

Article

Development and Evaluation of a Machine Learning Model for Predicting 30-Day Readmission in General Internal Medicine

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Abstract: Background/Objectives: Hospital readmissions within 30 days are a major challenge in general internal medicine (GIM), impacting patient outcomes and healthcare costs. This study aimed to develop and evaluate machine learning (ML) models for predicting 30-day readmissions in patients admitted under a GIM unit and to identify key predictors to guide targeted interventions. **Methods:** A prospective study was conducted on 443 patients admitted to the Unit of General Internal Medicine at Sultan Qaboos University Hospital between May and September 2023. Sixty-two variables were collected, including demographics, comorbidities, laboratory markers, vital signs, and medication data. Data preprocessing included handling missing values, standardizing continuous variables, and applying one-hot encoding to categorical variables. Four ML models—logistic regression, random forest, gradient boosting, and support vector machine (SVM)—were trained and evaluated. An ensemble model combining soft voting and weighted voting was developed to enhance performance, particularly recall. **Results:** The overall 30-day readmission rate was 14.2%. Among all models, logistic regression had the highest clinical relevance due to its balanced recall (70.6%) and area under the curve (AUC = 0.735). While random forest and SVM models showed higher precision, they had lower recall compared to logistic regression. The ensemble model improved recall to 70.6% through adjusted thresholds and model weighting, though precision declined. The most significant predictors of readmission included length of hospital stay, weight, age, number of medications, and abnormalities in liver enzymes. **Conclusions:** ML models, particularly ensemble approaches, can effectively predict 30-day readmissions in GIM patients. Tailored interventions using key predictors may help reduce readmission rates, although model calibration is essential to optimize performance trade-offs.

Keywords: general internal medicine; readmission; machine learning; ensemble model; predictive analytics; Oman



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1. Introduction

Hospital admission for general internal medicine (GIM) patients has been a cornerstone of the GIM specialty [1]. Hospital readmission is considered an adverse event and is associated with increased patient death and healthcare costs [1–3]. These admissions account for a significant number of emergency department admissions and hospital bed days [4].

Many studies have identified predictors of hospital readmission for GIM patients. The following patient factors are associated with an increased risk of hospital readmission: old age [5], sex [5], marital status [5], substance abuse [5], smoking [6], number of comorbidities [5], polypharmacy [5], length of hospital stay [7] poor functional ability [8,9], frailty [10], discharge against medical advice [11], recent hospitalization [12], active malignancy [13], cognitive dysfunction [14], hyponatremia, primary diagnoses (e.g., heart failure, renal failure) [6,15], specific comorbidities (heart failure, COPD, dementia, diabetes, atrial fibrillation, hypertension, dyslipidemia, and anemia) [6,15], C-reactive protein (CRP) [16], hemoglobin on discharge [17–19], sodium level on discharge [17], chloride level on discharge [20], inpatient glycemic control [21,22], heart rate on discharge [18,23], systolic blood pressure on discharge [24], respiratory rate on discharge [2–4,25]. Additionally, certain diagnoses, including cardiovascular diseases, pulmonary diseases, and malignancy, are associated with an increased risk of hospital readmission [1]. Several system-related factors are also identified as predictors of hospital readmission, including the availability of inpatient or outpatient services [5], incomplete discharge summaries, failure to relay important information to outpatient healthcare [26], an inability to keep appointments after discharge, high workloads, a lack of adequate post-discharge follow-up, and unstable therapy at discharge [1]. Also, certain interventions, including patient education, medication rationalization, multidisciplinary care, home visits, and early follow-up, are associated with a reduced risk of admission [3,27]. However, the indiscriminate implementation of effective discharge interventions for all hospitalized patients is time-consuming and expensive [28].

Predicting the risk of readmission helps guide healthcare providers to target the delivery of transitional care interventions to patients at the highest risk of readmission [29]. Several prediction models using various patient information points have been developed in different healthcare settings across the globe [17,29]. Donzé et al. developed the HOSPITAL score, which is based on seven independent factors (hemoglobin on discharge [30], discharge from oncology service, sodium level on discharge, procedure during admission, length of hospital stay, number of admissions in the last 12 months, and index type of admission) to predict the risk of 30-day hospital readmission [17]. The LACE index is a popular risk assessment tool to predict 30-day hospital readmission. It is based on four components: length of stay, acuity of admission, Charlson Comorbidity Index, and the number of visits to the emergency department in the past six months [2]. Similarly, other models rely mainly on clinical data to stratify the risk of hospital readmissions [29]. Validation studies showed that most readmission risk prediction models have a poor discriminating ability to predict 30-day hospital readmission in many subgroups of patients, and adding social or functional variables may improve overall performance [2,9,31–33]. Fortunately, the widespread use of electronic health records provides a vast amount of patient data that could lead to more precise predictions of future readmissions [34]. Many models using Machine Learning (ML) have been developed to predict the risk of hospital readmission and have yielded promising results; however, it is very important to recognize that the performance of readmission risk models varies tremendously between different patient populations across different healthcare settings [34].

