IJPSR (2023), Volume 14, Issue 10 (Research Article)

INTERNATIONAL JOURNAL OF PHARMACEUTICAL SCIENCES AND RESEARCH

Received on 27 January 2023; received in revised form, 02 April 2023; accepted 26 April 2023; published 01 September 2023

UTILIZATION OF MACHINE LEARNING TO IMPROVE PRODUCTIVITY OF INTERVENTIONS CLASSIFICATION FOR A UNIVERSITY TEACHING HOSPITAL IN SINGAPORE

Beng Yi Sia [*1], C. W. Yap [2], Y. R. Chen [1], L. T. Tan [1], K. T. Ng [1], T. M. Ng [1], J. W. Lin [1], S. L. Yap [1] and H. Y. Lim [1]

Division of Pharmacy [1], Tan Tock Seng Hospital, Singapore.
Health Services & Outcomes Research [2], National Healthcare Group, Singapore.

Keywords:

Machine learning, interventions, classification, artificial intelligence, pharmacy

Correspondence to Author:
Beng Yi Sia

Principal Pharmacist (Clinical), Division of Pharmacy, Tan Tock Seng Hospital, Singapore.

E-mail: bengyi_sia@ttsh.com.sg

ABSTRACT: Introduction: Pharmacists have an integral role in the medication use process in performing interventions. In TTSH, accurate classification of interventions is important for supporting a learning culture within the hospital. Pharmacists spend at least 80 hours to look through 10,000 interventions monthly to ensure accurate classification. In recent years, artificial intelligence (AI) has been increasingly used in healthcare and may potentially be used to perform interventions classification. **Aim:** We aim to develop an intervention classification algorithm which can assist pharmacists in accurate classification of interventions. Pharmacists' time spent can be reduced substantially and be better channeled to other higher leveled tasks to improve patient's care. **Methods:** In designing the model for intervention classification algorithm, at least 80 000 pharmacist-checked intervention categories (PIC) were sent to Health Services & Outcomes Research, a division under the National Healthcare Group of Singapore (NHG). AI-predicted intervention categories (AIC) with a precision >90% matched PIC at least 95% of the time and exempted from manual pharmacists' checking. **Results:** After utilization of the ML algorithm, 28% of inpatient interventions were exempted from pharmacists' checking, corresponding to average time savings of 15.7 hours monthly and cost savings of $485.27. 33% of outpatient interventions were exempted from pharmacists' checking, achieving an average time savings of 9.7 hours monthly and cost savings of $299.30. **Conclusion:** A real-world implementation of a ML model to classify interventions had led to significant savings on pharmacists' time which could be channeled to perform clinical tasks to optimize patient outcomes.

INTRODUCTION: The medication use process is complicated and relies on the support and input from various professional disciplines to optimize patient safety. Pharmacists hold pivotal roles inmediation-related responsibilities such as ensuring access to medication, evaluating appropriateness of medication and medication management [1].

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DOI: 10.13040/IJPSR.0975-8232.14(10).4965-70

This article can be accessed online on www.ijpsr.com

DOI link: http://doi.org/10.13040/IJPSR.0975-8232.14(10).4965-70

Studies have shown that prescribing errors account for 39% of errors in the medication use process and can be due to several reasons such as prescriber's lack of knowledge of the drug, slips and lapses [2, 3]. These errors are identified and resolved by pharmacists and are described as interventions.

Pharmacy interventions have been proven to reduce medication errors during hospitalization [4], reduce medication errors by 37% at transitions of care, and reduce frequency of emergency department visits after discharge [5]. Tan Tock Seng Hospital (TTSH) is a university teaching hospital in the central of Singapore, with a capacity of 1700 beds and 16 specialist centers. Pharmacists work alongside physicians and initiate interventions to prevent prescribing errors. Interventions are documented and classified by the pharmacist performing the intervention according to an in-house definition of 25 different categories within the electronic medical records system – Electronic Inpatient Medication Record System (eIMR) for admitted patients, and Integrated Pharmacy (iPharm) for outpatient prescriptions. This data is used as recording of pharmacy workload and is further reported to the medication safety committee for analysis and creation of education materials and workflow changes to improve prescribing behaviors that leads to these interventions. It is important to have appropriate categorization to ensure accurate reports that can be used to inform practice change. As such, a team of 18 pharmacists spend at least 80 hours per month to review and re-classify at least 10,000 interventions monthly. Ensuring the accuracy of intervention categories is time and labor intensive, and may not be the best use of pharmacists' time. Artificial intelligence (AI) could potentially be used in various parts of the medication management system, such as verification of orders, processing of prescriptions, procurement and monitoring [7], thereby improving patient safety outcomes [8] and quality of patient care [9]. Several machine learning (ML) tools have been developed which can accurately predict outcomes based on learning patterns from vast healthcare data [10, 11].

