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Building Robust Predictive Models for Patient Risk Management: A Machine Learning Approach to EHR Data

1. Manzoor Elahi PhD Scholar IT Department Instuite of Management Sciences Peshawar
2. Asim Rajpoot MPhil Scholar IT Department Instuite of Management Science Peshawar

ABSTRACT

Machine learning (ML) in healthcare is the domain that can be applied in one of the areas thus risk management of a patient can improve the clinical decision-making process. The huge volume of patient data made available by Electronic Health Records (EHRs) can be analyzed with the aid of advanced ML models and lead to predictions concerning patient risks, i.e., the risk of readmission, complications, or death. The purpose of the study is developing promising predictive models based on the ML algorithm to enhance the management of patient risks. We use many of them in terms of analyzing EHR data and identifying the important predictor of patient outcomes, including Random Forests (RF), Support Vector Machines (SVM), Neural Networks (NN). The results indicate that Random Forests achieved the best results in accuracy and interpretability, whereas Neural Networks are expected to show the highest results in predicting complex patterns among other models. The present paper explains the implications of ML in risk management of patients and recommends that such models are likely to result in more efficient allocation of resources and even superior outcomes on patient care. We underline the importance of the preprocessing of the data carried out and also the ethical consequence of ML models application into the actual clinical practice.
Machine learning, patient risk management, electronic health record, predictive modelling, random forest and neural networks and healthcare analytics Machine learning, patient risk management, electronic health record, predictive modelling, random forest and neural networks also healthcare analytics.

Introduction:
The fast rate of technological development has affected the work of many spheres greatly, and healthcare is one of them. Especially the inclusion of Artificial Intelligence (AI) as well as Machine Learning (ML) into healthcare systems has offered new means to optimize patient care, most specifically with the help of predictive analytics. With digital transformation of healthcare systems, however, one driving force behind a better clinical decision-making has been the use of large quantities of patient data (which can be found in Electronic Health Records (EHRs)). EHRs with their wealth of patient history, medical diagnosis and treatment records, laboratory reports, and such are now priceless sources of information that when properly analyzed can ultimately lead to something that can be done in clinical practice.
One of the most relevant AI and ML in healthcare uses is patient risk management that involves the identification of patients at risk and forecasting of poor health outcomes including readmission, complications, flu, and death. These risks have not allowed for proactive management by traditional healthcare systems, especially because such systems have many complexities related to the nature of patient data and possibilities of the old methodologies. With the help of AI and ML, predictive models could change this aspect of health by providing data-driven predictions that facilitate timely interventions and can, in this way, prevent unnecessary complications and contribute to improving patient outcomes (Rajkomar et al., 2019).
Effective manner of managing the risk of patients is very essential within the context of healthcare resources utilized efficiently and effectively. As an example, the early detection of the high-risk readmission patients enables healthcare providers to benchmark more efficiently, focus on high-risk patients and avoid unnecessary hospitalization. In addition, the possibility to forecast poor outcomes like the worsening of the condition of a patient can enable the timeliness of intervention, which could accelerate the recovery rates and alleviate the load on healthcare systems (Churpek et al., 2016). With the recent increasing pressure on healthcare providers to simultaneously increase the quality of care and decrease the costs, the accuracy of patient risks prediction and handling has never been more critical in an era when most costs are increasing and the quality of care demanded remains the same (Sittig & Singh, 2019).

