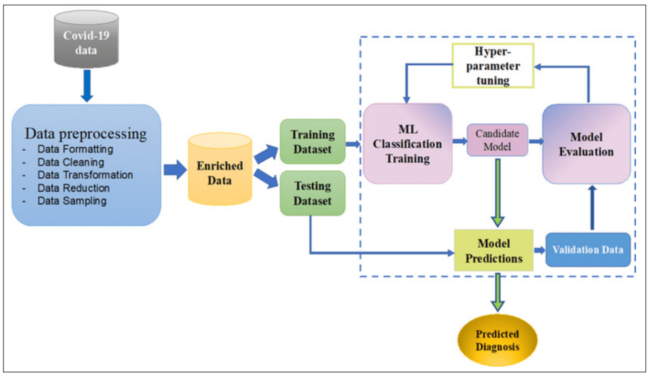


**Figure 5:** Machine Learning-Based Framework

### Model Development

The building of machine learning models for workforce allocation is usually a process that contains several key steps. First, according to the requirements of the problem to be solved, algorithms including decision trees, and reinforcement learning are chosen [19]. Every model is built based on past workforce data such as staffing plans, patients' needs, or any other limitations in performing the tasks. Such parameters are fine-tuned to enhance the models' learning ability about the given data. Cross-validation is applied to avoid overemphasizing and to ascertain the exact success rate of the models. Feature engineering is significant since the important features are identified as well as rearranged to improve results on the model. The final model is assessed by measures such as accuracy, precision, recall, and F1 score.

**Table 1: Methodology Overview**

| Step | Description | Techniques/Tools |
|---|---|---|
| Data Collection | Gathering relevant healthcare workforce data | Surveys, Hospital Records |
| Data Preprocessing | Cleaning and preparing data for analysis | Data Cleaning, Normalization |
| Model Development | Building machine learning models for prediction | Linear Regression |
| Model Evaluation | Assessing model performance | Accuracy, Precision, F1 Score |
| Result Analysis | Interpreting and analyzing the results | Data Visualization, Statistical Analysis |

## Model Evaluation

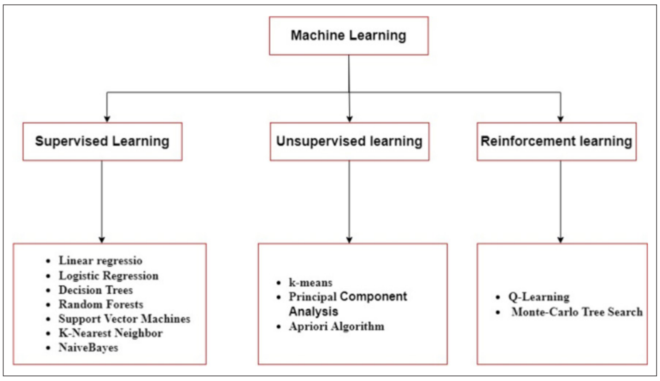


**Figure 6:** Healthcare Predictive Analytics using Machine Learning

The monitoring and quantifying of machine learning models include how effectively these perform and other measures that are employed on them. Evaluation of the model's ability to forecast workforce needs involves using measures like accuracy, precision, recall, and the F1 score [20]. Cross-validation is applied to see to it that the validity of the models holds when estimating with data other than the same data the model has been developed from. Furthermore, confusion matrices give information about the classification results and possible prevalence or recognition problems. The reasonability of the models is assessed with the help of sensitivity analysis to find out how the models react to changes in input values. Performance metrics are related to industry and prior data for the authorization of enhancements in workforce distribution. Having collected the evaluation results, the productivity of each model to manage shortages in the workforce or to maximize the choice of strategies is identified.

"x11+x21≥20 (Demand at Point 1)
x12+x22≥30x_{12} + x_{22} \geq 30 x 12+x 22≥30 (Demand at Point 2)
x13+x23≥25x_{13} + x_{23} \geq 25x13+x23≥25 (Demand at Point 3)
x11+x12+x13≤40 (Supply from Supplier 1)
x21+x22+x23≤35x_{21} + x_{22} + x_{23} \leq 35x21+x22+x23≤35 (Supply from Supplier 2)"