The estimated annual population growth is 9% in Oman, making it one of the most rapidly growing populations worldwide. According to a recent Ministry of Health report,

there are 15.6 hospital beds available for every 10,000 individuals compared with 28.7 beds for every 10,000 people in the USA [35]. In a tertiary care setting in Oman, GIM receives between 70 and 80% of medical patients admitted through the emergency department [35]. A study from Oman showed that the rate of hospital readmission of GIM patients was 24%, and factors including old age, the length of hospital stay, the presence of ≥ 3 comorbidities, and poor functional status were associated with an increased risk of readmission [3].

Previous prediction models focused on a single disease or a specific patient population, limiting their generalizability to our local healthcare settings. By implementing ML using patient data extracted from electronic health records, a readmission risk prediction model for GIM that is more relevant to Oman can be created. Achieving high precision in predicting the readmission risk will enable the healthcare system to prioritize transitional and follow-up interventions to target high-risk patients, improving their health outcomes and minimizing healthcare costs associated with unplanned hospital readmission. The objective of the study is to build a reliable model with high precision using ML to predict all-cause 30-day readmission risk for GIM patients.

2. Materials and Methods

2.1. Study Setting

The study prospectively included patients admitted under the care of the GIM Unit at Sultan Qaboos University Hospital (SQUH) between 1 May 2023 and 30 September 2023. SQUH is a 500-bed multispecialty tertiary referral hospital with several unique services and certain specialized medical facilities. The General Internal Medicine Unit receives around 70–80% of medical patients admitted through the Emergency Department. The range of patients varies between those with a single organ system disease, such as pneumonia, and those with complex diseases or undifferentiated illnesses [35]. Inclusion criteria include patients admitted under the care of the GIM Unit, aged 18 years and older. Exclusion criteria consist of elective admissions, the loss of follow-up, inpatient deaths, and deaths occurring less than 30 days after discharge. The study was approved by the Medical and Research Ethics Committee of the College of Medicine and Health Sciences, Sultan Qaboos University, Muscat, Oman (REF. NO. SQU-EC/125/2023, MREC #3005; dated 24 May 2023). Written informed consent was obtained from all participants involved in the study or from next of kin in cases of impaired capacity.

2.2. Data Collection

Data were collected prospectively by trained research assistants and validated by healthcare providers for comprehension and accuracy to ensure data quality. Readmission outcomes were determined via electronic health records and phone follow-ups. The dataset includes continuous variables like weight, height, BMI, length of stay, and medications, as well as blood markers recorded at admission and discharge. In addition, relevant vitals including heart rate, respiratory rate, and blood pressure were recorded prior to hospital discharge. Categorical variables cover demographics and lifestyle factors, such as gender, marital status, education, substance use, and comorbidities. Lastly, treatment details include code status, ICU admission, ventilation use, inotropic support, and ICD-10 classification.

2.3. Data Analysis

Data analysis was conducted using Python version 3.12.7, packaged by Anaconda, Inc., in a Jupyter Notebook environment (version 7.2.2). The analysis workflow included data preprocessing steps such as handling missing values, scaling continuous variables, and encoding categorical variables.

2.4. Data Preprocessing

Continuous variables were imputed using median values for their robustness to outliers and skewed distributions. Categorical variables were imputed using mode values. Missing data were low in variables <10%. Missing data are due to factors such as the lack of non-routine lab orders (e.g., CRP) for some patients and documentation variability. Continuous variables were standardized to a mean of zero and unit variance, while categorical variables were transformed using one-hot encoding. This ensured comparability and improved model performance.

