Machine Learning Based Medical Directives at Triage in Pediatric Emergency Medicine: *The First Step to Automated Pathways for Healthcare Delivery*

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Background: Wait-times in emergency departments (ED) have increased over 17% in the past 5 years in Canada, contributing to delays in diagnosis and treatment administration.[1] One common strategy for increasing patient flow, especially in adult EDs, is the use of nursing medical directives at triage. These directives enable nurses to order specific investigations such as bloodwork, urine testing, and chest radiographs (CXR), before the patient is seen by a physician. These medical directives are often designed to rule in a disease rather than it rule out. The physician thus has more information available prior to their initial assessment, leading to faster decision-making and shorter lengths of stay.[2,3] This model is less often implemented in pediatric patients due to concerns for over-testing and the relative invasive nature of tests in children compared to adults. With the proliferation of electronic health record (EHR) systems, there exists an opportunity to develop diagnostic machine learning (ML) based medical directives to identify children with common diseases to enable downstream testing prior to physician assessment. Conversely, conditions such as bronchiolitis, which are typically over-investigated can potentially be diagnosed directly, thus limiting unnecessary testing.[4] ML based medical directives may be able to identify patients with common diagnoses who fit into streamlined clinical care pathways leading to expedited care and potential for future automation of healthcare delivery.

Hypothesis: We hypothesize that pneumonia, urinary tract infections (UTI), and clinically significant infections (CSI) can be predicted with high true positive rates (TPR) and low false positive rates (FPR) in children (0-18 years of age) presenting to ED at triage. Furthermore, we hypothesize that ML models can predict bronchiolitis in children and potentially help physicians avoid unnecessary diagnostic testing and treatment interventions.

Methods: Data was collected from Epic EHR system at the Hospital for Sick Children (SickKids) in Toronto, Canada for all patients presenting to ED from July 2018 to March 2019 (48,803 patients). Logistic regression (LR), random forest (RF), and fully connected feed forward artificial neural network (ANN) models were trained with class weighting and prediction thresholds tuned to optimize true positive rates (TPR) when predicting the following at triage: *pneumonia, UTI, CSI,* and *bronchiolitis.* A binary cross-entropy loss function was utilized for all ANN models. Input features include: heart rate, respiratory rate, oxygen saturation, blood pressure, temperature, Canadian Triage Acuity Scale (CTAS) score, patient weight, time of triage, presenting symptoms, age, language, distance from home to nearest pediatric clinic, and average median household income per postal code. Labels for pneumonia, UTI, and bronchiolitis were determined using ED ICD-10 Canada diagnostic codes. CSI label was defined as any patient admitted to hospital, transferred to another hospital, or deceased, with an infectious ED ICD-10 Canada diagnostic code. Models were evaluated using area under the receiver operator curve (AUROC), TPR, and FPR. Feature importance was established using a node impurity method for the RF models.

Results: Our ANNs performed best compared to RF and LR models for all experiments with absolute improvements in AUROC ranging between 0.01-0.27. ANN model outcomes are as follows: ***Pneumonia***: AUROC 0.84, TPR 0.77, FPR 0.16. ***UTI:*** AUROC 0.88, TPR 0.80, FPR 0.06. ***CSI:*** AUROC 0.88, TPR 0.79, FPR 0.22. ***Bronchiolitis:*** AUROC 0.95, TPR 0.93, FPR 0.10. RF models had similar AUROCs of 0.86 and 0.94 for CSI and Bronchiolitis, respectively. Feature importance for these models were assessed. Top features for the CSI model included blood pressure (0.19), CTAS 2 score (0.1), weight (0.07), pulse (0.05), and fever (0.04). Top features for the bronchiolitis model are weight (0.18), respiratory rate (0.17), pulse (0.12), symptoms of cough/congestion (0.09) and shortness of breath (0.02).

Conclusion: Our ANN models obtained favourable AUROCs for ruling in specific diagnoses at triage with high TPRs. Given the proposed models are being used as a triage medical directives, if a disease is missed (false negatives) the patient undergoes the typical workflow within the ED and receives the baseline standard of care. Most notably, the high TPR for bronchiolitis may potentially enable these selected patients to be fast tracked towards supportive care helping avoid unnecessary investigations and treatments. The combination of high TPR and low FPR for UTI suggests that this model has potential to accurately automate the ordering of diagnostic urine testing at triage making results available faster for healthcare providers. Results for pneumonia are promising however the downstream pathway involves obtaining a CXR (low dose radiation exposure). Given this context and the FPR of 0.16, further work will be needed to improve model performance. We will also test how this rate compares to the performance of healthcare specialists as a clinical benchmark. When determining feature importance for high performing RF models the top-ranking features are all clinically relevant. Pulse, respiratory rate, weight, and fever are all features utilized by physicians when assessing for both CSI and bronchiolitis. Next steps include further model optimization to improve predictions, the inclusion of more data, and prospective testing in the form of a silent trial to validate findings. If successful, we hope to demonstrate how ML based medical directives can be implemented safely in a pediatric emergency medicine setting without leading to over-testing. Identifying patients in this fashion at the time of triage is an important step towards building automated clinical care pathways for common disease presentations in children.

References:

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