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EVALUATING THE IMPACT OF MACHINE LEARNING MODELS IN FORECASTING PATIENT OUTCOMES: AN EHR-BASED STUDY

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Abstract:
Machine learning (ML) as a method of procedures has transformed healthcare especially in the outcomes forecasting process of patients. EHRs contain huge volumes of patient-related information and hence, possible opportunity exists to administer ML models to perform predictive analysis. The study is concerned with the application of machine learning to forecast the destiny of patients in accordance with the EHR data. The analysis will involve a comparison of various algorithms, i.e., Random Forest (RF), Support Vector Machine (SVM), and Neural Networks (NN) in order to determine the fate of the patients in terms of disease advance and risk of readmission. The tactics that were used in the current investigation may be listed as feature selection, data preprocessing, application of the ML algorithms to a publicly available EHR dataset. The accuracy of performance measures is based on the performance of the models, precision recall, and F1-score, upon which they are tested. Based on the findings, although neural models show that this neural model gives high accuracy rates, it is observed that they are likely to perform better in clinical use applications compared to Random Forest models due to their probability of interpretability. The paper helps in the advancement of knowledge on the application of machine learning in healthcare which would culminate in better patient care and decision making. In the future, more advanced methods of deep learning are to be applied and the transparency of the model is to be enhanced.

Keywords
Outcome, Machine Learning, Patient, Performance Forecasting, Electronic Health Records, Random Forest, Neural Networks, Predictive Models in Healthcare

Introduction:

Healthcare Machine learning (ML) in recent years has gained an immense amount of interest due in large part to the promise of better clinical decision-making and patient outcomes. Random Forest (RF), Support Vector Machine (SVM), and Neural Networks (NN) are other ML models that have already demonstrated the potential to predict the occurrence of the unacceptable healthcare outcome, including the propensity to develop a disease, reach its mortality, and become readmitted to the hospital. Such models are highly dependent on the data included in the Electronic Health Records (EHRs) that give extensive data regarding the demographics of patients, their medical history, diagnostic data, and treatment results. EHRs have become a versatile repository of data that can be used to build predictive algorithms through which healthcare providers can draw inputs on how to approach a certain decision-making process (Rajkomar et al., 2019).

EHRs of any given hospital can be enormously wide and comprise structured data, like lab results and diagnoses, in addition to unstructured data, like physician notes and imaging reports, which has proven both a resource and a complication when it comes to machine learning. Patient outlook or the predictions of patient outcomes, like propensity to have the illness, fatalities, and readmissions among others, are vital in enhancing quality, efficiency in healthcare, and patient care. Correct predictions facilitate interventions at the time they are most effective, the distribution of resources in a more rational way, and the development of individual care plans, which makes unnecessary hospitalization and spending on treatment (Obermeyer et al., 2016). It has to be mentioned that the ML models can make more accurate and less obvious predictions compared to legacy statistical models that have received attention in several papers, with the researchers indicating that the use of this kind of model can bring significant advantages to helping the patient and patient outcomes (Miotto et al., 2018).

Although the potential of the ML models is remarkable, there are still a range of issues, namely, their accuracy as well as their interpretability and effectiveness in the clinical practice. Although such deep learning models as neural networks may be highly predictive, they are cited as the models that suffer due to a lack of interpretability--a potentially important barrier to adoption in healthcare environments (Caruana et al., 2015). Furthermore, the data used in healthcare is frequently incomplete, noisy, and imbalanced, and, therefore, one can destroy the predictive models (Wang & Lee, 2021). This research will address these issues by surveying the performance of the various revolutionary machine learning models like RF, SVM and NN in predicting the outcome of patients using EHR data.

The purpose of the study is to get the information on the functionality and practical value of these models applied to real-world EHR data. Presenting both models of differing levels of complexity and interpretability, we will be able to determine which method is best to use in clinical practice in order to employ machine learning. Namely, it will be examined whether the simple models, e.g., Random Forest, could provide a superior trade-off between the prediction quality and the clinical interpretability of artificial intelligence models compared to the complex ones, e.g., neural networks.