We aim to develop and implement a ML-based classification model which can be used to improve the productivity of interventions categories checking. Through the utilisation of ML to perform manual and routine tasks of reclassifying interventions, we hypothesized that pharmacists' time spent on checking of interventions classification accuracy can be reduced substantially [13].

MATERIALS AND METHODS:

Model Development: To design the ML model, previously checked inpatient (Jun 2018 to Dec 2018) and outpatient (Apr 2018 to Dec 2018) interventions were used. The interventions were split into a training set and testing set. The training set contained 62757 inpatient interventions and 24626 outpatient interventions, and the testing set contained 5654 inpatient interventions and 2910 outpatient interventions (Supplementary **Table 1**). Separate models were developed for inpatient and outpatient interventions because of the variations in interventions across each category due to different practice settings. The interventions were first pre-processed to prepare it for the ML algorithm. Rules using regular expressions were used for standardization of the interventions. For example, commas were removed from numbers, and abbreviations such as Mg were converted to magnesium while mg were converted to milligram. The interventions were then converted to lower case and then tokenized into individual terms. Plural terms were converted to their singular form and wrong spellings were corrected. Some individual terms were then replaced with trigrams (e.g. "liver function test") or bigrams (e.g. "salicylic acid"). Lemmatization of the individual terms were then performed using Word Net Lemmatizer in the Python library NLTK. Word embedding were performed on the tokens (individual terms, trigrams and bigrams) from the training set using GloVealgorithm implemented in the Python library genism [14].

Briefly, the GloVe algorithm calculated a vector with 300 dimensions for each token in the training set. The tokens in each intervention in the training set were then converted to these word embedded tokens for the subsequent ML algorithm. Only the first 60 tokens were retained for each intervention. Interventions with more than 60 tokens were truncated and interventions with fewer than 60 tokens were post-padded with zeros. Word embedding were also applied on the testing set using the learned GloVe algorithm. Y hot encoding was performed on the 25 intervention categories. Attention-based bidirectional long short-term memory [15] were then used to develop the ML-based classification model using the training set. The optimal value for batch size (128, 256, or 512), learning rate (10-6 to 10-1), regularizer (0 to 0.1), dropout (0 to 0.7) and optimizer (ADAM, SGD, or RMSProp) were determined using hyper parameter optimization with categorical cross entropy.

Utilisation of ML-based Classification Model: Monthly interventions were sent to the ML model, where it would return with the AI-predicted intervention category (AIC) with an associated precision, ranging from 0 – 100%, where precision is derived by number of correctly classified interventions in that category divided by the total number of interventions in that category. From January to June 2019, pharmacists continued to manually check intervention categories and returned the checked interventions for further refinement of the ML model. Thereafter, pharmacy used the interventions from the refined ML model and compared AIC to pharmacist-checked intervention categories (PIC). The percentage of match between AIC and PIC for each corresponding precision value was computed by the pharmacy team and defined as accuracy. Seeing that AIC matched PIC more than 95% of the time for precision > 90%, pharmacy decided to adopt all AIC with a precision of > 90%, over-riding original pharmacist intervention categories. Interventions where AIC was =<90% were returned to the pharmacists for manual checking.

Evaluation of Improvement in Productivity: With the use of ML model, there was reduction in the need to check for accuracy of interventions classification, corresponding to pharmacists' time savings, as each inpatient pharmacist took an average of 25 seconds to check the accuracy of classification for an intervention, while each outpatient pharmacist took an average of 36 seconds. To evaluate the improvement in productivity, pharmacists' time savings were translated to cost using pharmacist hourly salary estimated from published local data in June 2020[16]; the median monthly gross wage of full-time pharmacist was S$5440, corresponding to an hourly pay of S$30.91, based on up to 44 hours weekly of contractual work hours for a full-time employee [17].