2.5. Data Training and Feature Selection

To prepare the data for model training and evaluation, we split the dataset into 80% training and 20% testing. We applied a preprocessing pipeline with imputation and scaling for continuous variables and imputation with one-hot encoding for categorical variables. The preprocessor was fitted on training data and used for transforming both datasets to ensure consistent preprocessing. After initial data preprocessing, we trained a random forest classifier to compute feature importance scores for all available predictors. Features were ranked according to their relative importance in the model. To balance predictive accuracy with model interpretability and avoid overfitting, the top 20 features were selected for final model training and evaluation.

2.6. Model Training and Hyperparameter Tuning, Handling Class Imbalance

Four machine learning algorithms were selected: logistic regression, random forest, gradient boosting, and support vector machine (SVM). These models represent diverse approaches, balancing linear modeling, ensemble learning, and margin-based classification. Logistic regression served as a baseline, random forest and gradient boosting captured non-linear interactions, and SVM offered strong regularization. Deep learning and advanced ensemble methods like XGBoost and CatBoost were not used due to the small sample size.

To address the imbalance between readmitted and non-readmitted cases (85.8%), we used several strategies: Class Weight Adjustment was applied to all models to give more importance to the minority class, reducing bias. Threshold Tuning involved testing different probability thresholds to optimize recall for readmitted cases. SMOTE was explored to generate synthetic examples for the minority class, improving recall in some models, but was not included in the final workflow due to lower generalizability. Extensive hyperparameter search methods (e.g., grid search) were deliberately avoided as preliminary testing indicated marginal performance improvement at the cost of increased risk of overfitting.

The evaluation of predictive models involved analyzing performance metrics across different probability thresholds. The logistic regression model was the primary focus, alongside random forest, gradient boosting, and Support Vector Machine (SVM).

Predicted probabilities for 30-day readmission were generated, and a custom function was implemented to compute metrics such as accuracy, precision, recall, F1 score, and area under the curve (AUC). The model was tested at thresholds of 0.3, 0.4, 0.5, and 0.6 to assess precision–recall trade-offs. At a 0.5 threshold, logistic regression was compared to other models, highlighting differences in performance metrics.

2.7. Ensemble Model for Predicting 30-Day Readmission

An ensemble model was developed to enhance 30-day readmission prediction using logistic regression, random forest, and SVM combined with soft voting. Logistic regression ensured convergence with balanced weights, random forest addressed class distribution with the same, and SVM used an RBF kernel with probability estimates. The ensemble averaged predicted probabilities and was initially trained on the top 20 selected features,

evaluated at a 0.5 threshold. To further optimize performance, a weighted voting classifier was created, giving more emphasis to logistic regression (weight = 2) compared to random forest and SVM (weights = 1 each). An adjusted threshold of 0.3 was then applied to improve recall, particularly in identifying positive cases. Model evaluation included accuracy, precision, recall, F1 score, and AUC, examining how the weighting scheme and lower threshold influenced the balance between precision and recall.

3. Results

A total of 443 patients were included in the study, while the dataset included 62 variables, 34 being continuous variables (Table 1) and 28 being categorical variables (Table 2).

Table 1. Demographics and clinical characteristics of the included cohort for the continuous variables (n = 443).

Variable (n = 443)	Median	Interquartile Range (IQR)
Age, years	63.0	32.0
Weight, kg	68.9	17.0
Height, m	1.61	0.1
Body mass index (BMI), Kg/m ²	26.6	6.7
Length of hospital stay hours	116.3	114.9
Number of regular medications	4.0	5.0
Laboratory investigations upon admission		
Glucose level, mmol/dL	8.0	5.7
Peak blood sugar level, mmol/L	10.0	7.9
Nadir peak blood sugar level, mmol/L	5.6	2.1
C-reactive protein (CRP), mmol/L	19.0	66.0
Vitamin B12, pg/mL	343.0	156.0
Haemoglobin, g/dL	12.0	3.1
Mean corpuscular volume (MCV), fL	76.7	14.0
Albumin, mmol/L	37.0	10.0
Alanine aminotransferase (ALT), U/L	18.5	23.5
Aspartate aminotransferase (AST), U/L	24.0	19.0
Alkaline phosphatase (ALP), U/L	91.0	46.0
Creatinine (Cr), mmol/L	88.0	52.0
Estimated glomerular filtration rate (eGFR), mL/min/1.73 m ²	82.0	36.0
Laboratory investigations upon discharge		
Haemoglobin, g/dL	11.0	3.1
Estimated glomerular filtration rate (eGFR), mL/min/1.73 m ²	84.0	32.5
Alanine aminotransferase (ALT), U/L	22.0	17.0
Aspartate aminotransferase (AST), U/L	24.0	14.0
Alkaline phosphatase (ALP), U/L	94.0	36.0
Albumin, mmol/L	35.0	8.0
Serum chloride, mEq/L	102.0	6.0