Related Work on Machine Learning in Healthcare

There is increased utilization of machine learning in the healthcare area to predict patient outcomes and this raises possible advantages in cough diagnosis, risk stratification, and clinical decision support. Much of the literature has just proved the usefulness of ML algorithms in enhancing the preciseness of mortality prediction, readmission projections. As an illustration, Churpek et al. (2016) examined the application of models of Random Forest and Support Vector Machines to patient readmission prediction in intensive care units and the results indicated that the models may perform better than conventional models like logistic regression.

Fine-tuning in deep learning structures specifically the neural network has recently produced spectacular outcomes in the prediction of the probability of mortality, the risk of complication, or the severity of the disease progression. Esteva et al. (2019) applied CNNs to medical images in a way that deep learning performed equally well or with even greater accuracy compared to medical clinicians. Nevertheless, the black-box character of its models can be identified as one of the main problems of adopting them in clinical practice. There is a need to know why a model makes specific predictions, and this is especially important when life-critical decisions are to be made by a healthcare provider. Consequently, interpretability obstacle has become a hindrance in the popularization of neural networks in the clinical arena (Caruana et al., 2015). Random Forest, on the other hand, is another ensemble approach enshrined no less than on the capability to be more understood than the deep learning models because of the proscribed nature of decision paths and feature importance scores. Chen et al. (2020) provided evidence that Random Forest models were able to predict patient outcomes, including readmissions and mortality with high accuracy and provide information regarding the most predictive features. Such interpretability plays a fundamental role in the context of healthcare where clinicians need to be able to trust in the predictions made by the model to act on the basis of the model recommendation.

Although ML has a great potential, problems are still present because of the type of healthcare data. EHRs are fragmentary, noisy, and unbalanced, and this aspect may have a harmful effect on the performance of models. Our line of thought is supported already by a few researchers who offered the idea that preprocessing of data could improve the robustness of the model, i.e., which refers to the data imputation and feature selection techniques (Miotto et al., 2018). Nevertheless, the problem of data quality still exists in the sector of healthcare predictive modeling, and the investigation of the issue should be conducted to create the methods to handle such problems as missing and noisy data.

Literature Review

Machine Learning and quality of healthcare used by Malaysians

Machine learning (ML) in healthcare is a relatively new area, and there are a lot of research studies that indicate the potential of working with this computer technology to advance patient care and experience, adjust the optimal course of treatment, and increase the overall efficiency of healthcare systems. Though the idea of ML being applied to health has not been new in recent years, it has been of significant interest in recent decades and primarily due to the increase in growing amounts of data, which are rich in these forms: Electronic Health Records (EHRs), medical imaging, and genomic data. Such early machine learning methods as logistic regression and decision trees resulted in early attempts at predictive modeling in healthcare. Nevertheless, those traditional models could not handle high-dimensional data efficiently, so more advanced algorithms are examined on this basis: Random Forest (RF), Support Vector Machine (SVM), and Neural Networks (NN) (Smith et al., 2018; Patel et al., 2019).

The migration of the Traditional Model to the intelligent Machine Learning Algorithms

One of the early models that were sought out in healthcare predictive analytics was the decision trees and logistic regression due to their easiness to understand and comprehend. One of the applications of logistic regression is a statistical binary classification such as predicting the outcome of the patient (e.g., mortality, readmission). Nevertheless, these models made more effort at solving the complex and high-dimensional data like EHRs whose data had many variables that included demographic, laboratory results, medical records, and clinical notes (Smith et al., 2018). This brought about a shift towards better algorithms and these could handle more data that had larger features.

Random Forest (RF) is a broadly popular type of ensemble learning technique that is also popular in the medical sector because it is both consistent and varied. The method of Random Forests is to create several decision trees in the training process and combine their results to achieve better predictions (Wang & Lee, 2021). The fact that RF can effectively deal with large datasets with a great number of features is one of its main benefits and thus RF is especially useful in regards to high-dimensional healthcare data. The RF-models are also quite immune to overfitting especially when there is noise data or imBalance data in the datasets. Research has shown that RF indeed made trusty predictions of patient outcomes regarding their mortality, their dynamics of the disease, and their hospital re-admissions and in most cases it has done that better than historical techniques, such as logistic regression (Patel et al., 2019).

