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# THE EFFECTIVENESS OF RANDOM FOREST MODELS IN PREDICTING READMISSION RISK: AN EHR-BASED APPROACH

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**Abstract:**
Risk of hospital readmission is one of the crucial tasks in the sphere of healthcare management that directly impact patient outcomes and resource distribution. As EHR data is increasing, machine learning models, like Random Forests, have become particularly popular when it comes to readmission risk prediction. In the study, the authors discuss Random Forest models in the framework of the prediction of readmission risk among patients though EHR data. It aims to consider and compare the predictive capacity of the Random Forest model with a few other machine learning models, i.e., the common logistic regression and the decision tree models. The population size of data of the current study is formed by patient demographic, medical history and treatment data of various hospitals. Such measures as accuracy, precision, recall, and F1-score are used to analyze the performance of the model. The findings show that the Random Forest model is more effective than traditional methods and it has a 85 percent level of accurately predicting readmission risk. Results exhibit the possibility of Random Forests in healthcare and provide a good insight to hospitals trying to enhance the management of patients. Conclusions and suggestions are carried in the conclusion at the end of the research concerning the implication of the research and research in the future in the field of EHR-based predictive modeling.

**Keywords**
Random forest, readmission risk, machine learning, healthcare analytics, prediction models,

## Introduction:

One of the most burning issues in the modern healthcare system is hospital readmission of patients in both senses, patient-wise and system-wise. Readmission of patients to hospitals shortly after they were released shows a low level of health status since these patients would take long recovering, increasing the rate of mortality and low life quality. Moreover, when patients are readmitted to the hospital, this is a costly process to healthcare organizations and insurance schemes. Wang and Lee (2021) state that readmissions are frequently an indicator of both the quality of care during the first admission and the effectiveness of post-discharge planning and delivery and follow-up of healthcare. Decreasing readmission rates have thus become the primary concern of health policy formulation and policymakers in healthcare administration, aimed at enhancing patient outcomes and cost reduction of healthcare expenditures (He et al., 2020).

The significance of hospital readmission prediction is that it can be used to select patients who have high chances of readmission in order to subject them to interventions before they are discharged so as to prevent unnecessary readmission. Earlier determination of the risk patients enables better organization of patients care, more purposeful follow-up, and possibly overall better dealing with the chronic condition. As such, there has been a lot of interest in the area of hospital readmission risk prediction by researchers, medical professionals, and machine learning (ML) experts. Not only needs to be chosen those who were at risk, but it should be high to the point of being done in a timely manner and in a way that could be acted on within the context of clinical workflows (Jiang et al., 2020).

Over the past few years, Electronic Health Record (EHR) systems have taken over and transformed how the data of a patient is obtained and processed. EHRs hold loads of information of patients, such as their demographics, histories, lab tests, diagnosis, treatment plans and results. This abundance of data will be a good asset when it comes to devising some predictive models that can guide clinical decisions. Logistic regression and simple decision trees are the traditional methods of predicting readmission risk that have prevailed in the healthcare sector (Johnson et al., 2019). Nonetheless, they have a bit of problems addressing the complex nature of EHR data that can be non-linear, high-dimensional in addition to noisy at times. So, there is an increasing necessity of more sophisticated machine learning algorithms in order to efficiently process and make sense of such data.

Random Forest (RF) model is one of the machine learning techniques that have been particularly promising in healthcare applications. Machine Learning the RF algorithm has its roots in the works of Breiman (2001), and it is an ensemble being based on multiple decision trees, whose results are combined to enhance the overall accuracy and robustness of predictions. RF has gained wide adoption across various disciplines owing to its capacity to overcome the challenge of overfitting to large data, its high strength and the fact that it can model an intricate non-linear relationship. Moreover, RF gives feature importance scores, which can be used to determine the most important variables in terms of making predictions, which is an advantage over other methods in areas wherein interpretability and transparency matters, such as in healthcare (Hastie et al., 2017).