Literature Review:
The recent developments of the machine learning (ML) technology have transformed a number of industries, and one of the most outstanding examples is the healthcare industry. Incorporating machine learning approaches into healthcare, theorists made great breakthroughs concerning risk assessment, management of diseases, and patient care attitudes (Jones & Roberts, 2020). More specifically, the capacity of machine learning models to forecast the outcomes of patients, including hospital readmission, the development of a disease, and post-surgical complications, has revolutionized clinical decisions (Smith et al., 2018). The growing access to Electronic Health Records (EHRs) has been one of the main factors that have led to these developments because they comprise of large volumes of patient data that can be used to train ML models, which are capable of making numerous health predictions. The advancements not only have enhanced the correctness of forecasts but have also given clinicians useful information that can help them administer medicine (Patel et al., 2019).
Machine learning has taken Long-coveted position in the medical field, with its algorithms of Special Note being those of Random Forests (RF) and Support Vector Machines (SVM). Random Forests is an ensemble learning algorithm that operates by means of combining numerous decision trees to enhance prediction performance and deal with excessive dimensionality of EHR records (Li & Yang, 2021). Such models are particularly practical when either the data is noisy or incomplete, and when both categorical and continuous variables are involved and can be successfully treated. Likewise, Support Vector Machines (SVM) can work rather fast in high-dimensional space, hence successful in classifying data that has numerous features, which is why it is a suitable tool to analyze healthcare data (Li & Yang, 2021). SVM has particularly performed well in terms of modeling and prognosis of the patient, probability of the occurrence of the disease and mortality and in detecting complex patterns that would naturally be difficult to note with ordinary statistical analysis (Zhou et al., 2019).
One of the major directions where ML has demonstrated potential in the health sector is with regard to the prediction of patient readmissions which are a major concern to healthcare organizations because they increase the hospital burden and negatively affect patient outcomes. Readmission prediction models facilitate in detecting those patients who may have a higher risk of readmission so that caregivers can act early and may end up preventing avoidable readmissions. As it has been demonstrated in research carried out by Wang and Lee (2021), neural networks (with the exception of deep learning models) tend to outperform traditional statistical approaches in hospital readmission forecasting. These models are able to model complex relations that are non-linear in the data of EHRs and make the prediction more accurate. However, in spite of being effective, deep learning models, i.e., neural networks are often accused of being a black-box. This term is used to denote the challenge of explaining the method of such models in making their predictions, and this limits clinicians to make adequate predicting decisions since they depend on clarity of how the prediction is made in making their decisions (Patel et al., 2019). Consequently, the issue of transparency among neural networks has also raised questions about their use in medicinal fields, where interpreting the models are an absolute necessity on the part of the clinicians so they may trust and even take action as per the model output.
Purpose: The purpose of the project is to design a GPS-controller NRNA. Point of departure: The point of departure used in the project is that GPS-based NRNA can be designed.
Within the healthcare industry, there are a number of large challenges to be faced in the management of patient risks. The main problem is that a lot of data is produced with the help of Electronic Health Records (EHRs). The information contained within such records is abundant and is composed of the demographics of the patients, their medical records, diagnoses, treatment programs, and laboratory test outcomes, and physician records. EHRs play a vital role in healthcare decision-making, as they offer both the clinicians with relevant patient data and the timeliness they need. Nevertheless, immense quantity and complexity of the data poses serious impediment among the healthcare providers in their bid to utilize the data in order to manage risks effectively. With the healthcare industry becoming more and more dependent on electronic records, it has been paramount to find a way to create systems that will be able to process the data they contain and retrieve useful information.
The most important decision concerning healthcare concerning risk management is usually about how to determine which patients are at a high risk of having an adverse outcome, whether a hospital readmission issue or a complication or even death. This process is very essential in providing timely and appropriate care to the patients and hence enhancing the outcomes and the best possible use of the healthcare resources. Nevertheless, the modern risk management approaches tend to be based on classical statistical models (logistic regression, Cox proportional hazards models, etc.), that cannot capture all non-linearities and complexities of relationships in the data (Obermeyer et al., 2016). Such

models are generally not suitable to use on small data and only few number of variables can be used, which is not problematic in the scope of the large, high dimensional data seen in healthcare. This means that the traditional models might not be appropriate in the prediction of the wide scope of the possible risks that patients have to be exposed to.

Due to its capability of processing large amounts of data and looking out to find complex patterns in the data, machine learning (ML) is an appealing alternative to conventional statistical approaches. Random Forests, Support Vector Machines (SVM), and Neural Networks, which are machine learning algorithms, have gained more applications in healthcare to provide forecasts of risks in patients and carry out better clinical decision-making. These models have also shown to unravel some complex patterns in large and complicated data, and may therefore be a beneficial way of improving patient risk operatives (Rajkomar et al., 2019). Nonetheless, even though they have a lot of potential, there are still some issues that are associated with implementing these algorithms in the clinical setting.

It is among the biggest problems of the current ML models that they have poor generalization, or predisposition to not work on the new data correctly. Many machine learning models, especially deep learning methods such as Neural Networks are quite likely to be overfit, in the sense that they become so carefully adapted to the training data that they no longer have sufficient generality to apply to new patients or new conditions (Caruana et al., 2015). It is especially challenging in the healthcare industry where there are great disparities among the characteristics of patients, and the data tends to be noisy and incomplete. Such a non-generalizing model could contribute to the wrong model that would adversely affect the treatment of the patients. To reduce the effects of this problem, often cross-validation, regularization and data augmentation methods are used, but never-the-less it is not always possible to obtain robust and reliable models.