## Result and Discussion

### Result

| | Date | Total_Patients | Staff_Available | New_Admissions | Discharges | Staff_Shortage | Predicted_Staff_Need |
|---|---|---|---|---|---|---|---|
| 0 | 01-01-24 | 150 | 50 | 10 | 5 | 0 | 52 |
| 1 | 02-01-24 | 155 | 51 | 12 | 8 | 0 | 53 |
| 2 | 03-01-24 | 159 | 49 | 15 | 10 | 1 | 55 |
| 3 | 04-01-24 | 162 | 48 | 14 | 11 | 1 | 56 |
| 4 | 05-01-24 | 165 | 47 | 16 | 12 | 1 | 57 |
| 5 | 06-01-24 | 168 | 50 | 18 | 15 | 0 | 55 |
| 6 | 07-01-24 | 170 | 52 | 20 | 14 | 0 | 54 |
| 7 | 08-01-24 | 175 | 53 | 25 | 18 | 0 | 56 |
| 8 | 09-01-24 | 178 | 55 | 22 | 19 | 0 | 57 |
| 9 | 10-01-24 | 180 | 54 | 24 | 20 | 0 | 56 |

**Figure 7:** Display the First Few Rows of the Dataset

This figure shows the initial glimpse into the dataset known as 'Healthcare_Workforce_Optimization.csv.' The above figure includes the first few rows, showcasing columns such as 'Date,' 'Total Patients,' 'Staff Available,' 'New Admissions,' 'Discharges,' and 'Predicted Staff Need.' This serves as a foundational overview before delving into deeper exploratory analysis.

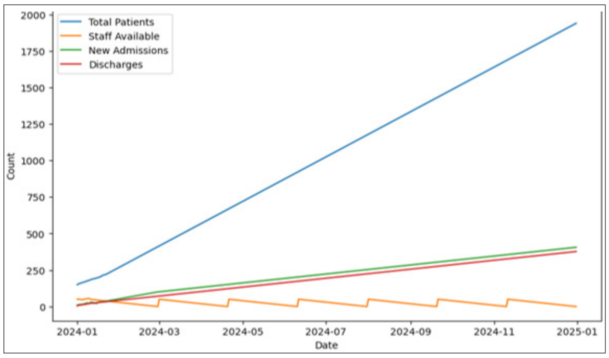


**Figure 8:** Time Series of Patients and Staff

This figure depicts a time series plot illustrating trends in 'Total Patients' and 'Staff Available' over the dataset's timeline. Here the x-axis contains the date and the y-axis contains the count. In this figure blue line reflects "Total Patients", the orange line reflects "Staff_Available", the green line reflects "New_Admissions" and the red line reflects "Discharge" This visualization provides insights into the dynamic fluctuations of patient volumes and staffing levels within the healthcare facility [21].

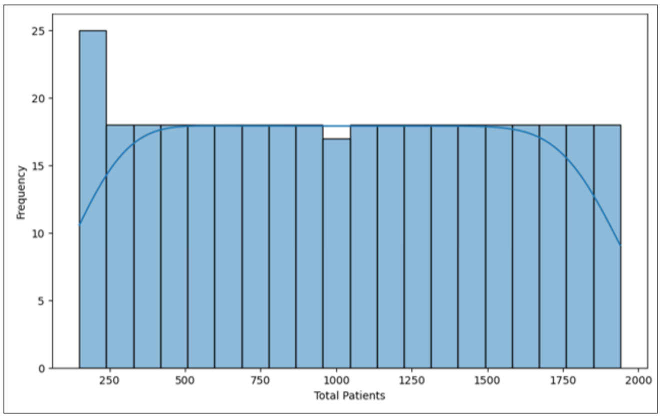


**Figure 9:** Distribution of Total Patients

A histogram displays the distribution of 'Total Patients' observed across the dataset which is shown in the above figure. Here this figure shows the x-axis contains the "total_patients" and the y-axis contains frequency. It highlights the frequency of different patient volume levels, shedding light on the typical range and variance inpatient admissions [22].

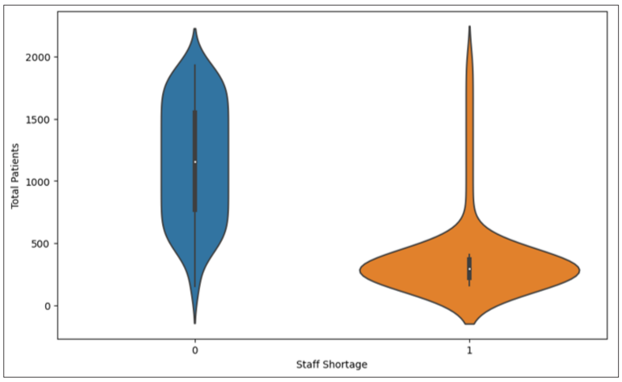


**Figure 10:** Violin plot of Total Patients by Staff Shortage

The above figure shows a violin plot showcasing the distribution of 'Total Patients' categorized by 'Staff Shortage.' The x-axis indicates the staff_shoratge and the y-axis indicates the toatl_patients. This visualization offers a comparative view of patient volumes during periods of sufficient staff versus shortages, revealing potential correlations between staffing levels and patient influx.