Other research works have shown that the Random Forest models can be used to make predictions of different outcomes in healthcare such as disease diagnosis, patient mortality, or patient readmission risk assessments. To extrapolate, Tang et al. (2019) used RF to forecast the likelihood of diabetes-associated complications with an accuracy level of 87%, implying that it is an efficient healthcare application. On the same note, the RF model was used by Patel et al. (2020) to predict risks about readmission of patients with cardiovascular diseases, and this model performed better as opposed to logistic regression and other conventional techniques. RF is a useful tool in medical predictive modeling because it has the flexibility to include a large variety of variables (both structured such as lab values, and unstructured such as clinical notes).

Nevertheless, even though Random Forest models have numerous strengths, little research has been conducted in using the models to predict who will be readmitted to a hospital. The lack corresponding to this literature creates a lot of research potential that the present research can bring about useful findings to the area of employing RF in readmission prediction. Also, although it has been indicated that the RF gives better results when compared to classical models, there is an insufficient knowledge on how this model performs as compared to other advanced ways of machine learning models namely the support vector machine (SVM) and the neural networks in predicting hospital readmission. Besides, a lot of research is dedicated only to the predictive accuracy, without paying much attention to the clinical relevance and interpretability of such models. In the context of healthcare, interpretability is critical because clinicians must be able to comprehend the rationale behind predictions so that they may make decisions regarding patient care (Rajkomar et al., 2018).

This study is aimed at assessing the relevance of Random Forest models as a measure of the probability of hospital readmission based on EHR information. In writing this paper, we hope to bridge the literature gap in this area by underutilization of more advanced machine learning in the prediction of readmission risk. This paper will not only compare the predictive power of RF but will also compare it with other popular tools such as logistic regression, decision tree. We will also discuss clinical implications of applying Random Forest in readmission prediction, especially when it comes to increasing patient care in hospitals, as well as resource management therein.

The major research question that will drive this research is the following: How successful is the Random Forest model in predicting the risk of hospital readmission as opposed to traditional models used, including logistic regression and decision trees? In response to this question, we are going to estimate the performance of RF model according to the set of metrics i.e. accuracy, precision, recall, and F1-score. Moreover, interpretability of the model will be analysed evaluating feature importance scores and considering how the given knowledge can be utilised in clinical decisions making.

**Literature Review**

The concept of predictive modeling has found its way in healthcare to improve the care given to patients, lower the costs of hospitals as well as improve healthcare provisions. A significant use-case is the prediction of the risk of hospital readmission, which has implications on the health condition of patients and the healthcare spending. Readmission risks can be predicted to provide oversight of its causes and establish preemptive actions, customized care plans, and improved resource distribution (He et al., 2020). These tasks have been addressed by different machine learning (ML) algorithms over the past years, and each of them have its advantages and disadvantages.

The main features of logistic regression, a very popular statistical model to predict the risks of readmission, are simplicity and interpretability. It gives insightful information concerning the correlation between predictor variables, and outcomes, something that is pivotal in healthcare. Nevertheless, the logistic regression cannot work with high-dimensional and non-linear data, which is characteristic of healthcare records and where the relationships between variables are complicated (Poh et al., 2018).

Decision trees (CART) are another alternative and they handle categorical data, as well as continuous data, which they all do well with. However, they tend to overfit, and this is especially likely when the dataset is small or noisy (Breiman et al., 1986). In order to deal with this, methods such as Random Forest have become popular in ensemble methods. RF combines several decision trees in an attempt to increase the generalizability and work on high-dimensional, imbalanced health care data (Breiman, 2001). It has been demonstrated that RF performs better than logistic regression and decision trees in predicting readmission risks especially where structured and unstructured data are combined or dealt with (Tang et al., 2019; Patel et al., 2020).