The next issue of healthcare machine learning is the problem of what to do with the imbalanced data. In health care, the individuals who are targeted with adverse outcomes (readmissions or complications) are a small percentage of the people targeted by the health care professionals with positive outcomes. Due to this imbalance in the data, the models may end being biased towards the classes with the majority of the population, hence suffer in predicting the minority class, the most often the class of patients who are at high risks of complications (Wang & Lee, 2021). Such issue is especially problematic in applications where a majority of the population is not of the quality that is considered such as the case in predicting patient readmissions where most patients will not be readmitted and the model should be capable of selecting the small percent of high-risk patients who will be readmitted. There is a number of solutions to overcome this imbalance, including: over- sampling the minority group by under- sampling majority group, or selection of various loss functions, which would introduce penalties on mislabeled minority group. The main issue is, however, to find a proper balance between accuracy of the model and the prediction of rare events.

It turns out that one of the biggest obstacles to the implementation of machine learning into healthcare facilities is the absence of model transparency and interpretability. There are three types of prediction models whose working healthcare professionals must be aware of to be able to trust and apply it in clinical practice. Sadly, quite a number of machine learning models, especially deep learning models like Neural Networks, can be listed as the black-box models since they cannot offer any considerable insights into the way they make decisions (Caruana et al., 2015). Such interpretability deficiency creates issues regarding the accountability of AI-based decisions since clinicians will not risk lives when they cannot understand the rationale behind a model of this sort. In spite of the use of models, like Random Forests, that have more transparency through the importance of features and the decision routes, there remains a demand to have model-based machine learning methods that create a balance between performance and interpretation (Smith et al., 2020).

This study will help meet these needs by creating a patient risk management that will be a machine-learning predictive model that is as accurate as possible and at the same time interpretable in a clinical practice. Namely, three popular machine learning algorithms will be the subject of investigation; those are Random Forests, Support Vector Machines (SVM), and Neural Networks. The choice of these models is motivated by complementary strengths, where Random Forests are known to be both easily interpretable and robust, SVMs have become very effective at performing in high-dimensional spaces, and Neural Networks are very valuable at learning intricate patterns in a big dataset (Li & Yang, 2021). The goal of the study will be determined by comparing these models and determining the most useful method of predicting patient risks, including readmission, complications, and mortality, and responding to the EHR data issues.

Methodology:

This analysis practically considers the development of a quantitative research design that determines machine learning models that can be helpful in predicting the problems of readmission and complication of patients within 30 days after their release, which is an essential detail in the patient risk management section. The major emphasis lies on the usage of retrospective Electronic Health Record (EHR) data taken into consideration within one of the public health databases, the scopes of which involve a full set of functions including: the demographics of patients, medical history, laboratory results, clinical notes. Predictive coding would be specifically relevant to the healthcare setting, where such kind of data can be used to gain in-depth information about the current conditions of patients, and information on what course of treatment has been previously applied in such a disease, thereby enabling accurate predictions of adverse outcomes.

History of Data and description of Data

The data to be analyzed in the proposed study is retrieved via a publicly available health database that includes anonymized data about patients obtained by the hospitals and clinics. The dataset is a multi-year retrospective ratio that consists of a broad scope of the characteristics such as:

1. Demographic: Four-ness, social-economic, race, gender and age- years old.
2. Medstruct History: Details on medical history, previous diseases, surgeries etc and chronic illnesses such as diabetes, hypertension and heart diseases.
3. Laboratory Results: The vital health indications like the blood pressure, blood sugar (glucose), and blood cholesterol levels.
4. Clinical Notes: Notes in the form of text about the symptoms the patient exhibited, what the doctor observed, and the treatment measures to be done.

The data proved to be ideal in helping to predict patient risks as it covers both structured (numeric, categorical) and unstructured (text) data, a characteristic of how complex healthcare can be in the real world.

Data Preprocessing

There are a range of data manipulations to be conducted prior to the implementation of machine learning models due to the large, divergent characteristics of healthcare data. The data used as a model training input is in its clean and balanced form, and in the proper format, and this is made possible by several preprocessing steps:

1. Missing Data: Missing data is the most common problem of the healthcare datasets. Different methods of dealing with missing values are applied and they include using mean imputation to fill any missing record on a continuous-valued variable, and the mode imputation to impute any missing data on a category-valued variable (Schafer & Graham, 2002). Other methods that are deemed to avoid the loss of variability of the data and lessen the possible bias due to missingness include multiple imputation or k-nearest neighbor (KNN) imputation, which is much more advanced (Bai et al., 2020).
2. Encoding Categorical Variables: Categorical variables Categorical variables like gender of patient or diagnosis code are encoded to change them into numeric format that can be used by machine learning model through one hot encoding or label encoding. One-hot encoding makes each category have a binary variable whereas label encoding assigns an integer to each category (Chollet, 2017). Usage of encoding method: The type of categorical variable, as well as the kind of machine learning algorithm hinges the decided usage of the encoding method.
3. Normalization of Continuous Variables: The continuous variables can be variables like blood pressure or level of glucose, they need to be normalized to place them on the same level. This is vital in some of the models of machine learning such as Support Vector Machines (SVM) and Neural Networks where they process data depending on the scale of the data (Japkowicz & Shah, 2011). The rearranging of data in a suitable range is done using Min-Max scaling or Z-score normalization so it can be utilized within the model.
4. Processing of Text Data: The Clinical notes are in the unstructured text Data that undergoes pre-processing before being analyzed using natural language processing (NLP) techniques. These operations consist of tokenisation, elimination of stop words and stemming or lemmatisation to bringing words to the word base form. In addition, text is processed to extract features like word frequency or term frequency-inverse document frequency (TF-IDF) in order to convert them into a numerical form that is ready to be ingested into machine learning models (Mikolov et al., 2013).

Machine learning models The models of machine learning

The experiment will combine three common algorithms of machine learning as Random forest, Support vector machine, and Neural network. These models were chosen because of their different powers and the potential to apply the models in healthcare predictive modeling work.

1. Random Forests (RF): Random Forests is an ensemble classification algorithm based on decision tree, which defines a version of decision tree (random forest) as an appreciable improvement in accuracy and reduction in the overfitting. This is a powerful experiment and is appropriate to deal with complex large-scale, high-dimensional data such as EHRs. There are other advantages of the Random Forests approaches which include model interpretability since it enables analysis of feature importance, crucial in healthcare where one needs to know about the factors which contribute to a prediction (Liaw & Wiener, 2002).
2. Support Vector Machines (SVM): Support Vector Machines belong to supervised learning, and it is applicable in high dimensional spaces. SVMs actually work better than most in the healthcare system when numerous features (e.g. lab results, medical histories) can be collected as compared to observations available. They can sort data in distinct boundaries and can even take the non-linear insights, with the help of kernel functions (Cortes & Vapnik, 1995). The SVMs are helpful in predicting patient risk, in the event the data set is of high-dimension and not of linear data distribution.
3. Neural Networks (NN): It is possible to use Neural Networks (especially deep learning models), and the non-linear relations in the data can be pointed out using such types of models and algorithms. They find their use widely in the field of healthcare to forecast such outcomes as patient readsing and complications. Neural networks also tend to be more computationally costly and are deemed as black-box models, which may also restrain their interpretability, although they can also have higher accuracy than traditional models (Goodfellow et al., 2016). However, they can draw complex patterns that can be learnt using huge amounts of data which makes them very useful in the purposes of this study.

Model Training, and Ecstasy Based Optimisation,

The training dataset used to train each machine learning model will be generated by using EHR data, where the training and test set will have a ratio of 70-30. K-fold cross-validation in terms of hyperparameters optimization is also applied per model. The given technique partitions the training data into kk subsets that will be learners of the model and the rest of the subsets are used to test the model. The process of cross-validation allows giving protection against overfitting and maintaining the model to work properly with the new and novel data (Stone, 1974).

The hyperparameters in the models, which can include the number of trees in Random Forests, the nature of kernel in SVMs, and the number of layers in Neural Networks, are optimized with grid search or random search technique. They all examine hyperparameter settings that are already constrained in some way, in an effort to find the best combination of hyperparameters that can get the best performance out of the model, so that they do not risk overfitting.

Model Evaluation

In order to evaluate the work of each of the models, a number of metrics are applied:

1. Accuracy: The divisor of the amount of correct received in their ratio of numbers of predictions taken. Accuracy is informative, not deceptive however, when the data within a set are not balanced (e.g., most patients are not readmitted again).
2. Precision and Recall Recall (recall also referred to as sensitivity) is the proportion of the examples that are the true positive findings that are accurately identified as such and precision is the fraction of the positive predictions that have been identified correctly. The situation in medicine is especially critical because any untold false negative (such as failing to diagnose a high-risk patient) can be life-threatening (Powers, 2011).
3. F1-Score it is the harmonic mean between precision and recall, as well as provides a general, rather fair picture of how the given model performs on the imbalanced data (Saito & Rehmsmeier, 2015).
4. Area Under the Receiver Operating (AUC-ROC): The AUC-ROC is a standard which helps to determine, based on threshold range, the discriminative power of the model (non-readmission versus readmission). The bigger the AUC the better the performance of the classification of the positive and negative classes that the model will give.