RESULTS:

Precision of Initial ML-based Classification Model: The precision of the ML-based classification model on the inpatient training set ranges from 23.2% to 100% for the 25 intervention categories, with an overall precision of 62.4%. On the other hand, the precision of the ML algorithm on the outpatient training set ranges from 8.3% to 100% with an overall precision of 69.3%. There was variation across the different categories for both inpatient and outpatient models, with some categories unable to consistently return a high precision (**Table 1**).

TABLE 1: PRECISION OF ML MODEL ON TRAINING SET (INPATIENT AND OUTPATIENT)

Intervention Category	Intervention Category description	Inpatient Interventions		Outpatient Interventions	
		No. of interventions	Precision, %	No. of interventions	Precision, %
1	Wrong/incomplete med history	741	71.0	444	70.0
2	Transcribing error	1350	82.8	272	66.2
3	Duplicated therapy/orders	112	67.0	59	77.8
4	Incomplete/unintended dosage regimen (dose and frequency)	1928	89.4	164	65.4
5	Wrong/ missing dosage form/strength	53	42.9	68	61.2
6	Wrong/missing route/site	16	55.6	3	NA
7	Wrong/ missing dilution	16	55.6	0	NA
8	Wrong administration rate (parenteral)	50	90.0	0	NA
9	Wrong/incompatible diluent/container	1	NA	0	NA
10	Wrong / missing duration /quantity	191	87.2	66	39.0
11	Wrong patient	0	NA	1	NA
12	Wrong/ Ineffective drug	15	75.0	9	100.0
13	Drug omission (Indication)	313	56.3	8	8.3
14	Drug without indication	163	70.1	15	66.7
15	Drug incompatible with patient's condition	254	85.0	27	80.8
16	Allergy/ADR	5	25.0	25	88.9
17	Drug-food interaction	18	68.2	0	NA
18	Drug-drug interaction	29	100.0	20	100.0
19	Monitoring	57	62.3	1	NA
20	Simplify regimen/ deprescribing	42	54.8	0	NA
21	Cost reduction	6	15.8	63	76.1
22	Therapy recommendation	96	34.2	22	NA
23	Clarification	198	23.2	1109	69.5
24	TCU mismatch	0	NA	222	77.3
25	No prescription/ No original prescription	0	NA	312	88.5

NA – data is not available because there are no interventions under that category. Precision is derived by number of data points of that category which are classified correctly by the model divided by the total number of data points classified by the model into that category.

Adoption of Refined ML-based Classification Model: Using the refined ML model and computing the percent of match between AIC and PIC, we found that accepting AIC with a precision of >90%matched PIC at least 95% of the time (**Table 2**). Hence, pharmacy accepted a 5% error in classification and accepted all AIC with precision >90% to override PIC for both inpatient and outpatient settings. All other interventions were returned for pharmacists' checking.

TABLE 2: ACCURACY OF AIC OVER 6 MONTHS FOR INTERVENTIONS WITH PRECISION > 90% (INPATIENT AND OUTPATIENT)

Inpatient Pharmacy interventions						
Month	**Aug 2019**	**Sep 2019**	**Oct 2019**	**Nov 2019**	**Dec 2019**	**Jan 2020**
Accuracy (%)	1600/1677 (95.4)	1599/1625 (98.4)	1595/1649 (96.7)	1579/1620 (97.5)	1791/1845 (97.1)	2203/2253 (97.8)
Outpatient Pharmacy interventions						
Month	**Jan 2021**	**Feb 2021**	**Mar 2021**	**Apr 2021**	**May 2021**	**June 2021**
Accuracy (%)	729/769 (94.8)	368/392 (93.9)	937/967 (97.0)	718/739 (97.2)	447/467 (95.7)	631/662 (95.3)

Accuracy is defined as number of Artificial intelligence predicted intervention categories (AIC) which match with Pharmacist-checked intervention categories (PIC).

Time and Cost Savings: After utilization of the ML-based classification model, inpatient pharmacy managed to adopt an average of 2256 AIC monthly (28% of total interventions),corresponding to average time savings of 15.7 hours monthly which translates to cost savings of SGD $485.27. Encouraging results were also replicated for outpatient pharmacy, with an average of 33% of AIC utilized, achieving an average time savings of 9.7 hours monthly and cost savings of SGD $299.30 (**Table 3**).

