Asthma's Patient Continuity of Care using Machine learning Models

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Abstract

Continuity of care (COC) has been found to provide various advantages for people's health with chronic conditions such as asthma. This work focuses on constructing a machine learning algorithm to forecast how asthma patients will be treated in the future. For chronic disorders, continuity of care (COC) has been found to provide several health benefits. The application of a prediction methodology to determine the COC in patients, on the other hand, has received little attention. This work aims to fill a research gap by developing a machine learning approach to forecast asthma patients' future COC and investigating the relevant parameters.

Index Terms—*COC, Asthma,*

I. INTRODUCTION

COC is a method of delivering structured care.[1] It is found to have several health benefits in the management of chronic diseases, including fewer negative outcomes and lower expenses . Low COC patient will benefit from improved long-term healthcare management. As a result, knowing the COC level is critical for initiating care measures. Its measurements have so far been various, with the majority of them focusing on finding a mechanism to assess the "interpersonal relationship" between patients and collaborators like physicians, caretakers, and patients themselves [2,3,4]. Despite the availability of various metrics, there has been little research into getting COCs using a generalizable methodology. The predictive model, in particular, is an artificial intelligence tool that can be used in the clinic to make judgments more quickly . A breakthrough would be the use of an effective technique to forecast the COC of patients. However, this development is hampered by the significant reliance on transdisciplinary expertise and enormous data collecting . We employed a machine learning classification model to accurately assess the level of COC in patients and focused on one of the major chronic diseases, asthma.

[5,6] Asthma is a prevalent chronic illness that, if not continuously controlled, would have unfavourable effects. Asthma affects 7.8% of the population in the US, leading to 1,629,469 ED visits, 178,530 hospital stays, and more than 10.0 million annual fatalities. Asthma affects a wider age range than other chronic diseases, suggesting that more sufferers will benefit from

any significant improvements. In addition, asthmatic patients who are younger had lower COCs and more episodic exacerbations. Up to 60-75 percent of future ED visits can be prevented by being aware of the COC beforehand and enhancing it with useable techniques.and It is possible to prevent 25% of hospitalizations for asthma patients.

II. RELATED WORK

[7]Previous research has sought to establish a link between the COC and asthmatic patient outcomes. However, prior to investigating the association between COC and outcomes, adequate measuring of COC and outcomes should be prioritised, as evidenced by the research . Many studies have created a predictive model for the former

Most crucially, determining a patient's COC has so far relied on historical data . Patients with long-term visit records, such as the continuity of care index, have been used in studies to calculate the COC (COCI). All of the available quantitative methods relied on historical data and had a small sample size. Furthermore, it is not available for a new patient who has never been in a certain healthcare system. Roughly 40% of new asthma patients at the University of Washington Medicine (UWM) receive medical care each year.

The highest prediction accuracy would be less than 60% if the previous COC could be utilised to predict the upcoming level.

Furthermore, because patients' COC is likely to alter over time, previous COC cannot accurately predict future COC for existing patients. We used the historical COC for outpatients with asthma who got care from the UWM for 5 years to calculate the prediction accuracy. Table 1 shows that the highest accuracy was 57.94 percent. As a result, the baseline prediction accuracy in this study was established at 57.94 percent. Despite the fact that it appeared to be a simple procedure, it was insufficient. Furthermore, other obstacles would stymie this strategy:

Between 2016 and 2018, the patient and data instance distributions are analysed.					
Outpatients with Asthma who received care at UWM are classified as follows:	Number in 2016 (N= 11,017), n (%)	Number in 2017 (N = 12,151), n (%)	Number in 2018 (N = 12,894), n (%)		
Patients who have been returned	6453 (58.57)	7549 (62.13)	8186 (63.49)		
New patients	4564 (41.43)	4602 (37.87)	4708 (36.51)		

[8,9,10]The institutional review boards of the University of Washington Medicine, the University of Utah, and Intermountain Healthcare assessed and approved this study, which consists of a secondary analysis of retrospective data.

III. PROPOSED SOLUTION

The goal of this study was to close the research gap described before. For outpatients with asthma, we proposed a machine learning algorithm to predict future COC. The EHRs and administrative data were combined in our final model to estimate three different categories COC Severity levels: High . Mid and Low.

