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Machine Learning Models Predicting Hospital Admissions During Chemotherapy Utilising Longitudinal Symptom Severity Reports and Patient-Reported Outcome Measures

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Abstract. Chemotherapy toxicity can lead to acute hospital admissions, negatively impacting the healthcare system and patients' well-being. Machine learning (ML) models identifying patients at risk of emergency admissions are often developed on data lacking patients' perspective. This study used longitudinally collected symptom severity reports and 4 ML models to predict hospital admissions risk during chemotherapy, and short-term admissions risk (within 14 days of a report). It also compared performance of models developed with, and without the use of patient-reported outcome measures (PROMs). Random forest and extreme gradient boosting models predicted admissions with excellent balanced accuracy, recall, and specificity of over 0.9. However, short-term admissions risk predictions were poor. PROMs improved overall model performance. The results advocate for longitudinal collection and use of symptom severity reports and PROMs. This can support understanding of chemotherapy toxicity patterns leading to emergency admissions, and inform clinicians and patients of potential future complications.

Keywords. Patient-reported data, Hospital admissions predictions, ML

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1. Introduction

Emergency hospital admissions resulting from chemotherapy toxicity can negatively impact patients' quality of life (QoL) and the healthcare system. Machine learning (ML) has been successful in predicting acute hospitalisation during cancer treatment [1], which can help to identify patients at risk of severe chemotherapy toxicity, plan for emergency admissions, and inform treatment decisions.

Nevertheless, studies predicting clinical outcomes often neglect patients' perspective and develop models using only clinical and demographic data. Our previous work has shown that including patient-reported outcome measures (PROMs), which capture patients' QoL, improves model performance predicting emergency admissions [2]. However, the data were collected only at chemotherapy baseline.

Symptom severity reports are also patient-reported data, often collected longitudinally. They provide patients' perspective on their health status throughout the duration of treatment. The patterns in longitudinal reports can be identified by ML models to predict long-term, and short-term clinical outcomes [3]. However, limited research has been conducted on predictive value of longitudinal symptom severity data in predicting hospital utilisation.

This study aims to predict the risk of hospital admissions occurring during chemotherapy, and the short-term admissions risk (within 14 days from a report), using 4 ML models and longitudinal symptom severity reports, clincial, and demographic data. To establish the PROMs' predictive value, we compared performances of models including and excluding PROMs from feature sets.

2. Methods

Overall methodology: Logistic regression (LR), random forest (RF), multilayer perceptron (MLP), and extreme gradient boosting (XGB) were developed using symptom severity reports, clinical, demographic, and PROMs (included, or excluded) data to predict: 1) admissions during chemotherapy at any time after a report; 2) admissions risk within 14 days of a report (Figure 1). The models were selected due to their common use in similar studies [4]. A clinical oncologist was involved in the study design to ensure relevance of this study to clinical practice.

Dataset: The data (3260 records) were collected from 254 patients initiating chemotherapy for colorectal, breast, or gynecological cancer during eRAPID randomised clinical trial [5]. The patients were asked to complete symptom severity reports weekly for 18 weeks. Irregularity of reports were coded by a feature representing time since previous report. PROMs (obtained from Five-dimensional Visual Analogue Scale (EQ-5D-VAS), Functional Assessment of Cancer Therapy - General 28 items (FACT-G), and EORTC Core Quality of Life Questionnaire (QLQ-C30), cited in Absolom et al., 2021 [5]) were completed at baseline, 6, 12, and 18 weeks (most recent value selected for each record). Clinical and demographic data were derived from electronic healthcare records. The target variables - admissions during chemotherapy (following a report) and admissions within 14 days from a report were computed from clinical event dates. The

14 days window was chosen with input from oncology expertise to reflect a useful time frame for detecting change in clinical practice and alerting of potential admission.

