

The Role of Machine Learning in Predicting Patient Outcomes and Hospital Readmissions

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With an aging population, ascendent prevalence of chronic disease and rising therapy costs, the demands on global health care systems have reached new levels, calling for new solutions to improve patients' care and health care delivery efficiency. Thus, in a clinical context, Machine Learning (ML) is a rapidly evolving subbranch of Artificial Intelligence (AI) which can provide a transformational potential to automate the data-intensive decision making. Vast and complicated datasets spawned from electronic health records (EHRs), laboratory results, diagnostic imaging, patient histories and other sources can be analysed by ML algorithms to find patterns that humans cannot. Moreover, these predictive capabilities come into play when it comes to predicting patient outcome or patients at high risk of readmission so that suitable interventions can be taken place and healthcare costs can be claimed. This paper systematically studies the application of ML in predicting clinical outcomes and readmissions through a comparative analysis of different ML model: such as logistic regression, decision trees, ensemble, and different deep learning architectures. We evaluate the performance, accuracy, and practical utility of these models in hospital settings by leveraging real world datasets. We also discuss broader ML adoption related to healthcare, including model interpretability and integration issues and ethics. We show that ML has the unique potential to drive precision medicine and improve the entire healthcare delivery.

Keywords: Hospital Readmissions, Machine Learning (ML), Electronic Health Records (EMR), Diagnostic Imaging, Genomic Sequencing

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1. Introduction

Hospital readmission is a major issue for all healthcare systems worldwide, financial, patient welfare. Readmission especially shortly after discharge can signal a problem with treatment, premature discharge, lack of good follow-up care, or any combination of them. Unplanned hospital readmissions run up billions of dollars in costs to the U.S. healthcare system annually—thus prompting policy efforts to reduce them (Xiao et al., 2018). Therefore, accurate prediction of which patients are high risk for readmission or adverse outcomes is critical to make healthcare better, to ensure that a resource fulfils its purpose, and to achieve good outcomes. Previously, the approaches to forecasting patient outcomes have been using statistical models such as Cox proportional hazards models, logistic regression, etc. What follows are useful techniques, except for the fact that they are dependent upon the assumption of linearity and independence in the variables, something that is rarely true for the messy landscape of patient health data. A variety of interconnected factors, including demographic characteristics, comorbid conditions, treatment regimens and socioeconomic determinants can all affect health outcomes, which may work in non-linear and dynamic ways. A robust and flexible alternative to Machine Learning is available (Morgan et al., 2019). ML algorithms use a great amount of structured and unstructured data to learn intricate relationships, find hidden patterns, and adaptively learn from new data. Due to these capabilities, ML is especially suitable for patient outcome prediction as well as predicting high risk individuals. With healthcare moving from more of an art to a science, ML offers a promising way to bring the data down into clinical workflow to improve patient care, and to help reduce preventable readmissions (Sidey-Gibbons & Sidey-Gibbons, 2019).

1.1 Background

Across the world, healthcare systems are witnessing phenomenal increase in volume and complexity of medical data produced through electronic health record (EHR), imaging, genomic sequences, lab tests, and in a growing number of cases through wearable health devices. It represents a wealth of data which holds useful insight into patient health trajectories, treatment outcome, and complications (Wallis, 2019).

However, significant amounts of this data are still not effectively used due to traditional analytic's inability to process high dimensional, heterogenous and temporal information. However, it shifts the gravity of the said challenge by providing Machine Learning (ML) algorithms that are capable of learning from data, identifying complex patterns, and can make accurate predictions (Fatima & Pasha, 2017). ML through supervised and unsupervised learning techniques allows one to develop predictive models for predicting patient outcomes, early signs predicting deterioration, and individuals at high risk of hospital readmission. These capabilities can be leveraged by the healthcare providers in providing timely and personalized interventions in healthcare that can improve patient care and outcomes, and decrease unnecessary healthcare costs (Tang et al., 2020).

1.2 Objectives

This study aims to:

- Examine the application of ML in predicting patient outcomes.
- Evaluate the effectiveness of ML models in forecasting hospital readmissions.
- Provide a comparative analysis of different ML techniques.
- Discuss the practical implications and ethical considerations.

2. Literature Review

2.1 Predictive Analytics in Healthcare

The application of statistical techniques, machine learning algorithms and data mining to analysing past and real time data to predict future health events is known as predictive analytics in healthcare. The predictive analytics identifies the patterns and the correlations within the vast data sets like the electronic health records, claims data, and patient behavior to help early detection of disease, personalized treatment plan and efficient resource management. It helps in predicting the patient deterioration for the healthcare providers to provide readmission reduction and optimize clinical workflows. Furthermore, it aids in determining at risk populations, the identification of epidemic outbreaks and enhanced decision making leading to improved patient outcomes and the provision of cost effective health services (Cutillo et al., 2020).