Table 1. *Cont.*

Variable (n = 443)	Median	Interquartile Range (IQR)
Serum sodium, mEq/L	137.0	4.0
Other vital signs upon discharge		
Systolic blood pressure, mmHg	126.0	21.0
Respiratory rate, rate per minute	18.0	2.0
Heart rate, beats per minute	80.0	17.0

Table 2. Demographics and clinical characteristics of the included cohort for the categorical variables (n = 443).

Variable (n = 443)	Frequency (%)
Woman	223 (50.3%)
Marital status	
Married	265 (59.8%)
Widowed	88 (19.9%)
Single	78 (17.6%)
Divorced	12 (2.7%)
Educational status	
Illiterate	171 (38.6%)
Below high school	92 (20.8%)
High school diploma	84 (19.0%)
Literate without formal schooling	56 (12.6%)
Bachelor and above	40 (9.0%)
Employment status	
Unemployed	279 (63.0%)
Retired	67 (15.1%)
Employed	63 (14.2%)
Others	34 (7.7%)
Functional status	
Independent	264 (59.6%)
Dependent	106 (23.9%)
Partially dependent	73 (16.5%)
Medical history and comorbidities	
Polypharmacy	195 (44.0%)
Substance abuse	12 (2.7%)
Active or past smoking history	60 (13.5%)
Alcohol drinking	42 (9.5%)
Hypertension	244 (55.1%)
Diabetes mellitus	191 (43.1%)
Chronic kidney disease	74 (16.7%)
Heart failure	60 (13.5%)
Atrial fibrillation	40 (9.0%)

Table 2. Cont.

Variable (n = 443)	Frequency (%)
Solid tumour	23 (5.2%)
Liver cirrhosis	11 (2.5%)
Dyslipidemia	135 (30.5%)
Anaemia	28 (6.3%)
Ischemic heart disease	75 (16.9%)
Dementia	22 (5.0%)
History of stroke or transient ischemic attacks	54 (12.2%)
Diagnosis classified according to ICD 10	
Diseases of the respiratory system	91 (20.5%)
Diseases of the circulatory system	58 (13.1%)
Certain infectious and parasitic diseases	56 (12.6%)
Endocrine, nutritional, and metabolic diseases	51 (11.5%)
Diseases of the nervous system	44 (9.9%)
Diseases of the digestive system	43 (9.7%)
Diseases of the genitourinary system	28 (6.3%)
Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism	20 (4.5%)
Others	52 (11.7%)
Hospitalization data	
Not for resuscitation	48 (10.8%)
Requires invasive mechanical ventilation	5 (1.1%)
Requires non-invasive ventilation	43(9.7%)
Use of vasopressor	18 (4.1%)
Admisison to HDU or ICU	46 (10.4%)
Left against medical advice	23 (5.2%)

ICD 10: the International Classification of Diseases, 10th Revision; HDU: High Dependency Unit; ICU: Intensive Care Unit.

Among the whole cohort, 223 (50.3%) were women, the median age was 63 years (IQR: 32), and the median BMI was 26.58 kg/m² (IQR: 6.65). The median length of stay was 116.33 h (IQR: 114.96), and the number of regular medications had a median of 4.0 (IQR: 5.0) (Table 1).

Most patients were married (n = 265, 59.8%), with 171 (38.6%) being illiterate and 279 (63.0%) unemployed. Regarding functional status, 264 (59.6%) were independent, 106 (23.9%) were dependent, and 73 (16.5%) were partially dependent. The most common comorbidities were hypertension (n = 244, 55.1%) and diabetes mellitus (n = 191, 43.1%). Diagnoses were categorized according to ICD-10, with diseases of the respiratory system being the most common (n = 91, 20.5%), followed by diseases of the circulatory system (n = 58, 13.1%) and infectious diseases (n = 56, 12.6%) (Table 2).

There were 63 (14.2%) patients who were readmitted within 30 days of hospital discharge.