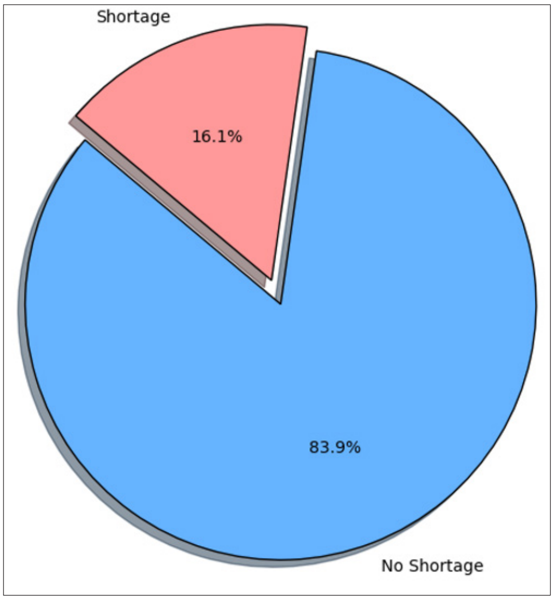


**Figure 11:** Pie Chart of Staff Shortage

The pie chart illustrates the proportion of days with 'No Shortage' and 'Shortage' of staff within the healthcare facility. It reveals that 83.9% of the days experience no shortage, while 16.1% face a shortage. This visual representation emphasizes the significant disparity in staff availability, highlighting the prevalence of adequately staffed days versus those with shortages.

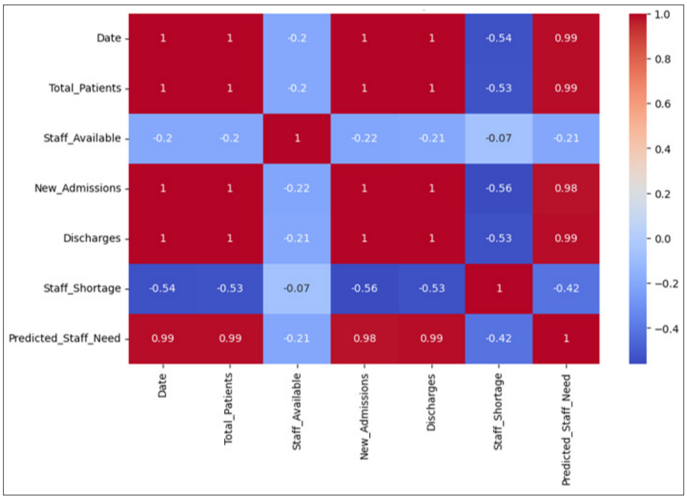


**Figure 12:** Correlation Heatmap

The correlation heatmap displays the relationships between various features in the dataset, such as 'Total Patients,' 'Staff Available,' 'New Admissions,' 'Discharges,' and 'Predicted Staff Need.' Strong positive and negative correlations are indicated by red and blue hues, respectively [23]. This visualization aids in identifying which variables are closely related, informing feature selection and understanding the interplay between different metrics in healthcare workforce management.

```
Accuracy Score: 0.9636363636363636
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.97      0.98        93
           1       0.84      0.94      0.89        17

    accuracy                           0.96       110
   macro avg       0.92      0.95      0.93       110
weighted avg       0.97      0.96      0.96       110
```

**Figure 13:** Accuracy and Classification Report of the LR Model

The Logistic Regression (LR) model achieves an accuracy score of 0.96. The classification report provides detailed metrics: precision of 0.99 for 'No Shortage' and 0.84 for 'Shortage,' recall of 0.97 for 'No Shortage' and 0.94 for 'Shortage,' and F1-scores of 0.98 and 0.89, respectively.