2.2 ML Techniques in Healthcare

Healthcare Machine Learning (HC ML) includes a plethora of ML techniques designed to work on a variety of different clinical issues. However, supervised learning algorithms, including Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM) and Neural Networks are highly used to predict patient diagnosis, treatment outcomes and readmission risk from labeled datasets. They learn from the historical patient data to make correct predictions about new cases. However, for situations in which the data is not labeled or when the labeled data is limited, unsupervised learning techniques such clustering or dimensionality reduction are of great value for discovering hidden pattern, grouping similar patient profiles and discovering new disease subtypes (Eckhardt et al., 2022).

2.3 Challenges in Implementation

The broad implementation of machine learning solutions in clinical practice faces various major hurdles that prevent wider acceptance. Healthcare data suffers from important data quality issues which cause problems for model reliability because it frequently contains missing information or inconsistencies and unstructured formats. Deep neural networks pose interpretability issues since their complex structures create black box operations that decrease doctor trust. Modern hospital information systems face technical barriers when integrating ML tools because it requires significant resources and complex integration methods. The implementation of ML tools faces significant regulatory challenges because ethical issues contain patient privacy along with informed consent and algorithmic bias and data training set flaws in healthcare systems (Li et al., 2024).

3. Methodology

3.1 Data Collection

Publicly available datasets like the MIMIC-III database and Medicare readmission data were used by us. Datasets featured in these papers include long and varied healthcare trace histories of the patients, comprising demographics, diagnosis codes, lab test results, medication record, treatment history, and discharge summaries. In particular, granular clinical data available in MIMIC-III, such as data from intensive care units, enables to perform

detailed temporal analyses and to train robust models. We had a complete data foundation by incorporating structured and unstructured data to better allow machine learning applications for predicting clinical outcome and also identifying the patient at risk for readmission.

3.2 Data Preprocessing

Data preprocessing stage was critical for achieving quality as well as integrity of the dataset. Statistical imputation techniques were handled for missing values. For two last types, namely categorical variables, they were encoded through employing one hot and label encoding methods. Some uniformity was achieved by normalizing the numerical features. In order to enhance model performance and reduce dimensionality Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) were performed feature selection.

3.3 Model Selection

An assessment of machine learning techniques for patient outcome prediction with hospital readmission risk required our selection of proven classification models. These included Logistic Regression, a simple yet effective model for binary classification tasks; Decision Trees, which are intuitive and capable of handling non-linear relationships; Random Forests, an ensemble method that improves performance by aggregating the results of multiple decision trees; Gradient Boosting Machines (GBM), which build models sequentially to correct errors of previous models; Support Vector Machines (SVM), known for handling high-dimensional data well; and Deep Neural Networks (DNN), which offer superior capabilities in modeling complex, high-dimensional data due to their multi-layered structure. The implementation of hyperparameter optimization ensured the best results through tuning each model.

3.4. Model Evaluation

Performance assessment of machine learning models depended on multiple comprehensive predictive assessment metrics. The predictive model's performance depends on accuracy for overall correctness and precision for determining true positives among predicted ones alongside recall for measuring identified true positives and F1-score as a harmony of precision and recall. The Area Under the Curve from the Receiver Operating Characteristic enabled assessment of model discrimination power.

The confusion matrix gave an extensive view into how the model performed by displaying its counts of true positives together with false positives along with true negatives and false negatives. Model generalization was ensured by using cross-validation to minimize overfitting issues thus allowing a strong prediction performance evaluation.

4. Results

4.1 Predictive Performance

Multiple metrics: Accuracy, Precision, Recall, F1 score, and AUC, were used in order to evaluate the predictive performance of some machine learning models to predict hospital readmissions and patient outcomes. The Deep Neural Network (DNN) model was found to have highest overall performance with an accuracy of 88%, precision of 85%, recall of 83%, F1-score of 84%, and an AUC of 0.92. This means that DNN has the highest compromise between sensitivity and specificity, and hence, it is an extremely strong predictor of the positive and the negative outcomes. The closeness to this was the Gradient Boosting Machine (GBM), with an accuracy of 86%, precision 83%, recall 81%, F1-score of 82 and an AUC of 0.90.