The ability of RF to work with multidimensional information and feature languid rankings along with reduction of the in-equality of classes renders the RF especially attractive in the medical field. These aspects make the identification of at-risk patients better, which is crucial to enhancing the clinical decision-making and patient care (Rajkomar et al., 2018). In addition, although RF models have known strengths, they still need improvement regarding interpretability to make the predictions trustworthy by the clinicians to use in practice.

This study focuses on the serious problem of hospital readmissions that are the priority area of concern in health care systems across the globe. Not only do hospital readmissions impact patient health outcomes, but they also come at a disastrous price to a medical system. There is potential to analyze readmission risks and predict them in a successful way so as to make timely interventions and achieve better results and save on the healthcare system costs. The traditional models, such as logistic regression, may have difficulties in processing complex and high dimensional data where more sophisticated machine learning models, such as Random Forest (RF), have been found to have potential to overcome these difficulties.

The models are able to handle heterogeneous and large quantities of data that are structured and unstructured also, and feature significance can be produced, which makes them valuable analytical tools in personalized healthcare. The importance of the study is in finding out in what way RF models can foresee the risk of readmission based on more precise findings than the conventional ways and also finding out as to what can

be done regarding the interpretation of models. This plays an essential role in adopting machine learning models in clinical practice where medical professionals must have trust and clarity on how and why their predictions were made so that they can make the relevant decisions. The proposed study will help to make a breakthrough in predictive modeling in healthcare and enhance more efficient treatment of patients, decreased readmission rates, and hospital management.

**Research Objectives:**

To evaluate the predictive accuracy of Random Forest models in forecasting hospital readmissions.
To compare the performance of Random Forest models with traditional predictive models like logistic regression and decision trees.
To assess the interpretability of Random Forest models in healthcare decision-making processes.

**Research Questions:**

In what exact way shall Random Forest models help identify the risks of hospital readmission as opposed to their conventional approaches?
What are some of the advantages of Random Forest over Decision tree and logistic regression in the prediction of readmission?
What would be the best ways to increase interpretability of Random Forest models as a means of clinical use?

**Theoretical Framework**

The theoretical justifications of the study are predictive modeling, machine learning, and explainability. Predictive modeling theory is instrumental in explaining how machine learning algorithms, particularly Random Forests, are able to interpret massive healthcare data to make projections of the patient outcomes in terms of predicting the risks of readmissions. In healthcare, individualized care is a necessity, and one way to make healthcare individual is machine learning. The idea behind explainable AI (XAI) has also been integrated, where clinicians have to be able to trust the interpretability of the model. The framework focuses not only on making predictions to be more accurate but also makes them easier to interpret, and therefore lets predictions be based on and integrated into clinical decisions. The solution to this problem is key to making machine learning models practical and useful in the real world of healthcare applications, consisting of the predictive power in addition to interpretability.

**Methodology**

The quantitative research approach is computed by the study with the aim of evaluating Random Forest models in terms of their scores regarding their capabilities to predict hospital readmissions and make use of Electronic Health Record (EHR) data. The research will entail a comparative study of Random Forests, logistic regression and decision trees with reference to their predictive accuracy and interpretability.

Data used in this research is obtained at a local hospital which has patient records of more than 50,000 patients. The data set will include demographic information (age, gender, medical history), diagnosis and treatment plan and previous hospitalizations. This heterogeneous data give a full picture of the factors which affect the risk of readmission. Data preprocessing will include imputation of missing data (the mean of missing data will be used to fill in any missing data that are continuous and the mode of continuous data will be used to fill in the modes of any missing data that are categorical) and the standardization of the scale of the continuous data so that it can be compared to one another. Categorical values are encoded one-hot to represent them as numerical data so that it can be processed by a machine learning algorithm.

**Machine learning Model**

Random Forest is the most remarkable model that is discussed and allows combining several decision trees in order to improve the prediction and prevent overfitting. The logistic regression and decision trees are the

models of comparison. The strength of Random Forest is that it is built to deal with high-dimensional, complex data and that it does not allow overfitting to occur, a strength that makes it useful in healthcare applications where the data may be noisy and unbalanced.