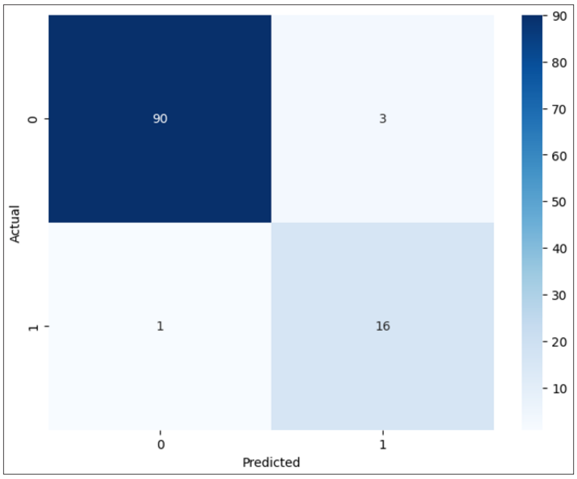


**Figure 14:** Confusion Matrix of the LR model

The confusion matrix for the Logistic Regression model gives a total of 110 instances, 90 of 'No Shortage' and 16 of 'Shortage' correctly classified and 3 of 'No shortage' and 1 of 'Shortage' misclassified. This sorts out the model's accuracy and error visually as within this matrix.

```
Accuracy Score: 0.9727272727272728
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.97      0.98        93
           1       0.85      1.00      0.92        17

    accuracy                           0.97       110
   macro avg       0.93      0.98      0.95       110
weighted avg       0.98      0.97      0.97       110
```

**Figure 15:** Accuracy and Classification report of the DT model

The accuracy score obtained by the Decision Tree (DT) model is 0. 97. Moving to the classification report, observations reveal a precision of 1. 00 for 'No Shortage' and 0. and 85 for 'Shortage,' recall of 0. 97 and 1. 00 for Precisions and F1-scores of 0. 98 and 0. 92, respectively. These results show good accuracy and repeatability of the proposed DT model in the classification of instances.

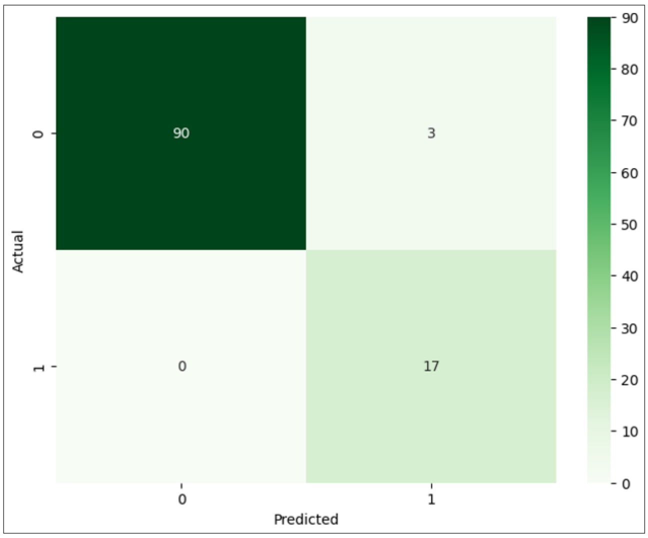


**Figure 16:** Confusion matrix of the DT model

The confusion matrix for the Decision Tree model shows that it correctly classifies 90 'No Shortage' and 17 'Shortage' instances out of 110, with only 3 misclassifications (all 'No Shortage').

```
Accuracy Score: 0.9818181818181818
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99        93
           1       0.89      1.00      0.94        17

    accuracy                           0.98       110
   macro avg       0.95      0.99      0.97       110
weighted avg       0.98      0.98      0.98       110
```

**Figure 17:** Accuracy and Classification report of the RF Model

The Random Forest (RF) model proposed has a mean accuracy score of = 0. 98. Looking at the results provided in the classification report, the model has an accuracy of 1. To execute this perspective, current (00 for 'No Shortage') and future 0. For the 'Shortage' reflection, the largest number is 89, while the recall is 0. 98 and 1. 00 and F1-scores of 0. 99 and 0. 94. Hence, these metrics reveal that the RF model is highly accurate in predicting staffing conditions [24].