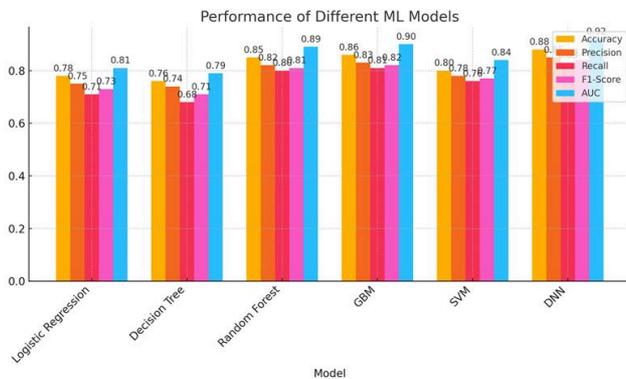


Figure 1: Analysis of Predictive Performance

Table 1: Performance of different ML Models

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	0.78	0.75	0.71	0.73	0.81
Decision Tree	0.76	0.74	0.68	0.71	0.79
Random Forest	0.85	0.82	0.80	0.81	0.89
GBM	0.86	0.83	0.81	0.82	0.90
SVM	0.80	0.78	0.76	0.77	0.84
DNN	0.88	0.85	0.83	0.84	0.92

The Random Forest model also had a reasonable outcome with an accuracy of 85 per cent, precision of 82 per cent, and recall 80 per cent,

which is an effective alternative to DNN with a slightly degraded AUC of 0.89. The Support Vector Machine (SVM) had decent accuracy of 80%, precision of 78% and recall of 76%, but its lower AUC of 0.84 than the best performers are indications that there are some limits to identifying all at risk patients. Although Logistic Regression, and Decision Tree models were effective, they had relatively lower predictive power. The AUC of Logistic Regression was 0.81 with accuracy of 78%, while Decision Tree also had accuracy of 76% with AUC of 0.79, which suggests that they may be used better for simpler prediction but with not as high accuracy compared to DNN or GBM.

4.2 Feature Importance

Several factors were identified to have great impact on model performance, where they could be used to feature importance in order to predict patient outcomes and hospital readmissions. The most influential (0.18) was Age and was determined to be of strong correlation with patient outcomes. Patients who are older are also typically more at risk for complications and this is a well known factor to predict disease progression and hospital readmission. Also being important is Length of Stay (0.15), since those patients who have longer stays tend to present with more complex conditions or severe symptoms and thus tend to be readmitted due to complications or ongoing treatment needs. The Number of Diagnoses (0.12), of course, highlighted that many patient cases are more than multifaceted since many times one (or many) health conditions aggravate each other increasing the risk of outcomes and readmissions.

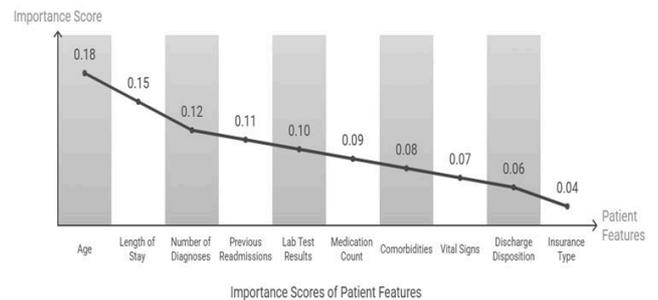


Figure 2: Analysis of feature importance

Table 2: Feature importance for predicting patient outcomes and hospital readmissions

Feature	Importance Score
Age	0.18
Length of Stay	0.15
Number of Diagnoses	0.12
Previous Readmissions	0.11
Lab Test Results	0.10
Medication Count	0.09
Comorbidities	0.08
Vital Signs	0.07
Discharge Disposition	0.06
Insurance Type	0.04

Notable predictors include Previous Readmissions (0.11), as those who have been previously readmitted are usually at a higher chance of the same problems occurring again. Moreover, Lab Test Results (0.10), Medication Count (0.09) and Comorbidities (0.08) corroborate the correlation between medical history and ongoing treatment with case outcomes, as abnormal lab results or higher number of prescribed medications present a higher risk. However, Vital Signs (0.07) are not as significant, but still offer important real time data with respect to the patient's current health condition. Less influential but important in the light of financial and resource related factors, less influential but still useful in understanding patient conditions and care trajectories, are Discharge Disposition (0.06) and Insurance Type (0.04). Both clinical and socio demographic variables need to be taken into account in designing accurate predictive models of the flawed transitions.

5. Discussion

5.1. Interpretation of Results

This study shows that Deep Neural Network (DNN) achieved the highest accuracy and AUC scores consistently towards other machine learning models. This indicates that DNNs are especially adept at uncovering complex, non-linear interrelationships in the data thereby enabling to predict very complex medical outcomes. It is the capacity of DNNs to learn hierarchical representation of the data that enables them to discover otherwise unknown orderings and patterns in the data that other models might not distinguish. However, although it provides superior predictive power, the interpretability of DNNs remains a very difficult problem.