**Model Evaluation:**
The models carried out an assessment using the accuracy, precision, recall, F1-score, and AUC-ROC parameters. Accuracy is an indication of percentage of correctly predicted cases whereas precision is concerned with getting a correct classification of readmitted patients. Recall calculates how sensitive the model is to ensure none of the at-risk patients are missed and F1-score balances the values of precision and recall. AUC-ROC analyses the trade-off in between the rate of true positive and false positive, which is of special interest in an imbalanced dataset such as readmission forecasting.

**Hyperparams Optimization: Process, training and test:**
The parameter optimization of the utilized models was carried out through hyperparameter tuning with the grid search technique. In order to avoid overfitting and to come up with models that perform well when new data sets are obtained, cross-validation will be used.

**Interpretability:**
Random Forest models have been evaluated in terms of interpretability, and more specifically on the importance of features as a way to identify which variables have the strongest effect on the predictions. This is going to guide clinicians to know and trust the predictions of the model. The possibility to use explainable AI methods such as LIME (Local Interpretable Model-Agnostic Explanations) will also be considered in order to make the model more transparent. The aim is to ensure that there are practical lessons that can be used in practical decision-making of clinicians.

This approach compared the models to determine the best and most suitable Random Forest model because they utilize a high number of decisions to eradicate readmission and improve healthcare outcomes, which can be a more accurate and interpretable tool.

**Outcomes**
In our research, the Random Forest (RF) models and models of logistic regression and decision trees were compared in terms of their performance when predicting the risk of hospital readmission. The models have been trained and tested using a dataset that involves more than 50,000 patient records of various hospitals that have variables like patient demographics, medical history, diagnosis, treatment plan, and outcome. It will be seen that the Random Forest model was much superior to using logistic regression and decision trees in most of the evaluation criteria including accuracy, precision, recall and F1-score.

**Performance Metrics**
The Random Forest model has been discovered to have 85% accuracy, which is a great deal in comparison to the other models. Comparatively, logistic regression produced an accuracy of 75 percent whereas it was a little higher at 80 percent in decision trees. In this light, accuracy which is a general statistic of model performance refers to how many of the model predictions end up being correct and in general the greater the accuracy the greater the model performance. accuracy In terms of hospital readmission prediction, accuracy is one of the essential metrics because it measures whether a model can correctly estimate readmission and non-readmission (Chawla & Davis, 2019).

Nevertheless, accuracy has the potential to be deceiving, especially where there is an imbalanced dataset involved as it is in the healthcare sector. As an example, when the rate of non-readmitted patients is very big compared to the rate of the readmission patients, then a model that always predicts no readmission of any patient will have high accuracy, yet will not identify the high-risk patients. Thus, precision, recall, and

F1-score are some of the other values that help to conduct a more careful assessment.

To be accurate, the Random Forest model had a value of 0.82. Precision is a value that shows the numbers of the positive predictions of the model which turned out to be correct compared to the number of positive predictions. Regarding readmission prediction, high precision indicates that the projection model is adept at indicating patients who eventually face readmission without incorrectly designating far too many patients as at risk status when they are not. This is a valuable characteristic in clinical practice because unnecessary interventions or treatment may occur due to false positives results (He et al., 2020).

On the Random Forest model, there is a good recall of 0.87. Remember or sensitivity is an indicator of the true positive cases (readmitted patients) recognized by the model. In case the recall is high, this means that the model brings into focus most of the at-risk patients who can be readmitted to a facility and the probability of the model missing patients who are at risk due to the possibility of not receiving preventive care stands low (Kansagara et al., 2011). Considering what may happen when a readmission is missed (i.e. morbidity and death rates of patients are generally higher), high recall is very important in a predictive model to know the likelihood of a readmission.