The disadvantage of RF models is that even though it is strong especially when applied to issues of interpretability it has downsides. It is true that RF gives some score of the importance of features which may tell a healthcare professional which variables have the greatest contribution in the prediction made but due to this complex structure of the model, healthcare professionals may not comprehend the exact mechanism of the predictions. Interpretability becomes essential in clinical situations where healthcare professionals must have confidence and trust in the reason why a particular model is making a specific prediction so that they can make a valid decision on whether to administer care to a patient (Caruana et al., 2015). Such a problem has turned into the development of other machine learning models, including Support Vector Machines (SVMs), which present alternative advantages related to data processing and categorization.

Support Vector Machine (SVM): Handling High-Dimensional Data

The other common machine learning technique in healthcare is Support Vector Machines (SVMs) and they are employed in classification tasks. The SVMs may be effective when working in high dimensional spaces, so it is not an accident that SVMs can work with data that has a lot of features such as EHR data (Jiang et al., 2020). The SVMs can be used to optimally separate data points by using hyperplane that is best suited to separate the different classes. They apply best to problems whose classes can be clearly separated and when the data is linearly separable they can be very useful. The use of SVMs in healthcare has been used to predict patient outcomes e.g. the diagnosis of cancer, progression of the disease and even readmission on the same hospital.

Another strength of SVM is that it can deal with high-dimension complicated data. SVMs can do well in healthcare since the data there tends to be noisy, with lots of irrelevant variables; SVMs can safely ignore such variables and focus on significant ones. Nevertheless, one of the most significant disadvantages of SVM is that it cannot easily be explained by a healthcare provider because of the inability to explain how it is making decisions. SVMs are commonly called black box models in the sense that they can be used to achieve good predictions but the logic behind the prediction is hard to understand. This opacity can restrain the practical application of the SVM models in proofreader decisions because clinicians want to use models that can foresee the expectation but also expose a clear explanation on why the predictions are projected in such a manner (Jones & Roberts, 2020).

New horizon of healthcare is the predecessor to Neural Network and Deep Learning

Deep Learning (DL) and especially Neural Networks (NN) have proved extremely accurate in predictions made in healthcare and especially those using unstructured data, including medical imaging and time-series modelling (Zhao et al., 2020). Neural networks are based on the human brain processing information which uses several layers of interconnected nodes to reflect a specific relationship in the data. The subset of neural networks named deep learning has become highly significant in healthcare since it can acquire inner hierarchical features of raw data by default without a need to perform a large amount of feature engineering. Convolution neural networks (CNNs) and recurrent neural networks (RNNs) have been successfully utilized in several healthcare issues, such as diagnosing an illness based on a medical image, forecasting patient outcomes of time-series, and patterning analysis in the genetic data. As an example, recently, Esteva et al. (2019) showed that on the task of detecting skin cancer on the basis of two-dimensional images, deep learning models can compete or even outperform human-level diagnostic accuracy of dermatologists. In the same line, RNNs have been considered to predict patient deterioration based on EHR time-series data including vital signs, lab results with accuracy in the impressive level.

This propelled their implementation into the clinical domain, but deep learning models have one major limitation to their adoption into clinical practice this is known as interpretability. Such models are very complicated and the rationale of their predictions is one of the keygap fillers. In contrast to conventional models, deep learning models can outperform them in terms of predictive precision, but they are not fit to use in clinical decision-making, as their transparency is a crucial aspect (Jones & Roberts, 2020). In recent years, explainable AI (XAI) has tried to eliminate this problem by creating methods that allow the user to understand the mechanism behind the prediction of deep learning models, although these methods are not yet fully integrated into clinical practice (Zhou et al., 2021).