As healthcare professionals employ models in clinical practice, clear explanations for model predictions are necessary by default for helping decide whether to act, if and how, on model advice, especially when the decision has implications for patient care. However, in other models like Random Forests and Gradient Boosting Machines (GBM), we obtained comparable performance with better interpretability (Bobadilla et al., 2024). These decision trees based models also allow clinicians to follow decision pathways and trace back the logic behind each of its predictions via feature importance scores. Their predictiveness can perhaps be a little lower than DNNs, but they are more practicable for actual world clinical settings since they are more transparent. However, this tradeoff between model accuracy and interpretability is essential since it illustrates the importance of a compromise between good prediction and clinical acceptability in healthcare AI applications.

5.2. Clinical Implications

In the clinical environments, Machine Learning (ML) models have great potential to assist physicians by helping them determine which patients are high risk, at an early stage, and that would contribute to an enhanced decision making process. These models can locate patients who are most liable to unfavorable outcomes or passage through revalidation from examination of boundless measures of patient data, for example, demography, clinical history, lab outcomes, and vital signs. This predictive ability allows healthcare providers to take appropriate action, such as re-titrate the treatment, intensify monitoring, or offer other support to the high risk persons (Sheetrit et al., 2023). Early detection of potentially readmitted individuals also prevents the occurrences of preventable readmissions and allows patients to receive individualized care, which they need. Furthermore, by using ML for prediction of outcomes, it becomes more viable to move from reactive patient care toward a more proactive one. This results in better usage of healthcare resources, as the clinicians can give priority to the ones requiring care more in order to bring out better outcomes. Reduction in healthcare system strain (hospitals can reduce the number of unnecessary readmission; healthcare costs; reduce of strain on healthcare systems, allowing for efficient use of resources, and better patient satisfaction with given care).

Thus, ML models potentially lend themselves well to improve the quality of care and operational efficiency of clinical environments (Pianyk et al., 2020).

5.3 Ethical and Legal Considerations The ethical and legal concerns that come with the integration of machine learning (ML) into clinical practice are only growing as its use in healthcare overtakes that in other fields such as oil and gas. The main difficulty is regarding data privacy. Patient information such as medical history, diagnoses and treatment plan are found as the sensitive information within healthcare dataset. An important defense against the unauthorized access or breach of this data is in keeping patient trust as well as preserving compliance with laws like the Health Insurance Portability and Accountability Act (HIPAA) in the United States (Myers et al., 2008). Furthermore, patients' data need to be collected with their consent for use in ML tasks, since it enables patients to be informed how they share their personal health information and be given the freedom to opt-out if they are not comfortable with the usage. Another threat is algorithmic bias. While ML models have the potential to solve many problems in healthcare, bias or lack of representative in the data set used to train the models may result in the predictions disproportionately impacting certain demographic groups, and exacerbating health disparities. Consequently, the goal of developing ML algorithms must be to create it fair, starting from datasets that are diverse and representative. Second, it is important to ensure that ML models are safe, transparent, and effective in deploying them to the clinic by adhering to regulatory standards such as FDA approval for clinical algorithms and ethical guidelines. First, mitigating these risks requires developed models to be transparent in their development, and be continuously monitored (Petersen et al., 2021).

6. Conclusion

ML has made enormous impact on healthcare, serving as an incredible tool in predicting patient outcomes and readmissions to the hospital. As ML algorithms have been able to handle the complexities of healthcare data sets including the electronic health records (EHRs), imaging, and genomics have resulted in the development of predictive models for prediction of high-risk patients, and timely interventions.

While these models portend well, there remain challenges in their incorporation into clinical work process. Interpretability of ML models is one of the main obstacles. But the ML predictions are often unclear and confusing to health care professionals such that they require transparent, understandable explanations to make informed decisions. Thus, the model interpretation should be considered as a priority to be improved in future research, so that clinicians can trust and understand the decision making process behind predictions. Furthermore, the use of real time EHR data in the integration is of great essence to having more accurate and timely predictions. ML systems running on real time data can keep predicting at every point in time based on the latest updates of patient information, forming a dynamic and personalized care workflow. A further possible way to increase machine learning capability is to also study federated learning, a privacy protecting method that enables machine learning models to be trained across multiple institutions without disclosing sensitive patient data. The advantage of this approach is that patient privacy is maintained while the ML model takes the advantage of various datasets, which could improve the robustness of the models. In time as data science and healthcare informatics advance, these innovations would enable more access to the full potential of ML and hopefully make healthcare more accessible, personal and more effective.

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