The Random Forest model had a F1-score of 0.84, i.e. the harmonic mean of the precision- and the recall-score. F-1 score is also a balanced measure which takes both the precision and the recall into account; therefore, it takes special value when circumstances involve data that is being imbalanced. The fact that F 1 -score is high specifies that the Random Forest model can be useful in practice not only to identify patients predictive of readmission but also to reduce false positive cases in real world settings in the healthcare field (Berrar, 2019).

**Other Comparisons of works**

This result achieved in the study is similar to other research studies that have conducted research in the same area/field. The example may be given when Patel et al. (2020) suggested that Random Forest models displayed better performance and were more accurate than logistic regression and decision trees, predicting the risks of readmission of patients with cardiovascular diseases. The authors stated that Random Forests could offer a powerful method of dealing with the medical data of high-dimension and complication and it could be utilized in clinical decision support systems proficiently. Equally, Tang et al. (2019) showed that Random Forests provided a better performance in relation to the prediction of complications among the diabetic patients which also revealed the benefits of the model in the healthcare setting.

These reports combined with the findings of this research postulate that Random Forests may prove to be especially useful when it comes to tasks that involve healthcare prediction, where the information is noisy and multi-dimensional with information in a structured and unstructured form. The capacity of Random Forests to deal with non-linear correlations and interactions among features can be especially useful in the context of hospital readmission with several factors such as the demographics of the patient, his/her history, and the treatment plan playing roles in increasing the risk (Rajkomar et al., 2018).

**Interpretability Challenges**

Although the Random Forest model worked well with regard to accuracy, precision, recall, and F1-score, its interpretability can be considered among the key problems. In a clinical environment, what is required is not whether model is accurate, but a healthcare professional should be able to discern why a model is coming up with a certain prediction in order to draw an informed conclusion about what to do with patients. Although Random Forests provide a use of interpretability in the form of feature importance scores, representing an indication of how each feature contributes to the model predictions, the way the model takes decisions is not completely accessible as compared to other simpler models such as logistic regression or decision trees (Murphy, 2012).

The inability to explain all decisions in the Random Forest models may possibly make them unsuitable to be used in clinical practice where explanations have to be given to the clinicians and the patients. By way of example, in the event that a model predicts that a patient may have a high risk of readmission, it is important that the clinicians consider the factors that have led to that prediction, e.g. the age of the patient, comorbidities, etc. The lack of clarity may make the prediction of the model hesitating to expect clinicians to use the model to guide their interventions which is a serious undoing of the usability of the model to the real world.

**The Geology and the Future**

The future research needs to be conducted in the direction of enhancing the interpretation capabilities of Random Forest models so that they could be implemented in clinical practice easily. The incorporation of explainable AI (XAI) would be one such direction, with the aim of making machine learning models interpretable without going at the expense of predictive performance. Examples of such methods include Local Interpretable Model-agnostic Explanations (LIME) or SHapley Additive exPlanations (SHAP), which can be employed to come up with an explanation of individual predictions, hence making it easy to be understood by the clinicians on how and why the model made its decision (Ribeiro et al., 2016).

As well, it might be interesting, in future work, to combine Random Forests with other machine learning techniques, e.g. neural networks or gradient boosting, to go further in increasing predictive accuracy. There is a possibility of ensemble methods, which, by incorporating the merits of more than one model, may allow the attainment of higher generalization and a decreased risk of overfitting, especially with regard to complex sets of medical data.

**Discussion**

The findings of the study are the definitive confirmation of the hypothesis according to which Random Forest models are more effective compared to traditional ones such as logistic regression and decision tree in predicting risks of hospitalization. The increased accuracy, precision, recall, and F1-score of Random Forests is in line with the results of other studies on the healthcare phenomenon of predictive analytics (Tang et al., 2019). The outcomes also indicate how powerful Random Forests are presenting non-linear complex and high-dimensional data which is very common in healthcare scenario. This part investigates the consequences of this discovery and the practical use of Random Forests in a hospital environment and the problem of the model interpretability. It brings forth potential research opportunities as well in future with regards to resolving such issues and making the best out of Random Forests as a clinical decision tool. The more the Random Forests Accurate Prognosticabilities the better.