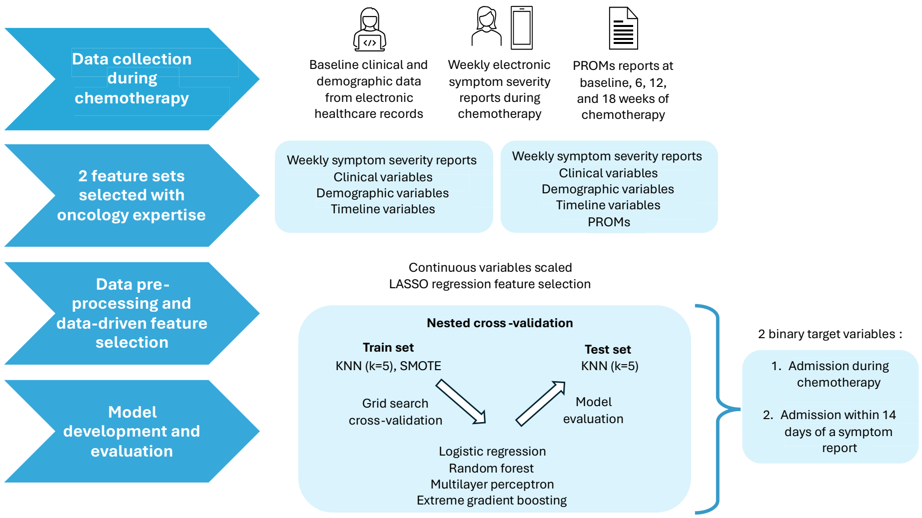

Figure 1. Flow diagram illustrating study methodology.

Data pre-processing: Details of data pre-processing are presented in Figure 1. Due to a class imbalance (640 reports followed by an admission after report, and 175 reports within 14 days), Synthetic Minority Oversampling Technique (SMOTE) was applied on train set (80%) to balance the data. Test set (20%) was left imbalanced, enabling model evaluation on real patients' data and relevance to clinical practice. Feature selection was consulted with oncologist and further conducted using Least Absolute Shrinkage and Selection Operator (LASSO) regression with cross-validated minimised lambda value to reduce bias [6].

Model development and evaluation: Nested cross-validation was performed during model development and evaluation to prevent data leakage. LR, RF, MLP, and XGB were developed with grid search hyperparameter tuning, performed on train set. Models with hyperparameters maximising balanced accuracy (BA) were evaluated on test set. BA, specificity (SP), and recall (TPR) were the main performance metrics, as they best evaluate models as screening systems, providing information on correct classification for both (even imbalanced) classes. Accuracy, precision, F1 score, and area under the ROC curve (AUC) were also reported. All model hyperparameters, results, and selected features are provided in supplementary file: https://github.com/zuzawojcik/MIE.

3. Results

Admissions predictions: Admissions during chemotherapy predictions had higher performance than admissions within 14 days of completed reports. All models achieved an outstanding BA of over 0.9. These models also had very high SP and TPR, suggesting successful predictions. In contrast, predicting admissions within the 14-day interval resulted in poor BAs (below 0.7). The SPs were very high for all models, apart from LR, but TPRs were extremely compromised, with the lowest values being below 0.2 (Figure 2).

Model comparison: In predicting admissions during chemotherapy, XGB had the highest BA (0.989) and all other metrics, indicating a great overall performance. MLP classifier was the least successful, although all its metrics were above 0.8. In contrast, BA of predicting admissions within 14 days was the highest for MLP, and the lowest for XGB. SPs of all models, except for LR were high, but TPRs were compromised.

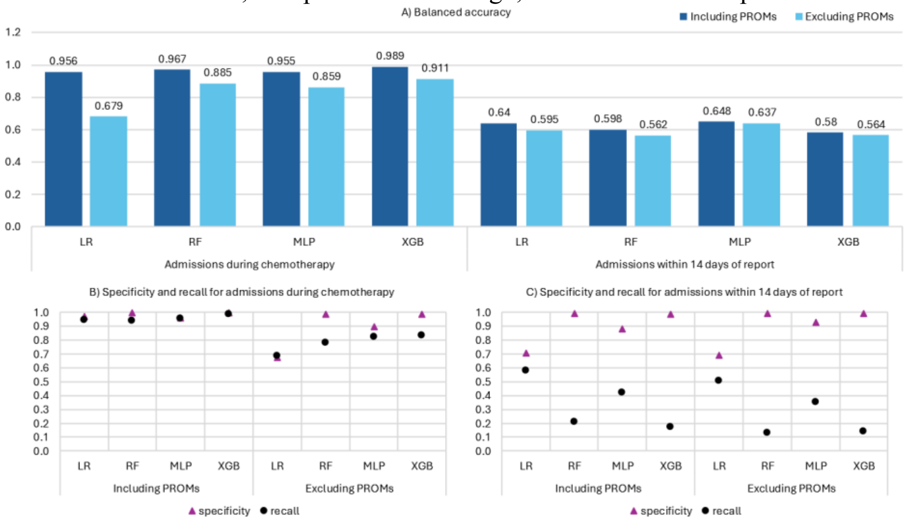

Figure 2. Balanced accuracy, specificity, and recall of all models.