Figure 1 illustrates the top features affecting the risk of readmission using a random forest classifier, and Table 3 and Figure 2 further provide information on the coefficients and their associated risks (increased or decreased). Reduced risk was associated with the length of hospital stay (importance: 0.040993), systolic blood pressure prior to discharge (impor-

tance: 0.039452), albumin levels on admission (importance: 0.034048) and discharge (importance: 0.029432), mean corpuscular volume (importance: 0.031286), hemoglobin levels on admission (importance: 0.023767), and ALT on discharge (importance: 0.025746). While increased risk of 30 days hospital readmission was linked to weight (importance: 0.038601), age (importance: 0.032036), number of regular medications (importance: 0.027527), AST on discharge (importance: 0.029085), ALT on admission (importance: 0.028759), heart rate prior to discharge (importance: 0.023112), and peak blood sugar level during admission (importance: 0.027610).

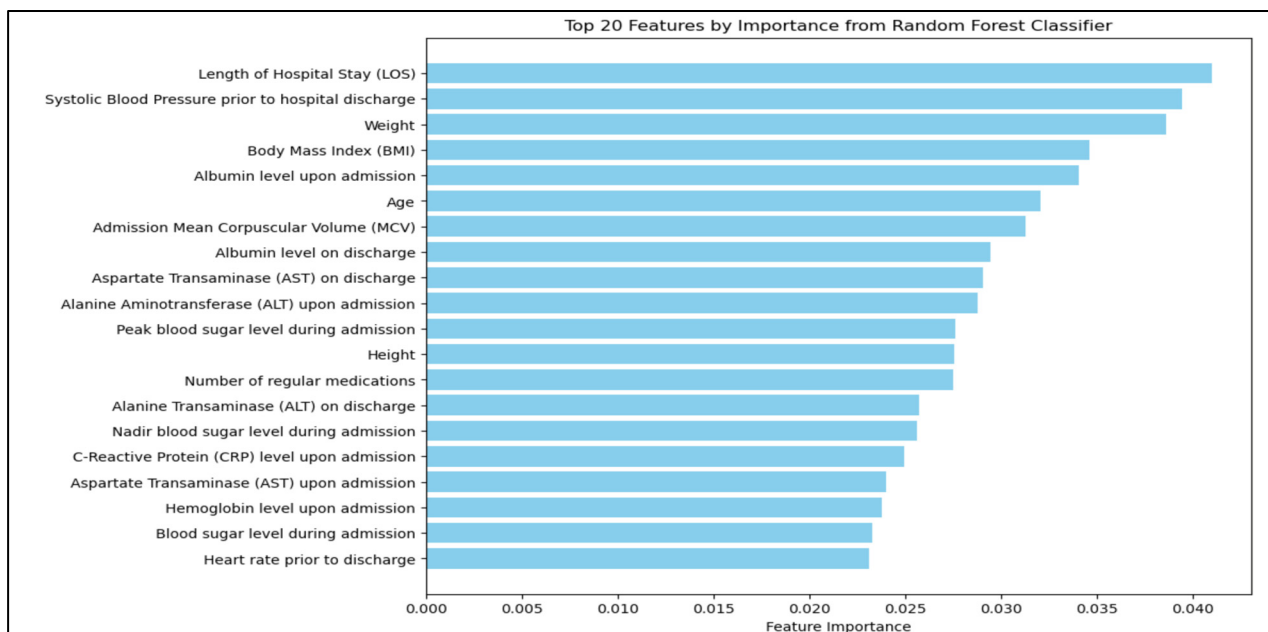


Figure 1. Top 20 features by importance from random forest classifier contributing to 30-day readmission.