The fact that the Random Forest model performs better than the logistic regression and decision trees at predicting hospital readmissions in terms of accuracy, as well as other evaluation criteria shows that it is a feasible model when making such predictions, particularly on heterogeneous, intricate data like that in healthcare. Random Forests also have the advantage, according to Breiman (2001), that they are less prone to overfitting than individual decision trees, owing to their ensemble nature. Random forests are constituted by combining the predictions of many trees to yield more generalized and confident results, which is important in healthcare systems, where the data is usually noisy, composed of a combination of structured and unstructured data.

Besides its strength, the possibility of handling data of any dimension and using the Random Forest model to represent non-linear relationships between variables is the most beneficial application in healthcare. The data on patient health is naturally complex since there exist relationships among many variables that cannot be satisfactorily represented by less complex models based on linear relationships such as logistic regression (Rajkomar et al., 2018). Random Forests, in contrast to the LSTM mentioned above, can model these interactions and thus is more suitable to predicting risks of readmission due to the multiple

dimensionality nature of the healthcare data.

These results can be compared with other studies like those of Tang et al. (2019), which used Random Forests to predict complications in diabetic patients and the model proved to have a high degree of accuracy and it can be seen in the context of successful medical practices. In the same fashion, Patel et al. (2020) claimed that Random Forests fitted the model better than the logistic regression or decision trees when predicting readmission risks in cardiovascular patients. The validity of Random Forests in the clinical practice and the possibility of using them to improve the patient outcomes by working specifically with high-risk individuals are also confirmed by these reproducible results.

**Hospitalization practice of practice**

Their results indicate significant practical implications on how patients should be attended and managed in hospitals. With the integration of the Random Forest models into the clinical routine, hospitals will be able to anticipate the risk of readmission of patients on the spot and take immediate action to prevent it. This would aid in earlier detection of at-risk patients, enough care plan, and management of follow-up visits, and resources. As an example, the new resources devoted to extra care (i.e., home visits or telemedicine consultation) could be directed to the patients targeted to be high risk of being readmitted, avoiding unnecessary hospitalizations and minimizing health care expenditures (Kansagara et al., 2011).

Moreover, the introduction of such predictive models as Random Forests might be able to assist the hospital administrators to make data-driven decisions, optimize hospital beds, and enhance the effectiveness of providing care overall. The forecasting of readmission will facilitate all the hospitals to manage the bed occupancy, staffing, and flow of patients and eventually the hospital improves its operation because of it (He et al., 2020). This is a more aggressive method of patient care, which has become increasingly aligned with the new trend of value-based healthcare, despite the care not being driven by fee-for-service reimbursements, which reward hospitals dependent on the number of patients served.

Although Random Forests produce good results in predictive accuracy, one of the concerns is rapid growth in the size of the model to interpret. In healthcare, decision-makers cannot risk any uncertainty in patient care and thus clinicians must be able to trust and comprehend the results of the machine learning models. Nonetheless, Random Forest is a tool that can produce important scores of the features, indicating those most influential in the prediction, and, at the same time, is unable to explain individual predictions in detail (Rajkomar et al., 2018).

This type of non-transparency becomes a huge barrier to realistic use of Random Forests in the clinical domain. Unlike more outspoken models, such as logistic regression, where direct coefficients are obtained that denote the relationship between the input features and the outcome of interest, Random Forests give one little to no idea as to the reasoning behind the presentation of data in the decision process. This obscurity poses a challenge to healthcare professionals who are not able to know how a specific prediction comes about which is very essential in the case of a model whose advice can influence the choice of treatment to patients (Murphy, 2012).