A machine-learning model was created to predict the COC of asthma patients in the future. The COCI was used for improved identification and to determine its level, as it is the most commonly used algorithm by patients and physicians. The greatest results were from the XGBoost model, which had the highest accuracy, AUROC, and F1 score. Because of its better big data processing capability, XGBoost won this investigation.

However, other algorithms, such as random forest, worked admirably on the UWM data, thanks to our strong feature engineering modelling method. Furthermore, assessing the COC purely based on demographic or comorbidity data was insufficient, demonstrating the superiority of the modelling technique. In general, this work fills a research vacuum in the application of a predictive method to determine the COC of asthma patients, which could aid clinical decision-making and resource allocation, ultimately improving patient outcomes.

There were 140 features evaluated in total, with 91percent (127/140) being used in the final model.

The majority of classification algorithms only accept numerical features. As a result, we used one-hot encoding to convert categorical characteristics into numerical features before adding them to the classifiers. Furthermore, because the COCI is a longitudinal prediction goal, the matching values were computed when the patient was first seen in the UWM dataset. The study lasted for 5 years, from January 2014 to December 2018.

By inputting labelled data for supervised learning, machine learning classification algorithms predict the likelihood of an objective variable. The COCI of asthmatic patients was categorised into three categories: high (3), mid (2), and low (1). (1). For this multiclass classification task, machine learning classifiers are the best option. This paper proposed using the extreme gradient boosting (XGBoost) algorithm , an efficient and distributed realisation of gradient boosting, to develop a predictive model.

[11,12,13,14]Random forest, k-nearest neighbour (k-NN), support vector machine (SVM), decision tree, XGBoost, and Naive Bayes are the top six classification algorithms used to create sophisticated prediction models known in the data mining and machine learning literature. Tree-based algorithms (e.g., random forest, and XGBoost) and the SVM, in particular, are both high-performance classification methods. According to the aim, the former divides the input space into hyper-rectangles. [15]The latter employs the kernel method to transform a linearly nonseparable problem into a linearly separable one, extending the training time. After testing the six preliminary algorithms, the XGBoost method was chosen due to its higher performance.

IV. CLASSIFICATION RESULTS

The top six classification methods used to generate advanced prediction models known in the data mining and machine learning literature are random forest, k-nearest neighbour (k-NN), support vector machine (SVM), decision tree, XGBoost, and Naive Bayes. High-performance classification approaches include tree-based algorithms (e.g., random forest, and XGBoost) and the SVM in particular. The former, according to the goal, separates the input space into hyper-rectangles. The latter uses the kernel approach to convert a linearly nonseparable problem into a linearly separable problem, which increases the training time. The XGBoost approach was chosen after testing the six preliminary algorithms because to its superior performance.

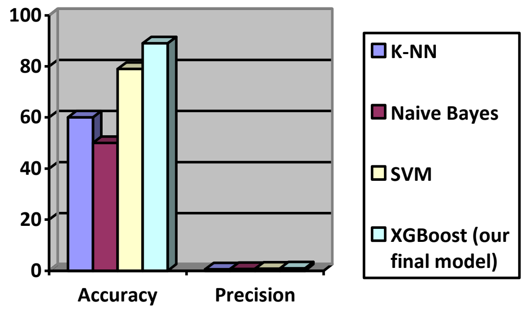

Figure 1: Prediction performance of various machine learning models.

With a Precision score of 0.9 and the ability to automatically calculate each feature's relevance value based on its model contribution, our final model, which used the XGBoost classifier, achieved the best accuracy (89 percent).

V. CONCLUSIONS

The highest accuracy, AUROC, and F1 score were produced by the XGBoost model, which also had the best overall performance.

For patients in this study with low COC levels, the model with the highest AUROC, 0.98, outperformed the other models. Although the prediction goals are incompatible, a similar modelling approach is typically used when developing a clinical machine learning model. The broad and effective features and large amounts of data fed into the model enable the delivery of a higher AUROC. Additionally, our precise data extraction method for figuring out the prediction objective yields excellent results.

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