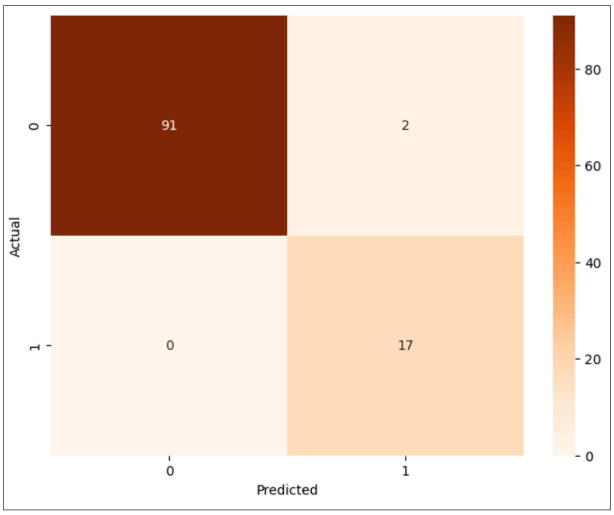


**Figure 18:** Confusion matrix of the RF Model

This matrix demonstrates the effectiveness of the model, and the ability to better navigate the complexity of the datasets and make fewer mistakes in classification. The confusion matrix, for the Random Forest model reveals that out of 110 instances, 91 instances are correctly classified as 'No Shortage' while 17 are classified as 'Shortage' with only 2 misclassifications, all being of the class 'No Shortage'.

```
Accuracy Score: 0.9545454545454546
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.96      0.97        93
           1       0.80      0.94      0.86        17

    accuracy                           0.95       110
   macro avg       0.89      0.95      0.92       110
weighted avg       0.96      0.95      0.96       110
```

**Figure 19:** Accuracy and Classification Report of the SVM Model

The Support Vector Machine (SVM) model achieves an accuracy score of 0.95 which is shown in the above figure. The classification report reveals a precision of 0.99 for 'No Shortage' and 0.80 for 'Shortage,' recall of 0.96 and 0.94, and F1-scores of 0.97 and 0.86.

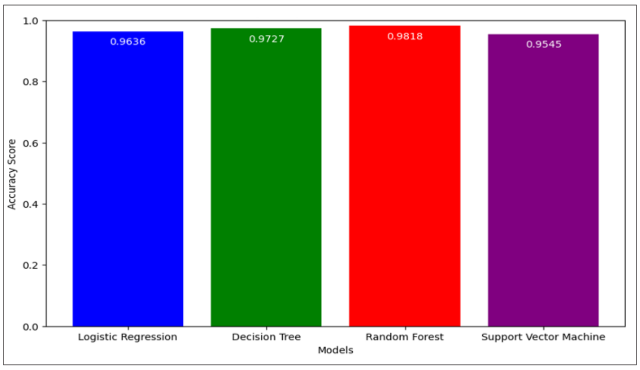


**Figure 20:** Accuracy Comparison of Each Model

The accuracy comparison chart showcases the performance of Logistic Regression (0.96), Decision Tree (0.97), Random Forest (0.98), and Support Vector Machine (0.95). The Random Forest model outperforms the others, followed closely by the Decision Tree and Logistic Regression models, with the Support Vector Machine model showing robust but slightly lower accuracy.

## Discussion

This study highlights the models demonstrate varying degrees of accuracy in predicting staff shortages. The Random Forest model outperforms the with a 0.98 accuracy score, the Decision Tree at 0.97, the Logistic Regression at 0.96, and the Support Vector Machine at 0.95. The classification metrics and confusion matrices validate their reliability in practical applications. Here in this study random forest classifier gives the highest accuracy among the other model

**Table 2: Accuracy Table**

| Model | Accuracy Score |
|---|---|
| Logistic Regression | 0.96 |
| Decision Tree | 0.97 |
| Random Forest | 0.98 |
| Support Vector Machine | 0.95 |

## Conclusion

The study shows the effectiveness of implementing machine learning models for improving healthcare workforce management as the models can help predict staff deficits. The Random Forest model demonstrates superior performance with an accuracy score of 0.98, followed closely by the Decision Tree at 0.97, Logistic Regression at 0.96, and Support Vector Machine at 0.95. These models provide robust predictive capabilities, essential for dynamic and efficient workforce management. This paper recommends healthcare facilities embrace the adoption and implementation of machine learning-based workforce management in staff scheduling, design, and operations. Future research should focus on issues such as the incorporation of real-time data and fine-tuning of the algorithms used in the constructed model for increasing accuracy and optimizing model performance in rapidly changing healthcare contexts.

The result highlights the possibility of applying machine learning to enhance. The strategic management of the healthcare workforce systems with a focus on staffing factors in the context of a challenging healthcare sector. Future studies should examine ways to improve the used models and examine how these models must be implemented in other healthcare contexts to ensure increased viability of utilizing the proposed models.

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