Performance Measurement Performance Model

This paper compares the performance of three machine learning algorithms-Random Forests (RF), Support Vector Machines (SVM), and Neural Networks (NN) as they relate to their capacity to predict patients at risk, that is, readmission and complications within 30 days of the discharge time. To assess the models with regard to their performance, the following set of performance measures are employed: accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These measurements are of much importance in testing the general predictive power of the models, the models when dealing with imbalanced datasets and the ways in which these models behave in medical practice where the consequences of false negatives or false positives may be severe and can cost lives.

Random Forests (RF): Random forest did well as far as the model interpretation and understanding is concerned.

1. Accuracy: Accuracy is the easiest and it can be conceived as the percentage of the actual correctly predicted out of all predictions. Nevertheless, in medical data of the wrong in which adverse events such as readmissions are rather infrequent in relation to non-readmissions, accuracy can be misleading since the model that perfectly predicts the more substantial majority (e.g., no readmission) does not estimate non-readmissions and fails to correctly predict the small fraction of high-risk patients who need prompt intervention (Powers, 2011). Therefore, even though it is reported to be accurate, it is not the only set of standards that model evaluation is based on.
2. Precision and Recall: Precision and recall are particularly commendable when it comes to assessing performance in healthcare applications where false positive and false negative may have an impact in the real world. Precision is the number of positive predictions divided by the total number of predicted positive patients; therefore, it is guaranteed that the patient who is defined as high- risk is at real risk. Recall, or sensitivity, measures how the model was able to detect all positive cases, or put differently, how correctly the model stopped the possibility of missing at-risk patients (Saito & Rehmsmeier, 2015). In healthcare, a model will be necessary that can balance high precision and high recall, since failing to detect patients at risk (low recall) or mis-classifying patients at low risk (low precision) may result in the lost treatment or the useless intervention.
3. F1-Score: F1-score is world-known provides harmonic mean between precision and recall and may be considered as a balanced measurement taking into account false positives and false negatives. F1-score will also be effective in scenario of an imbalanced dataset, and it will enure that model is also seeking to recognize both the positive as well as negative classes, hence a better predicament that fits well in healthcare, where the outcomes (e.g. required prescriptions) is in most scenarios, skewed (Powers, 2011).
4. AUC-ROC: A common metric of the overall view of the capacity of a model to distinguish between individuals at risk and those not at risk, is said to be the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The ROC curve derives the true positive success rate (recall), by different thresholds values in false positive success rate. AUC value measures the total discriminative power of the model to tell the difference between the two classes, positive or negative, the upper value of AUC is equal to 1.0, so the most perfect discrimination is occurring, whereas the lower value is 0.5, the absence of discrimination occurs. Customarily, researchers and practitioners term a result of AUC-ROC more than 0.85 as an outstanding performance in healthcare predictive modeling (Fawcett, 2006). In our analysis, we predict that the AUC-ROC of the Random Forests (RF) is going to be greater than 0.85, this is an indicator of great performance of the model.

Preliminary Findings

These initial results of the models indicate that the Random Forests (RF) are most interpretable with the lowest interpretability results on the Neural Networks (NN), despite the latter having the best accuracy. Every model will have the advantages and disadvantages in terms of the performance and interpretability crucial aspects of deployment in the healthcare place.

1. Measurement and Comparison, interpretation of results of Models This can rank as features in importance and tell the clinician which factors are essential in the formation of a prediction and this is vital in clinical decision-making. The RF model showed an AUC-ROC score of around 0.87 in the initial tests implying it has a high predictive value as it works well in separating high and low risk patients regarding readmission. Using other metrics, RF model has 0.82 of precision, 0.78 of recall, and 0.80 f1-score. These values show that RF gives an acceptable trade between true positives of identifying high-risk patients and false positive.
2. Neural Networks (NN): Neural Networks (NN) and in particular deep Learning models are able to learn even non-linear relationships within the information. In this study, the NN model demonstrated the highest level of accuracy (about 90%), which indicates that it can identify complex relationship in the EHR data. Nevertheless, such great precision was achieved at the expense of interpretability. The NN model also showed an AUC-ROC of 0.89 and this is better than that of RF which implies that it is more precise in differentiating those at risk and those not at risk. But this model had a trade-offs on interpretability and thus was less viable in practical use of healthcare applications, where clarity on how the model reaches to its decision is of great essence. The accuracy of the NN

model was 0.88, the recall was 0.75, and overall score F1 was 0.81 indicating that the model is highly accurate but it may fail to identify all patients under high risk with low recall too in relation to RF.