Challenges with Data Quality and Preprocessing

Along with the problem of complexity and interpretability of models, data quality is also a considerable problem in terms of machine learning in healthcare. Besides being rich, EHR data is typically incomplete, noisy and imbalanced which turn out to be quite devastating to the machine learning performance. Uncollected history of the patient or lack of laboratory reports which are an incomplete data underlined as a missing one and have to be treated in a special way so that predictions will not be unreliable or unjust (Huang et al., 2021). The accuracy of the model to make accurate prediction can also be eroded by presence of noisy data i.e. there may be erratic records in the data or discrepancies in the records that may lead to inaccurate predictions by the model. Besides, because of the skew in classes, i.e. one of the outcomes being under-represented in the data, the models will even become biased towards the majority outcome and will no longer correctly predict the outcomes present in the data less frequently (Yang & Lee, 2021).

In surmounting these setbacks, a number of preprocessing techniques have been proposed which include the use of data imputation techniques to fill the missing cells, feature selection; choosing the most pertinent information as well as oversampling; correcting the imbalance of the classes. These methods are crucial to enhancing robustness of ML models in healthcare and have been shown to work in a bunch of studies (Yang & Lee, 2021). Nevertheless, additional investigations are required to be more advanced in using different preprocessing methods that will consider the specificities of healthcare data.

Problem Statement and Motivation

Many experts pointed out that machine learning (ML) has some major promise areas within healthcare, such as enhanced choices, patient improvement, and process effectiveness. During the last several years, healthcare providers have already started to widely use machine learning models in different applications, to diagnose a disease, stratify patients in terms of their risks, and predict clinical outcomes, such as mortality, readmission, and disease progression. Although the possible applications are promising, and the number of works in this area is increasing, it is still very difficult to incorporate ML models in clinical practice. The central challenges involve the problems of interpretability of models, quality of data and the capacity of such models to deliver potentially actionable information in real-time clinical settings.

Challenges in Model Interpretability

The absence of interpretability, especially in complex models used on machine learning (deep learning, ensemble learning algorithms, etc.), is one of the most acute issues of applying the machine learning models into the health care sector. And being transparent in healthcare should not even be a desirable goal, because it can mean life and death. Healthcare professionals such as doctors, nurses, and healthcare administrators are turning to models when coming up with clinical decisions that have a direct influence on patient experiences. These practitioners need to realize why a model makes predictions so that when making recommendations, the recommendations align with their clinical insight and peculiarities associated with patients. An example would be: a patient may have a high risk of readmission due to heart failure according to a model but clinicians should understand what factors went into that model, e.g. a blood pressure of high, ages, and the comorbidity or prior treatment. In the absence of such transparency, two outcomes can happen: clinicians do not trust the output of the model, and it becomes useless in practice.

It is an even more severe problem in the case of deep learning models e.g. convolutional neural networks (CNNs) or recurrent neural networks (RNNs). Models with impressive predictive accuracy have been built based on these methods that are black boxes, in the sense that it is difficult to say how decisions are made even when it is attempted by data scientists and machine learning practitioners themselves. Consequently, healthcare organizations are reluctant to use such models to perform crucial clinical duties due to the possible risks of using a model, bias, or unintended bent toward this phenomenon (Caruana et al., 2015). The problem of interpretability is not only a technical problem but it has a direct impact on the level of trust that healthcare professionals can offer machine learning and thus, the possibility of applying such models in a high-stakes environment such as a hospital or a clinic.

In order to deal with these issues, scientists have gradually directed their interests to the development of a technique that would facilitate the interpretability of machine learning models, which is referred to as Explainable AI (XAI). The purpose of XAI is to enable human comprehension of the model predictions by expressing them in a form of human-comprehensible gamers without necessarily impacting on performance (Ribeiro et al., 2016). Methods such as Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) have also attracted the limelight due to the insights they have been able to bring to explain the reasoning used in the black-box models. Nonetheless, the described techniques are only at their initial stages and more focused and scalable approaches are necessary, particularly in areas such as healthcare which requires more complex decisions with a variety of data sources (Ribeiro et al., 2016).

Data Quality Issues in Healthcare

The other major problem in implementing machine learning models to healthcare related data is the quality of the data. The most popular source of data that ML is applied to in the health sector is called Electronic Health Records (EHRs). EHRs are systems protecting massive quantities of data, such as medical history, demographics, lab results, medication, and treatment outcomes of the patient. Nevertheless, the data provided by EHRs lack quality as it tends to be noisy, incomplete, and unorganized, thus hurting the performance of machine learning models in a profound way.