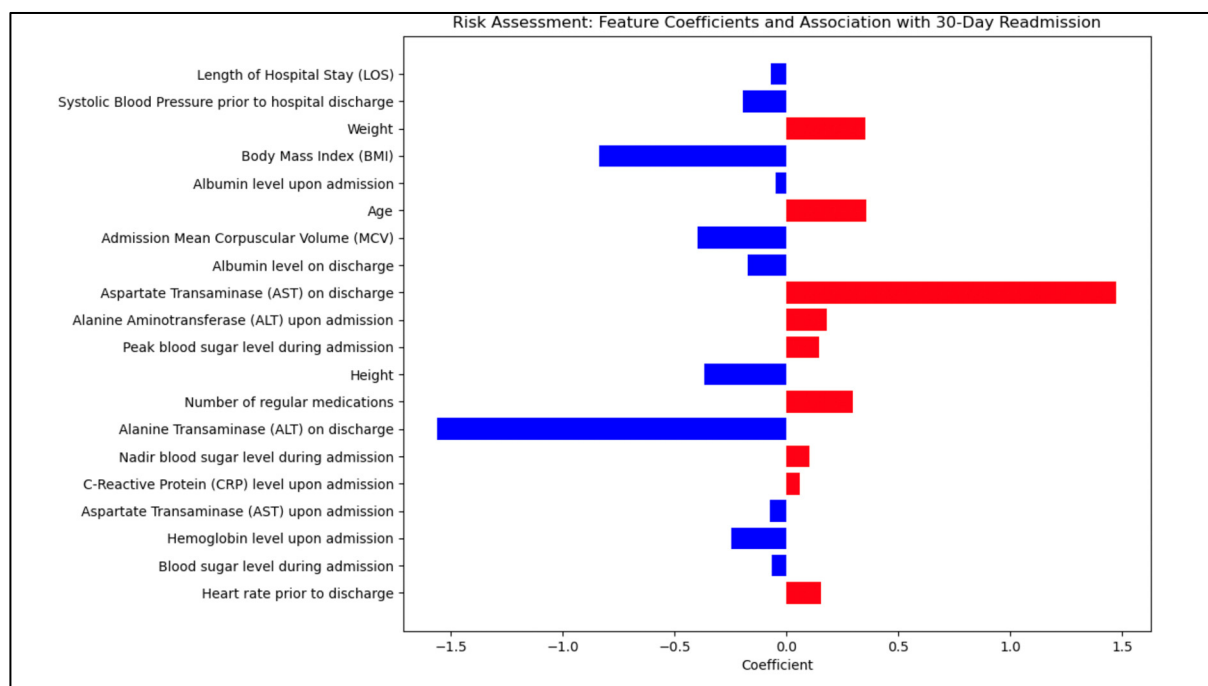


Figure 2. Risk assessment, feature coefficients, and association with 30-day readmission.

Table 3. The top 20 features by importance and their risk association.

Feature	Importance	Coefficient	Risk Association
Length of hospital stay (LOS)	0.040993	−0.071992	Reduced Risk
Systolic blood pressure prior to hospital discharge	0.039452	−0.193991	Reduced Risk
Weight	0.038601	0.352614	Increased Risk
Body mass index (BMI)	0.034642	−0.83929	Reduced Risk
Albumin level upon admission	0.034048	−0.049374	Reduced Risk
Age	0.032036	0.358211	Increased Risk
Admission mean corpuscular volume (MCV)	0.031286	−0.398924	Reduced Risk
Albumin level on discharge	0.029432	−0.175724	Reduced Risk
Aspartate transaminase (AST) on discharge	0.029085	1.475283	Increased Risk
Alanine aminotransferase (ALT) upon admission	0.028759	0.180201	Increased Risk
Peak blood sugar level during admission	0.027610	0.143536	Increased Risk
Height	0.027552	−0.36783	Reduced Risk
Number of regular medications	0.027527	0.297797	Increased Risk
Alanine transaminase (ALT) on discharge	0.025746	−1.562257	Reduced Risk
Nadir blood sugar level during admission	0.025628	0.101011	Increased Risk
C-reactive protein (CRP) level upon admission	0.024953	0.060043	Increased Risk
Aspartate transaminase (AST) upon admission	0.023982	−0.073751	Reduced Risk
Hemoglobin level upon admission	0.023767	−0.245768	Reduced Risk
Blood sugar level during admission	0.023307	−0.064745	Reduced Risk
Heart rate prior to discharge	0.023112	0.155211	Increased Risk

Table 4 presents the evaluation of the four models studied at a 0.5 threshold and shows varied performance in predicting 30-day readmissions. Logistic regression achieved an accuracy of 71.9%, with balanced recall (70.6%) but lower precision (0.375), resulting in an F1 score of 0.49. It performed well for non-readmissions (precision: 0.91, F1 score: 0.81) but struggled with readmissions (precision: 0.38, F1 score: 0.49), with an AUC of 0.735. Random forest had high accuracy (80.9%) and perfect precision (1.0) but no recall for readmissions, leading to an F1 score of 0.0 for that class. It performed perfectly for non-readmissions (recall: 100%, F1 score: 0.89) but had an AUC of 0.654, indicating limited discriminative ability. Gradient boosting achieved the highest accuracy (82.0%) but had very low recall for readmissions (11.8%), yielding an F1 score of 0.20. It performed well for non-readmissions (precision: 0.83, recall: 99%, F1 score: 0.90), with an AUC of 0.560. SVM also had high accuracy (80.9%) and perfect precision but no recall for readmissions, resulting in an F1

score of 0.0 for that class. It showed perfect recall for non-readmissions (100%, F1 score: 0.89), with an AUC of 0.655.