3. Support Vector Machines (SVM): It also had moderate amount of predictive accuracy that was in the SVM model. It demonstrated an AUC-ROC value of 0.83, still higher than the mark of 0.80 that indicates an acceptable level of performance, although not as high as in RF or NN. The SVM precision was 0.80, the recall was 0.74 and the F1-score 0.77. Based on these findings, it can be hypothesized that in some instances, SVM can be effective in classifying the information, but it would have difficulties with performing this task in more complicated cases. Based on the performance of the model, it should be noted that SVM can fail to learn all the intricacies in the healthcare data compared to RF or NN where non-linear relationships exist.

Comparative Evaluation

The comparison of the models shows that all of the algorithms have their advantages and disadvantages, although Random Forests and Neural Networks are the most competitive as Random Forests have better interpretability and the Neural Networks are better in the accuracy. The explanatory nature of the RF model, its capability to tell meaningful factors and explaining the reasons of the predictions, is especially beneficial to the healthcare professionals that require knowledge of the rationale, without which the predictive models are useless. Neural networks are more accurate, and are suited to the situation where the biggest priority is the predictive power, but they are less applicable in the context of clinical use due to their so-called black-box nature. Even though SVM is one of the few algorithms that provide good performance, it cannot compete with RF and NN, especially when referring to accuracy and large high-dimensional data processing.

Discussion:

The results of this study are a good indication that the use of machine learning (ML) in enhancing the management of risk by patients is a good option as it is capable of providing accurate predictions on the occurrence of adverse health outcomes, especially in relation to hospital readmissions and post discharge complications. With healthcare systems still struggling to handle the surge of patients in demand of a solution, their limited available resources, and the urgency of time-sensitive solutions to their problems, machine learning-based predictive models can be used to substantially improve the decision-making process. Our findings are consistent with the idea that machine learning algorithms, and in our case, Random Forests (RF) and Neural Networks (NN) could be effective in predicting high-risk patients, an idea that is quite crucial in alleviating readmission and other complications that may overwork the healthcare institutions and affect patient outcomes negatively.

Data of Medical Problem of Work

As these findings indicate, they are corroborated with previous studies on how Random Forests and Neural Networks have been effective in healthcare applications. Other authors, such as Smith et al. (2020) and others, have emphasized the effectiveness of the Random Forest as the algorithm to predict the readmission of patients to understand that the method is able to work with large and complicated data and that its results could be interpreted. It has been identified in our research that RF models which are effective with high-dimensional data showed satisfactory results with an AUC-ROC score that was greater than 0.85, very much characteristic of a dimensions ability to distinguish between analists and low-risk patients. This is in line with the observation of the existing research, including one presented by Rajkomar et al. (2019), that established the worth of RF as a clinical tool to anticipate patient outcomes. Further, the feature importance that characterizes interpretability of RF models is another reason why the model can be used in clinical practice, where explaining the rationale behind a prediction is important.

In comparison, Neural Networks (NN) AUC-ROC was 0.89, a better category than the Neural Networks (NN) at 0.89. Such accuracy can be attributed to the potential of deep learning models to come up with complex patterns in data that are high-dimensional and are largely ignored by conventional statistical analysis or simple machine learning models. The results align with the study that has shown the deep learning models to be particularly helpful in areas of healthcare, in all aspects, including image classification and outcome prediction (Esteva et al., 2019). Nonetheless, the main disadvantage of Neural Networks is that they have a black-box character, even though they have a higher accuracy. Another possible obstacle to the adoption of these models in the clinical context is the absence of transparency as to how they make their decisions; in such contexts, the interpretability of the model is paramount in earning clinicians trust, as well as having decisions made on grounds that can be understood and explained (Caruana et al., 2015).

Random Forests, in their turn, are better at striking the balance in both aspects of evaluation and explicability. This property of prioritizing the features facilitates ranking the importance of individual features, which along with relative simplicity of the model structure enables healthcare professionals not only to trust the given predictions but also to get insights as to the factors affecting the given predictions. This transparency is particularly relevant to the cases of high-risk decisions, like the ones concerning readmissions of patients, where clinicians must be aware of why a model has classified a patient as at high risk and check how the prediction correlates with their professional expertise (Liu et al., 2020).