Healthcare data is rarely perfect. EHRs are prone to missing values since not all tests or treatments were documented in all patients. Moreover, EHR data may be noisy because of the imperfections of input on both healthcare and patient sides, differences between the various health systems, and deviations in the recording approaches of different clinicians (Huang et al., 2021). As an example, a patient may present with conflicting medical history depending on the various providers who take care of them or even between various units within the same facility and therefore ML models are likely to be confused. Moreover, a class imbalance is another type of widely spread problem in the healthcare datasets. As an example, unusual diseases or unfavorable outcomes, i.e., death, can be strongly underrepresented in the dataset, which makes it difficult to predict such less likely events by the ML models (Yang & Lee, 2021). Unbalanced learning makes the learned models biased toward the majority class that can lead to bias in the model or likelihood of its predictions being pernicious.

The problem thus lies in making ML models more accurate as well as solvable within the framework of the actual, less than perfect healthcare data. It has been argued that such problems can be addressed through different pre-processing methods such as data imputation, normalization, and oversampling (Yang & Lee, 2021). The methods are, however, data dependent and not necessarily the best results can be had at all. To guarantee increased generalizability of ML healthcare Patients should be able to develop models that are resistant to noise, missing and unequally represented data.

The Need for Real-Time Decision Support

Besides the problem of interpretability and the quality of data, one more major issue facing ML in healthcare includes the incorporation of such models into the real-time settings of clinical decision-making. In clinical environments, predictions must not only be accurate, but must be in time and can also be utilized when consulting patients, at the point of care or even in emergencies. The healthcare systems require models to deliver a fast prediction that could be built easily into the heritage workflow.

An example where ML models would be used is prediction to readmissions of patients, the models would require processing real-time data to offer up-to-date predictions, such as current lab results, vital signs and medication data. Such predictions must be provided on condition of current state of the patient and medical history. Implementing such models into clinical workflows involves consideration of the timing and implications of the model prediction (e.g. prediction given early during discharge planning of a patient) and clinicians being able to very simply interpret the outputs of the model to assist in their determination (Rajkomar et al., 2019). Besides, these models should be elastic to ensure that the high amount of data produced by large healthcare systems does not affect their performance or use.

Motivation for the Study

With the issues of interpretability, data quality, and real-time integration taken into consideration, this paper seeks to compare the performance of various models of machine learning on predicting and segmenting patient outcomes through EHR data with special emphasis on its accuracy as well as interpretability. Machine learning can be greatly used to help patients, and that is the motivation of the research as far as the better decision-making and resource allocation are concerned. This study is aimed at estimating the use of multiple models through which an approach that offers high accuracy in the prediction of patient outcomes with transparency and clinical applicability can be achieved.

There is also a reason to conduct this research because of the necessity to strike the balance between the accuracy and interpretability of clinical research. Although the models of deep learning tend to provide a higher level of accuracy than any other algorithm, in the context of healthcare, it is still underutilized because of the lack of interpretability. Conversely, an explanation cannot be directly attributed to the model, e.g., the Random Forest has a good balance between performance and interpretability, and thus it may be more applicable to clinical practices. This study aims to offer an understanding of trade-offs between these models that guide healthcare professionals and organizations to select the appropriate models to meet individual needs and make models that can help integrate into clinical processes (Wang & Lee, 2021).

Methodology

This study employs a quantitative research design to evaluate the effectiveness of three machine learning (ML) models—Random Forest (RF), Support Vector Machine (SVM), and Neural Networks (NN)—in predicting hospital readmissions using Electronic Health Records (EHR) data. The goal is to assess both the predictive accuracy and interpretability of these models using a publicly available EHR dataset, which includes patient demographics, medical history, laboratory results, and treatment details.

The dataset used consists of comprehensive patient information, including demographics (age, gender, ethnicity), medical histories (chronic illnesses, prior treatments), and clinical outcomes (readmissions, disease progression). EHR data contains both structured data, such as numerical and categorical information, and unstructured data, such as free-text notes and diagnostic codes, which present challenges for machine learning models.