Table 4. Side comparison of the performance metrics for each model, highlighting the differences in precision, recall, F1 score, and AUC.

Model	Threshold	Accuracy (%)	Precision (Overall)	Recall (Overall)	F1 Score (Overall)	AUC
Logistic Regression	0.50	71.90	0.38	70.59	0.49	0.73
Random Forest	0.50	80.90	1.00	0.00	0.00	0.65
Gradient Boosting	0.50	82.00	0.67	11.76	0.20	0.56
Support Vector Machine	0.50	80.90	1.00	0.00	0.00	0.66

Lastly, Table 5 summarizes the performance metrics for the models using two thresholds, 0.3 and 0.5. The weighted ensemble model at a 0.3 threshold demonstrated improved recall (70.6%) for identifying readmissions but at the expense of lower precision (33.3%) and an overall accuracy of 67.4%. The F1 score for class 1 (readmissions) was 0.45, and the model achieved an AUC of 0.734, indicating moderate discriminative ability. In contrast, the ensemble model at a 0.5 threshold achieved higher overall accuracy (80.9%) and perfect precision (1.0) but failed to identify any positive cases, resulting in a recall of 0.0% and an F1 score of 0.0 for class 1. The AUC was 0.730, like the weighted model, but the model showed an extreme imbalance in predicting readmissions.

Table 5. Summary of the performance metrics for both the weighted ensemble model at a 0.3 threshold and the ensemble model at a 0.5 threshold.

Metric	Weighted Ensemble (Threshold 0.3)	Ensemble (Threshold 0.5)
Accuracy	67.4%	80.9%
Precision (Overall)	0.33	1.0
Recall (Overall)	70.6%	0.0%
F1 Score (Overall)	0.45	0.0
AUC	0.734	0.730
Class 0 Precision	0.91	0.81
Class 0 Recall	67%	100%
Class 0 F1 Score	0.77	0.89
Class 1 Precision	0.33	1.0
Class 1 Recall	71%	0.0%
Class 1 F1 Score	0.45	0.0
Macro Avg F1 Score	0.61	0.45
Weighted Avg F1 Score	0.71	0.72
Support (Total Cases)	89	89

4. Discussion

This study demonstrates the feasibility and reliability of developing a comprehensive model to predict key risk factors for 30-day hospital readmission for patients admitted to GIM units using ML for prospectively collected data that included a wide range of diagnoses and laboratory data. The study was able to evaluate the predictive models involved by analyzing performance metrics across different probability thresholds.

The rate of 30-day readmission was 14.2%, which has improved from the previously reported rate for GIM in our care setting (24%) [3]. This improvement could be attributed to the exclusion of patients who died within 30 days and improvements in the care of general medicine, including better discharge planning and improved follow-up in the medicine OPD clinic. Also, our rate of 30-day hospital readmission is less than the previously reported readmission rate for general medicine patients in other healthcare settings [30,36].

As reported in prior studies, older age, polypharmacy, and comorbid conditions have consistently emerged as strong predictors of hospital readmission [5,6,15]. Similarly, in our analysis, age and the number of regular medications were both significantly associated with increased readmission risk. These findings emphasize the vulnerability of elderly patients with multiple comorbidities and the potential impact of medication burden on readmission rates. The association between polypharmacy and readmissions highlights the need for careful medication management and efforts to deprescribe, particularly during transitions of care [37]. The length of hospital stay was a key predictor of readmission risk [7]. In our study, the length of hospital stay was highlighted by the random forest classifier and was linked to a reduced risk of readmission. This might be because longer stays allow more thorough treatment, reducing early readmissions, while shorter stays might result in higher risk due to unresolved issues or inadequate follow-up. This emphasizes the importance of effective discharge planning and post-discharge support, particularly for patients with shorter stays.

Systolic blood pressure (SBP) prior to discharge and heart rate are vital signs that reflect cardiovascular stability. Our study found that lower SBP and higher heart rate were associated with increased readmission risk, consistent with previous research indicating that hemodynamic instability is a risk factor for adverse outcomes post-discharge [38,39].