PROMs as input features: As expected, overall performance of models increased when PROMs variables were present. All models in all scenarios had higher BA when PROMs were included in analysis. PROMs especially increased the performance of LR model predicting admissions during chemotherapy. Overall, including PROMs also improved TPR values for admissions within 14 days interval predictions, but SP values were mostly unaffected.

4. Discussion

Overall findings: This study successfully predicted hospital admissions during chemotherapy from longitudinally collected symptom severity reports and PROMs data using ML. The models exceeded performance of admissions predictions from the study using baseline data only [2], encouraging the collection and use of symptom severity reports. The potential explanation for poor performance of predicting admissions within 14-day interval could be the inherent class imbalance, which was increased due to the shorter time-frame of interest. As in previous studies [2], PROMs improved model performance, which emphasised the high value of patients' subjective view on their health status.

Potential applications and strengths: Identifying patients at risk of acute admissions has the potential to forewarn both emergency healthcare workers and patients. The awareness chemotherapy toxicity likelihood could support shared decision making prior to, and during chemotherapy. Using longitudinal patient reported data reveals the patients' perspective on their health and increases the patients' participation in symptom management.

Future work and limitations: The inevitable consequence of using clinical trial data is the limited representability of study population. Therefore, external validation of these models is a crucial next step to ensure their real-world application. Longitudinal reports provide an opportunity for more complex modeling using deep learning methods, such as recurrent neural networks [3]. These could improve the more immediate admissions predictions following the reports.

5. Conclusions

This study incorporated longitudinal symptom severity reports and PROMs in ML models to predict emergency hospital admissions during chemotherapy, and admissions within 14 days of report. Overall results indicated excellent performance of models predicting admissions during chemotherapy, which advocates for patient-reported data collection. This has the potential to inform cancer treatment decisions and support planning for emergency hospitalisations.

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References

[1] Hong JC, Niedzwiecki D, Palta M, Tenenbaum JD. Predicting Emergency Visits and Hospital Admissions During Radiation and Chemoradiation: An Internally Validated Pretreatment Machine Learning Algorithm. JCO Clinical Cancer Informatics. 2018 Dec;(2):1-11.

[2] W´ojcik Z, Dimitrova V, Warrington L, Velikova G, Absolom K. Using Machine Learning to Predict Unplanned Hospital Utilization and Chemotherapy Management From Patient Reported Outcome Measures. JCO Clinical Cancer Informatics. 2024 Apr;(8):e2300264. Publisher: Wolters Kluwer.

[3] Wang Y, Van Dijk L, Mohamed ASR, Fuller CD, Zhang X, Marai GE, et al. Predicting late symptoms of head and neck cancer treatment using LSTM and patient reported outcomes. Proceedings International Database Engineering and Applications Symposium. 2021 Jul;2021:273-9.

[4] Krepper D, Cesari M, Hubel NJ, Zelger P, Sztankay MJ. Machine learning models including patient-reported outcome data in oncology: a systematic literature review and analysis of their reporting quality. Journal of Patient-Reported Outcomes. 2024 Nov;8(1):126.

[5] Absolom K, Warrington L, Hudson E, Hewison J, Morris C, Holch P, et al. Phase III Randomized Controlled Trial of eRAPID: eHealth Intervention During Chemotherapy. Journal of Clinical Oncology. 2021 Mar;39(7):734-47. Publisher: Wolters Kluwer.

[6] Muthukrishnan R, Rohini R. LASSO: A feature selection technique in predictive modeling for machine learning. In: 2016 IEEE International Conference on Advances in Computer Applications (ICACA); 2016. p. 18-20.