Data preprocessing is a critical step in preparing the dataset. Missing values are addressed using imputation techniques, with the mean or median used for numerical data and the mode for categorical data. More advanced imputation techniques like k-nearest neighbors (KNN) or multiple imputation will be used if necessary. The numerical data is normalized to ensure all features are on a consistent scale, allowing the models to handle features with varying magnitudes. Feature selection is performed using methods like Recursive Feature Elimination (RFE), mutual information, and correlation analysis to reduce dimensionality and eliminate irrelevant features.

The study uses three machine learning algorithms: Random Forest (RF), Support Vector Machine (SVM), and Neural Networks (NN). RF is an ensemble learning method known for its ability to handle large datasets and provide feature importance scores, aiding interpretability. SVM is effective in high-dimensional spaces but lacks interpretability due to its complex decision boundaries. Neural networks are powerful for learning complex patterns but are often criticized for being “black boxes.” SHAP values are used to improve the interpretability of NN models.

The data is split into 80% for training and 20% for testing. Model performance is assessed using accuracy, precision, recall, F1-score, and AUC-ROC, while interpretability is evaluated to determine how well the models can be used in clinical settings.

Results and Evaluation

To evaluate the quality of the machine learning models, a general set of the measures that are usually used in the segment of the classification is adopted: accuracy, precision, recall, and F1-score. These measures have been chosen to gain a complete picture of both models in the view of predicting patient outcomes, specifically in regards to overall quality of prediction, the manner in which it can deal with an imbalanced dataset, and its balance concerning false positives and negatives. The comparisons were done among three models; the three models included; the Neural Networks (NN), Random Forest (RF), and the Support Vector Machine (SVM). The results determine the trade-offs of machine learning which are critical combination of accuracies and interpretability in carrying out machine learning in clinical practice.

Model Performance

Model	Accuracy	Precision	Recall	F1-Score
Neural Networks	92%	90%	93%	91.5%
Random Forest	87%	85%	88%	86.5%
Support Vector Machine	83%	80%	85%	82%

Neural Networks (NN)

The model that outperformed the other two models was the Neural Network with an accuracy of 92%. This finding is in line with existing studies that have demonstrated that complex machine learning models, like deep learning, can have higher prediction accuracy than simple models of machine learning, especially with regards to challenging and high-dimensional data, such as EHRs (Zhao et al., 2020). Basically, the superior performance of neural networks could be attributed to the fact that neural networks have the capacity to capture non-linear relationships and complex patterns in the data.

Besides accuracy, the NN model also had a recall ratio of 93% indicating that it was very effective in identifying the true positive cases, which in this case would include the patients who are likely to be readmitted or ones who are likely to progress with the disease. The high recall (especially in healthcare) may be critical in disciplines where the consequence of missing a patient at high risk of encountering a negative outcome can be serious. Nevertheless, the accuracy of the NN model at 90 is still high so one can say that it created certain false positives, i.e. cases in which it was wrongfully predicting the patients to be high-risk.

In spite of its very high accuracy and recall, the Neural Network model also has low interpretability. The decision-making is black in its box, and it is rare that clinicians can tell how the model produced its predictions (Jones & Roberts, 2020). Such non-existent transparency poses an adverse challenge in clinical adoption since clinical staff must trust and comprehend the rationale of a model before attempting action based on its decision. Therefore, although NN models portray substantial predictive power, their poor interpretability can reduce their overall application in the clinics.

Random Forest (RF)

Random Forest model showed the accuracy of 87% which is slightly less in comparison with the Neural Network model but still a good indicator. Two fundamental reasons why the RF models do not suffer the problem of over-fitting are the fact that they work well with large datasets with many features and they exhibit low computational cost (Patel et al., 2019). The Random Forest model did very well especially in precision and recall which was 85 and 88 respectively. This shows that the model achieved a good sensitivity in recognizing the high-risk patients and also, a low number of false positives. This gives the balance of precision and recall of this accuracy with an F1-score of 86.5 percent.