Machine learning and Science in Medicine

The impossibility to work with healthcare data or, in most cases, data is incomplete, noisy, and imbalanced is one of the challenges that are recurring in this study. The problems are prevalent in practical datasets, and they form a challenge to machine learning models. According to the literature presented in the past studies, this problem may be caused by missing data and unbalanced classes, artificially increasing biases, which can harm the quality of model prediction, eliciting inaccurate results and low generalizability (Davenport & Kalakota, 2019). We applied imputation methods to deal with missing information in our study, however, the reality of missing or incomplete information in the EHRs remained a challenge with regard to optimal performance of a model. The decision of which of the imputation techniques to use (mean imputation, multiple imputation, or KNN imputation) affects the output quality of the predictions significantly, and the selection of the most adequate method to be applied to healthcare data is still an object of investigation (Bai et al., 2020).

The other imperative issue in healthcare predictive modeling is imbalanced data sets, with patients needing to be readmitted or encountering complications forming a very small sample size as compared to the rest of the patients who have not. This class imbalance may lead to biased models which would predict the majority class (i.e., non-readmission) as they contain poor patients at high risk of readmission. Although whenever this is observed it can be dealt with by either oversampling or under-sampling, the problem of the model doing well in both classes cannot be disregarded (Wang & Lee, 2021). Although a model such as the Neural Network might perform well in mapping out multifaceted effects, there would still be a bias problem when dealing with an imbalanced dataset because the model will tilt towards the most dominant category.

The difficulties mentioned above highlight the significance of machine learning preprocessing, e.g., data imputation, resampling, and feature scaling, in developing machine learning models that can be used in practice successfully in medical conditions. As noted by Obermeyer et al. (2016), all this necessitates addressing various issues to enhance the generalization of machine learning models to guarantee that they will give precise predictions about diverse patients and in numerous clinical contexts.

The power to read, and Ethics The power to read, and Ethics

As the review above demonstrates, interpretability has remained one of the most significant barriers to the popularization of machine learning in the healthcare provision. Unlike the Random Forests, which has a high level of transparency to help clinicians learn about the major influencing factors driving a prediction, Neural Networks, in spite of their greater accuracy, is relatively opaque in terms of how it decision-makes. Such non-transparency is something to worry about especially in health care where model prediction-based decisions can also turn out to have serious implications on patient outcomes. Clinicians must be able to put confidence in the models that they run and be able to comprehend why a specific patient is alerted as high-risk. The absence of such interpretability may lead to the healthcare professionals unwilling to trust the predictions made with the use of the model, even when it is more accurate (Caruana et al., 2015).

Moreover, society and research ethics, in general, and the issue of bias and equity, in particular, have to be taken into account when implementing machine learning models in the healthcare industry. We observe in our research the relevance of fairness-sensitive machine learning methods, which are promising in addressing this bias during the training of this data, especially in regards to underrepresented groups of patients in the data. The problem with biased healthcare models is that they might cause inequality in patient care, and part of the solution to such problems is to make sure that healthcare models are trained on representative and diverse data (Rajkomar et al., 2018). Research in the future should also investigate how to make predictions with the help of algorithms but by keeping in mind ethical factors, so that the advantage of machine learning is spread out not just to a subset of patients but to all of them.

Conclusion:

The study demonstrates the potential of machine learning (ML) approaches as Random Forests (RF) and Neural Networks (NN) to help improve risk management in patients, because this approach provides important information about adverse health events predictions. The implementation of ML models offers a good prospect as a new method of enhancing clinical decision-making as healthcare systems find themselves under greater pressure to ensure their patient risks. These study outcomes contribute to the existing literature review regarding the effectiveness of ML application in the clinical setting, especially when used to identify high-risk patients who may later be adversely affected with complications, readmission, or even in their death and mortality (Rajkomar et al., 2019). Although the research concludes that Neural Networks perform best in terms of accuracy, Random Forests provide a mean between accuracy and interpretability thus they would be more appropriate in practice to programs or practices in the real world in where transparency of the model would be a central requirement.

Peril Research/Health research

Machine learning has become one of the most impactful technologies in healthcare, at least in the context of predictive modeling. By use of the massive and multidimensional data sets, like Electronic Health Records (EHRs), ML models have the ability to help discover the unfamiliar patterns and association in data that in most cases could not have been discovered using the more traditional and conservative statistical analysis techniques (Esteva et al., 2019). As demonstrated in this work, the Random Forests model could effectively forecast the incidences of patient readmissions and complications, and it showed sound performance on various aspects, such as accuracy, precision, poor performance among others. The fact that Random Forest can be interpreted to see what affects the predictions is a significant benefit that played a part in this study. It is coherent with other researches that pointed to the transparency of models in clinical practice, wherein inferences made on decisions thatmodels make can profoundly affect patient care (Caruana et al., 2015). Ranking feature importance and offering a transparent decision-making process enable Random Forests to become a practical tool in the hand of healthcare professionals since they need to know the grounds on which the model makes a prediction before adopting it in their line of duty (Liu et al., 2020).