TABLE 3: TIME SAVINGS FOR TTSH PHARMACISTS

Inpatient pharmacy							
Month	**Jan-21**	**Feb-21**	**Mar-21**	**[c]Jul-21**	**Aug-21**	**Sep-21**	**Average**
Interventions not manually checked, no. (%)	2212 (28)	2068 (30)	2371 (28)	2345 (28)	2241 (28)	2300 (28)	2256 (28.3)
Time savings per month month, hr[a]	15.4	14.4	16.5	16.3	15.6	16.0	15.7
Cost savings per month[d], SGD $	$439.36	$410.93	$470.75	$465.04	$482.18	$494.55	$485.27
Outpatient pharmacy							
Month	**Jul-21**	**Aug-21**	**Sep-21**	**Oct-21**	**Nov-21**	**Dec-21**	**Average**
Interventions not manually checked, no. (%)	925 (27)	902 (28)	860 (27)	1532 (61)	722 (27)	865 (29)	968 (33.2)
Time savings per month, hr[b]	9.3	9.0	8.6	15.3	7.2	8.7	9.7
Cost savings per month[d], SGD $	$287.45	$278.18	$265.81	$472.91	$222.55	$268.91	$299.30

[a]Average of 25 seconds taken to check each intervention, [b]Average of 36 seconds taken to check each intervention, [c]Missing data of April to June due to COVID-19 situation outbreak in TTSH, and interventions were substantially lower than average, [d]Based on gross median monthly wage of $5440 of a full-time pharmacist working up to 44 hours / week.

DISCUSSION: To our knowledge, this is the first time AI has been utilized for the classification of pharmacy interventions. We presented a real-world use case common in pharmacy practices [5, 18, 19]. The implementation of AI in our hospital has shown utility is its ability to reliably predict intervention category based on picking up of commonly used words in the pharmacists' interventions. AI has been increasing adopted in healthcare systems, such as medical devices [20], diagnosis [12], medication management process [6], analysis of big datasets [21], robotically-assisted surgeries [22] and mitigating threats to patient safety [23]. By utilizing AI and ML to perform routine tasks, evaluating large complex datasets, pharmacists time can be directed towards providing clinical care and expanding their job scopes. Across the different intervention categories, AI was able to more reliably predict certain categories (E.g. categories 8, 15 and 18) because the documentation of certain interventions was more consistent and increases the classification precision of the AI algorithm. The lack of sufficient data for certain intervention categories (**Table 1**, Intervention categories 9, 11, 24 and 25 for inpatient and intervention categories 6-9, 11, 17, 19 and 20 for outpatient) affected the robustness of the AI algorithm development.

Limitations: Extracting clinical information from free text is a major challenge faced in the derivation and implementation of the ML algorithm, as shared by other authors [24].

Training on intervention documentation has to be done to reduce the variations in documentation which affects model prediction. Extensive data is required in the development of the ML algorithm, and pharmacy has to invest resources in implementing and validating the AI model.

Future Plans: TTSH will be transitioning from our current electronic systems to a harmonized system, next generation electronic medication record (NGEMR). In preparation for the smooth transition, tremendous effort and time had been put in to harmonize the intervention categories across various hospitals within Singapore [25].

To facilitate the development of a robust algorithm and automate the classification of interventions, pharmacists and technicians will be encouraged to utilize the SBAR [26] format: situation, background, assessment and recommendation for documentation of interventions, as well as using common phrases which are associated with the intervention categories. It is hoped that a single ML-based classification model can be developed and used across the hospitals sharing the NGEMR system, to provide greater time savings among pharmacists, and ensure consistency in categorizing an intervention.

CONCLUSION: A real-world implementation of a machine learning model to classify interventions in TTSH had led to significant reduction in pharmacists' time averaging 15.7 hours monthly which could be channeled to perform other value-added work.

As we digitalize and unify our medical data, it is hoped that the ML-based classification model can progress beyond TTSH and be shared among other institutions who are using a harmonized system of documenting pharmacy interventions. We envision that in future, ML can be used to predict accurately all pharmacy interventions, and take away the routine duty of classifying and checking the interventions for accuracy.

ACKNOWLEDGEMENTS: Nil

CONFLICTS OF INTEREST: Nil

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How to cite this article:
Sia BY, Yap CW, Chen YR, Tan LT, Ng KT, Ng TM, Lin JW, Yap SL and Lim HY: Utilization of machine learning to improve productivity of interventions classification for a university teaching Hospital in Singapore. Int J Pharm Sci & Res 2023; 14(10): 4965-70. doi: 10.13040/IJPSR.0975-8232.14(10).4965-70.