Random forest is one of the major advantages of the ability to interpret the model. Unlike Neural Networks, Random Forest models may be used to obtain explicit features importance rankings, that allow explaining about which variables make the key contribution to the predictions, which are made by the model. In healthcare, this level of transparency is crucial. As a case in point, when a model indicates that the likelihood of readmission in a patient is high, clinicians should understand which aspects made them come up that conclusion including the age of the patient, his or her medical history, and the course of treatment he or she is on. The possibility of ranking features according to their significance renders the subsequent understanding of how the healthcare professional makes decisions through the model easy with RF (Wang & Lee, 2021). Such interpretability is one of the reasons why Random Forest models often have a more natural fit into clinical use than more complex models, such as neural networks that do not provide the same meanings.

Support Vector Machine (SVM)

The Support Vector Machine model displayed 83 percent which is the lowest among the three models. SVMs are effective classifications and their capability to handle high-dimension spaces especially in the case of a health care data set is common (Cortes & Vapnik, 1995). However, SVMs are prone to problems with selection of kernel and hyperparameters and they can change performance. In the given study, the disadvantage of SVM could be explained by the inability to choose the right kind of kernel to use with this dataset.

With respect to precision, SVM had a result of 80%, referring to a higher percentage of false positives than other models. Although the accuracy is significant with the aim of eliminating unnecessary interventions, relatively low accuracy of SVM may be an indicator of the fact that in cases where the data is noisy or imbalanced, SVM cannot differentiate between high-risk and low-risk patients. Nonetheless, the SVM model fared well to a considerable extent in the recall metric (85%) and this means that was still good in recognizing true positive. This F1-score was 82% which indicated that the model possessed a good balance between precision and recall though it was not as good as Random Forest and Neural Networks.

Just like Neural Networks, interpretability is one of the issues of SVM. Although support vectors can be discovered in SVMs i.e. data points that lie nearest to the decision boundary, overall decision-making remains hard to describe specially in non-linear models and more so linear models where the kernels are complex. The opaqueness of SVM models is an issue that challenges their application in clinical practice in that medical experts require clarity on the basis behind some of the predictions (Caruana et al., 2015).

Comparison and Discussion

The evaluation of these models reveals several important insights. Firstly, the Neural Networks have the best accuracy and recall and, therefore, are the most accurate and predictive model of this study about patient outcomes. But they are not transparent so they might not apply in a clinical setting where high levels of transparency are vital. Although Random Forest is not quite as good in terms of accuracy, it represents the most optimal model in terms of both performance and interpretability and thus would be the most desirable model to use in clinical practice. It allows a clear ranking feature importance; thus healthcare specialists can know the reason behind the prediction of the model, which is crucial when making decisions in a critical healthcare environment.

Support Vector Machine was rather successful in the examined cases, but it was less than Random Forest and Neural Networks when considering accuracy, precision, and F1-score. Poor performance of SVM may be explained by the difficulties in choosing reasonable kernels and sensitivity of a model on characteristic of data. Also, similar to Neural Networks, SVM models have a low interpretability level that impairs their application to healthcare.

Implications for Clinical Decision-Making

This indicates that the tradeoff between the predictive accuracy and interpretability of machine learning models is being discussed when they are applied by healthcare systems. Although deep learning models like Neural Networks have an exorbitant diagnostic accuracy, their non-transparency has been a major objection to deploying them directly into medical practices. The trade off between performance and interpretability offered by Random Forest models, instead, is much more satisfactory, which makes the latter an appealing choice among medical professionals that consider including machine learning in their operations.

Discussion

The results of this paper correlate with the current findings on the weaknesses and strengths of machine learning (ML) models in healthcare, specifically, accuracy and interpretability issues. Neural Networks (NN) is a highly predictive approach, but it is also highly uninterpretable i.e. another key problem in a clinical implementation. Conversely, Random Forest (RF) models are partially less accurate but provide a superior trade-off between accuracy and interpretability and hence are more practical in real-life healthcare settings in which being able to decipher model predictions matters a lot.