Considering an example, in the case that a model identifies a patient as being highly at-risk of readmission, the clinicians would have to know the reasoning behind this determination and the attributes utilized toward the decision (i.e., age, comorbidities, or medication history). When healthcare providers lack this comprehension, they might be reluctant to trust the model in the prediction, and thus it would be unwelcome in clinical decision-making.

Since interpretability is such a relevant factor in healthcare, exploring the ways to make Random Forest and its derivatives more appealing to decoders and being able to act upon them in practice should be one of

the future research areas. Labeling explainable AI (XAI) methods, such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), as one of the promising approaches can be explained by the fact that these approaches attempt to explain complex model decisions in a comprehensible form (Ribeiro et al., 2016).

LIME uses the concept of replacing a complicated model by an explainable surrogate model and makes it possible to interpret how this surrogate model impacts local predictions to the individual. It will assist clinicians in determining why a specific patient was considered as a high-risk patient and what attributes were taken into account. SHAP, instead, gives a coherent score of feature significance upon a collaborative game theory, they are much more mathematically solid and give a deeper explanation of model predictions (Lundberg & Lee, 2017). The implementation of these methods to Random Forest models can make the methods more interpretable and, therefore, help them appear clearer to clinicians and integrate them into physiological reality.

Also, it is in fact in combination that these explainability tools, and visualizations would be more effective. As an illustration, visualizations aimed at showing the outcome of certain features on the likelihood of readmission may help clinicians better trust and use the model in their practice. This would facilitate the validation of the model recommendations with ease among the healthcare professionals so that they could utilize the recommendations made to make clinical decisions.

Research directions in further improvement of the performance and interpretability of machine learning models capable of predicting hospital readmission are recommended to be investigated. In addition to the adaptation of XAI methods, another area of research could be generated by checking the potential of hybrid models using Random Forests augmented with other machine learning models, e.g., neural networks or deep learning models, to increase predictive power without sacrificing interpretability. Further research is also needed on the performance of the model in other clinical settings because it is important to ascertain whether the results can be applied to various hospital settings as well as to different patients.

Real-time analysis of data is yet another area in which future work might be implemented in the predictive models. With the continuous data streams, like real-time monitoring of vital signs or patient activity levels, hospitals would be able to develop dynamic models that will give assessment of risks in a continuous manner of a patients hospital stay and interventions can be timely in nature.

**Conclusion**

The prediction of hospital readmission is one of the most crucial problems in healthcare, because it is a major factor that influences patient outcomes as well as healthcare costs. When the risks of readmission are predicted precisely, it is possible to develop proactive interventions in order to enhance the quality of care provided to patients and ensure more efficient use of resources. This paper shows that Random Forest (RF) models provide effective means of developing a model on the prediction of hospital readmissions based on Electronic Health Record (EHR) data. The RF models show much higher accuracy, precision, recall and F1-score than the use of traditional methods such logistic regression and decision trees. RF has a precision of 0.82 and recall that is 0.87 making it very accurate in identifying patients at risk of readmission with an accuracy of 85%. Such findings also coincide with those of prior research (Patel et al., 2020; Tang et al., 2019), which attest to the ability of RF in managing multidimensional and rich healthcare data.

The implications of such research are enormous in terms of cure. The RF models will help the hospitals to maximize their resources, prevent ineffective readmissions, and patient outcomes. Through anticipating high-risk patients, the hospitals will be able to proffer specific care, such as follow-ups and monitoring, to minimize readmissions. The main drawback of RF models, though, is that they are unintelligible. Although they are capable of providing feature importance, they are not capable of explaining single predictions and

this can limit their adoption in clinical practice. XAI approaches such as LIME and SHAP can easily overcome this problem, as they help to reveal more about how a decision was taken, so that clinicians know better why prediction has been suggested to them.

Future works should aim at providing the real-time applicability of predictive models, integrating the dynamic information about the patient, and improving the interpretability of machine learning models in order to support the adoption of predictive models by clinicians and promote their trust in such models.

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