Similarly, CRP, a marker of inflammation, was associated with increased readmission risk, and previous studies demonstrated that elevated CRP levels are generally associated with an increased risk of readmission across various conditions, including cirrhosis, ICU patients, heart failure, and post-surgical patients [40,41].

Low albumin levels at both admission and discharge were linked to a reduced risk of readmission in our study. Low serum albumin levels are a strong and consistent predictor of hospital readmission across various patient groups and medical conditions [42,43]. Also, hemoglobin levels on admission were associated with a reduced risk of readmission, aligning with studies that have shown an inverse relationship between anemia and adverse outcomes [44,45].

Liver function tests, including alanine aminotransferase (ALT) and aspartate aminotransferase (AST), were also significant predictors. Elevated AST levels on discharge were associated with an increased risk of readmission, while higher ALT levels were linked to a reduced risk. Liver enzyme abnormalities may indicate underlying hepatic dysfunction or systemic inflammation, potentially leading to complications post-discharge. A prior study found that low blood ALT activity was associated with an increased score of frailty in internal medicine patients [46]. The differential impact of ALT and AST highlights the need for a nuanced understanding of liver function in predicting patient outcomes.

ML models can effectively predict hospital readmissions, but their performance varies among patient populations and healthcare settings. These models are often trained on

specific patient groups with certain diseases. However, some studies showed that general, disease-independent ML models can accurately predict unplanned hospital readmissions. This approach could reduce the cost of developing and deploying ML models in clinical practice by utilizing a single, versatile model [47,48]. In our study, logistic regression provided a more balanced approach between precision and recall compared to other models such as random forest, gradient boosting, and SVM. While random forest and SVM achieved high accuracy and precision, they failed to identify positive cases, resulting in poor recall. Gradient boosting had the highest accuracy but struggled with recall, highlighting the challenge of developing models that perform well across multiple metrics.

To improve the performance of individual ML models, we used the ensemble approach, which combines multiple models for more accurate predictions than any single model. By aggregating predictions, ensembles enhance performance, improve generalization, and reduce overfitting, leveraging model diversity [49]. Techniques include hard voting (selecting the majority class) and soft voting (averaging class probabilities). Models may also be weighted based on performance [50]. Previous studies have shown that the ensemble approach improves prediction performance in clinical medicine [51]. The ensemble combined logistic regression, random forest, and SVM, showing potential to improve prediction performance. By adjusting thresholds and weighting schemes, we optimized recall, crucial for identifying patients at high risk of readmission. The weighted ensemble model at a 0.3 threshold improved recall for readmissions, though with reduced precision.

At high decision thresholds, ensemble models can underperform in recall compared to single models. This is because ensembles often prioritize precision or balanced performance, limiting their ability to capture all true positives. They may become more conservative, filtering out potential positives to avoid false positives, which reduces recall. When operating at high thresholds, ensembles may only classify positives if most base models agree, missing true positives detected by only some models [52,53].

Our findings have important implications for clinical practice and healthcare policy. Accurate prediction of readmission risk can assist healthcare providers in prioritizing high-risk patients for targeted interventions such as medication reconciliation, early follow-up appointments, enhanced patient education, and the provision of home-based services. The context of our study is particularly relevant to Oman, where the healthcare system is navigating the dual challenges of a rapidly growing population and limited hospital bed capacity. Tailored strategies to reduce hospital readmissions are urgently needed to optimize patient outcomes and healthcare resource utilization. Furthermore, the integration of electronic health records and machine learning presents a valuable opportunity to advance predictive modeling capabilities, enabling better-informed decisions around intervention planning and resource allocation [48,54].

Several limitations of our study should be acknowledged. First, the relatively small sample size and single-center design may limit the generalizability and discriminative ability of the findings. Additionally, although our model included a wide range of clinical variables, the absence of social determinants of health may have affected its performance. Future studies should incorporate these factors. Our models showed promising internal performance, but external validation with independent datasets was not conducted due to the single-center dataset. Future research will focus on validating and recalibrating the models across various institutions and patient populations for broader applicability and clinical robustness.

5. Conclusions

This study highlights the potential of ML to predict 30-day hospital readmissions for GIM patients. While the studied models identified key clinical predictors, their performance

emphasizes the need for further refinement and validation. Implementing such models in clinical practice could improve patient healthcare outcomes, but careful consideration of local context and patient population is essential. As healthcare systems continue to evolve, leveraging data-driven approaches will be crucial in enhancing patient outcomes and optimizing resource utilization.

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