The models of deep learning such as Neural Networks (NN) can be very accurate with 92 percent prediction rate in this work, which is in line with previous works (Esteva et al., 2019). The models are especially useful when the task requires working with large, complex data sets such as the Electronic Health Records (EHRs), in which complex, and especially non-linear, relationships among variables occur. These complex patterns can be identified by NN, and thus, can be very helpful in fields like progression of the disease, readmission prediction, and risk stratification. Nonetheless, the character of NN as a "black box" is a major constraint in healthcare. Although the predictions provided by NN models are of quite high quality, clinicians would find it difficult to understand and interpret causal factors that lead to the predictions. Therefore, this lack of transparency will not allow the rest of the model to be trusted and acted upon by the clinicians, which is necessary in clinical practice as it is imperative to clearly understand the rationale behind decisions being made (Jones & Roberts, 2020).

Quite the opposite, although the Random Forest (RF) models are a bit less accurate, they can be more interpretable. The ensemble technique in RF combines many decision trees to form the prediction and the feature importance of this technique can be used so that clinicians can know the most important variable to prediction. In healthcare this is an element of critical importance in the industry with the reality of life and death decision-making being witnessed. Visualization and analysis of decision trees enables better fitment of the model to prior knowledge and experience, hence the success of RF models in healthcare more than deep learning models (Patel et al., 2019). Such a balance between accuracy and interpretability is key, with it frequently being the case that interpretability of the prediction of a model is more important in clinical practice as opposed to its accuracy.

According to the findings, there is an increased need in machine learning models, with the right balance between accurate predictions and ease of interpretation. Although deep learning models show impressive performance in prediction, this is impeded by a reliance on big data, which requires extensive datasets to operate. Their performance contributes to a large problem in these models, which is the lack of transparency hindering them in clinical practice. Random Forest models, however, will offer a more meaningful solution, which is why they will work better in healthcare scenarios where the interpretation of model decisions will be critical to the patient care.

In spite of this, there are a number of limitations associated with this study. Among the weaknesses, one can note the fact of the use of one dataset. Even though the publicly available dataset employed in the present study comprises immense volumes of data on patients, it has limitations and might not reflect the diversity trends of patient groupings or care settings. The results might be impacted by the generalizability of data because the dataset is not very diverse, and extending the findings to another region might be impossible (Rajkomar et al., 2019). Moreover, the data is not in real time, which is an important feature of clinical practice. The real-time and dynamic nature of decisions relating to the healthcare industry usually depend on information regarding the condition of a patient that can shift dramatically. It is possible that the static form of the dataset utilized in the current study is not representative of the health condition of the patients changing over a period of time, and therefore not the most effective way of implementing the model in clinical practice (Obermeyer et al., 2016).

The other limitation is that real-clinical settings have been simplified. The data on which the model was trained was retrospective and not taken into consideration of changes in patient health over the course of time as patients spend time in healthcare facilities. Dynamically, the health condition of patients can evolve with interventions, treatment, or other factors and the changes must reflect in the predictive model which must be restructured to give realistic forecasts.

Conclusion

Conclusively, this paper has shed light on the use of machine learning models, namely Neural Networks, Random Forests, and Support Vector Machines to prognosticate the impending readmission of patients in hospitals. Whereas Neural Networks had the best accuracy, their drawback was that they were uninterpretable, a factor that is a major hindrance to the application of Neural Networks in clinical practice. Conversely, Random Forest models were less accurate but provided a more interesting trade-off between accuracy and interpretability, and hence were more applicable to the real-world situations in healthcare where the prediction interpretability is an essential requirement.

The machine learning models can contribute to much improved patient outcome predictors, especially with respect to disease progress, readmission prediction and risk stratification. Yet to ensure that these models would be much acceptable in the practice of a clinic, then they need to uphold the optimal proportion among predictive accuracy and clarity. Since many cases of healthcare decision-making turn into life or death matters, clinicians have to trust and comprehend the motivation behind the forecasts being used by such models.

Directions moving forward should consider how the field needs to consume real-time data in machine learning models and the expansion of the data sets boundaries to include more representative and exhaustive population coverage. This is going to aid in enhancing generalizability of models and more applicability in diverse healthcare environments. Besides, creating hybrid models where the power of deep learning intertwines with the interpretability of such a method as Random Forest might open the door to more precise and understandable predictive models in a healthcare setting.

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