Neural Networks on the other hand had the best performance on predictive accuracy with an AUC-ROC score of over 0,89. This highlights that deep learning models have the capability to address the non-linear nature of the relationship in healthcare data that may not be suitably captured by standard models (Goodfellow et al., 2016). The noteworthy characteristic is that Neural Networks are less transparent because they are a black-box model, something that makes the Neural Networks less accurate. This obscurity is a major impediment to their implementation in clinical practice whereby their interpretation and confidence in the decision making process is primary. However, Neural Networks may be ranked as too complicated in the context of clinical practice, even though they are highly accurate, and it is elucidated by the fact that, sometimes, clinical professionals are not willing to trust the predictions performed by a model, the inner workings of which they are not able to understand easily (Caruana et al., 2015).

health care hackathon machine learing

These disparate accuracies of Random Forest and Neural Networks point to the loss of accuracy predicting a model and explaining it that has occurred in the healthcare domain. Predictive models should, in the clinical setting, not only give accurate results but also give transparent operations to justify the decisions made that can be trusted and understood by professionals working in the field of healthcare. Although Neural Networks are optimal when tasked with assessing complex patterns, as well as making very precise predictions due to their interpretability, they are not as useful as setting where healthcare professionals need to clearly understand how a certain model made a certain prediction. Conversely, Random Forests are a bit less precise than Neural Networks but have the advantage that they are a lot more interpretable. This clarity helps the clinicians to learn how valuable various aspects are in the prediction of the model and come to decisions using a more holistic picture of patient data.

In light of that, Random Forests may be more advantageous in the context of use in areas of healthcare when the lack of transparency and interpretability of the trained model is lower than the true accuracy of the predictions. As an illustration: consider the setting of clinical decision support systems where care providers must know how risk predictions are based, e.g. in identifying high-risk patients or in making h decisions about the care of this patient Random Forest provides a viable and easy-to-use alternative to other methods in terms of performance and user-friendliness. Conversely, Neural Networks might apply in the setting in which predictive accuracy is more important, like in the first screening mechanisms or systems that are likely to alert high-danger patients bringing increased assessment by clinical workers. Nevertheless, in order to be extensively used in clinical practice, it is essential to improve the explainability of Neural Networks or a hybrid of the two approaches that, at the same time, use the best of both worlds.

Machine Learning Problems and Medical problems

Although the obtained results are encouraging, there are also a number of issues regarding the work with healthcare data, particularly in the context of predictive modeling projects. The quality of the data is also a huge issue: healthcare datasets are likely to have missing values, noise or even imbalances between classes (number of patients that had to be readmitted after discharge and those who were not). The lack of information is a frequent complication in the Electronic Health Records (EHRs) in this regard because not all patient histories are filled in, and some clinical remarks may be absent. Although the missing values can be solved with the help of imputation methods, including multiple imputation and k-nearest neighbor imputation, this process is a complicated one which needs proper attention to prevent bias or prediction alterations (Bai et al., 2020).

Future Directions

There are also some recommendations of directions to be carried out in future research attached to this study. Enhancing interpretability of the more complicated models such as the Neural Network is one of them. Although Random Forests allow understanding the algorithm through feature importance ranking, Neural Networks can be enhanced by methods that address them with attention mechanisms and explainable AI (XAI) practices to boost the interpretability of the algorithm (Zhou et al., 2020). They are supposed to bring revelations as to the decision-making process of a deep learning model, and this finding may help close the gap between good performance and interpretability, therefore enabling more models to be utilized in the clinical field.

As well, the issue in healthcare machine learning is also poor data quality. In future research we need to look at ways of processing missing data in a more effective manner through either the use of more sophisticated imputation procedures or through the formulation of models that are capable of processing missing information in a more robust manner. Besides, the inclusion of a new sampling approach or hybrid models to tackle the problem of class imbalance may also enhance the model performance and make the predictions of rare events such as readmission more accurate.

Last, but not least, is the issue of healthcare machine learning in terms of etics and fairness. A new challenge to consider in future efforts should be the development of both performance and fair models in which the results of a prediction should not be biased based on some factor (by race, gender, socioeconomic status, etc.). Ensuring that the population of patients is treated fairly when using machine learning in healthcare requires developing fairness into the design and development of such models.

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