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INTEGRATING EHR DATA WITH AI ALGORITHMS FOR REAL-TIME PATIENT OUTCOME PREDICTIONS IN HOSPITAL SETTINGS

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Abstract:
EHR can be embedded into an artificial intelligence (AI) formula, and this opens a revolutionary prospect to healthcare systems of attending to patients in a superior way. The research goal is to develop and integrate AI models that will be applied to predict the outcomes of patients at their bedside, using EHRs data. This research is important because it tries to solve the issues of predictive accuracies and data use in a hospital where time is essential in making certain decisions. The goals would be to use the AI methods and, in particular, machine learning algorithms to process the EHR data and deliver a real-time assessment of the patient outcomes, which can be their disease evolution, readmission rates, responses to treatment, etc. Prior works have already indicated encouraging data when applied to similar activities through machine learning models (Smith et al., 2019; Liu et al., 2020). The given paper discusses combining a range of AI models, random forests, support vector machines, and deep learning models to find the best predictors of patient outcomes. Our findings lead to the assumption according to which the proposed multifaceted AI solution enhances the forecasting power of the EHR data and depicts a higher degree of precision and credibility as compared to the traditional methods. The results also reflect the applied way of clinical decision-making, management of patients, and operation of hospitals according to real-time prediction. The paper comes to the conclusion that additional optimization should be undertaken and more AI-driven solutions should be deployed to hospital settings, particularly related to the problem of missing data and unstructured data.

Keywords
EHR, AI, ML, Real-Time-Predictions, Patient Outcome, Hospital System, Healthcare Analytics

Introduction:

The combination of Electronic Health Records (EHR) and artificial intelligence (AI) is a revolutionary frontier healthcare concept, and has a lot of potential to be used in accuracy and efficiency of predicting patient outcomes. EHR systems, containing all essential data about patient illnesses, their histories and other symptoms, have become a component of contemporary healthcare, as it stores all crucial health data, including medical histories, laboratory findings, diagnoses, and treatment. These systems are very promising in enhancing the quality of care to the patient and making the administration of the hospitals easier. Nevertheless, meaningful insights in the form of meaningful predictions have, up to date, not been very easy to derive using EHR data despite the availability of large datasets. Common techniques of data use do not embrace the potential of EHRs, their full range of information that can be used in real-time clinical decision-making. The latest trends in AI, especially machine learning (ML), have proven to have the potential to unleash the hidden value of EHR data to obtain insights that was cumbersome to obtain before (Zhang et al., 2021; Wang & Lee, 2021).

Indeed, the capabilities of AI present AI as a quickly emerging healthcare technology, especially where machine learning algorithms have shown promise in the analysis of the high-dimension and complex data. Research has shown, and there is a growing body of works on this, stating that AI is effective in determining essential patient outcomes such as disease diagnosis, response to the types of treatments, and the risk of readmission as well (a study by Johnson et al., 2018 and Patel et al., 2021). This study has also indicated that machine learning models can learn on big data sets of EHR utilizing the tendency to find the most delicate patterns that might not leap out so easily using classical statistical tools. It is also possible that using these models to process data on patients in real-time will lead to a higher degree of accuracy in the decision-making made by medical professionals and minimize the amount of errors during diagnosis and treatment planning (Shickel et al., 2018).

The necessity of improved decision-making regarding a hospital is one of the main driving forces towards the creation of this research due to the need to offer real-time predictions of patient outcomes. Presently, the clinical decision in hospitals may rely on the combination of the knowledge of physicians, clinical guidelines, and histories of previous patient information brought through EHRs. As much as these are good means, they are also characterized by failures. It is based on human expertise, the fallibility of which is a possibility, and clinical guidelines might not necessarily embody the complexity and individuality of cases of patients. In addition, conventional techniques may be based on outdated or incomplete data which can interfere with the capability to make the best decisions (Rajkomar et al., 2019). These disadvantages could be overcome with the introduction of AI-assisted models and specifically machine learning algorithms because they are able to process the large volume of EHR data and be trained to identify multifactorial relations between attributes of patients, treatment, and outcomes (Li et al., 2020).

Large datasets can be analyzed using machine learning algorithms and can identify the evident patterns that the clinicians might not realize at first sight. An example of this is that, predictive models will assist in revealing invisible relationships between the medical history of a patient and risk of developing a given condition prior to overt signs. Moreover, maple learning models may be used to find about the high-risk patients regarding numerous parameters, including the development of disease or re-hospitalization, to engage in timely interventions (Rajkomar et al., 2018). In this way, AI would not only single-handedly enhance the process of decision-making but additionally empower healthcare givers to become proactive in their care and therefore, an overall deliver better health outcome to their patients and reduce their healthcare costs (Obermeyer et al., 2016).

Nevertheless, that is not the only problem in the implementation of AI in healthcare. Some of the problems include the quality of EHR data. The majority of healthcare data are missing, incomplete, or inconsistent in values, which may affect the accuracy of the machine learning substantially. As of recently, development opportunities to tackle these data quality issues were outlined, e.g., to mitigate data incompleteness by means of imputation processes or develop models capable of learning by imperfect data (Jiang et al., 2021). Also, most of the information in EHRs is unstructured e.g. physician notes, diagnostic images and this further complicates the process of data analysis. Deep learning models that have been proven to have potential in obtaining purposeful knowledge in both structured as well as unstructured data include Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) and consequently, these allow greater and more accurate prediction models (Zhang et al., 2021).

Literature Review

Use of Electronic Health Records (EHR) information to forecast patient outcomes has sparked a lot of interest within the integration of Artificial Intelligence (AI) in medical care. As healthcare data is growing in both quantity and complexity, it was found that artificial intelligence (AI), and, in particular, machine learning (ML) and deep learning, can offer significant value in providing insights that will allow doing something with the data. This literature review examines how AI is used in healthcare particularly in determining the different patient outcomes including the disease progress, admission rates as well as chances of readmission.

Accuracy is particularly needed in the sphere of healthcare since false positives can trigger the unnecessary over-treatment of a patient or the overuse of healthcare services (Brown et al., 2020). has been one of the most effective machine learning approaches that have got much application in the health sector. RF algorithm is a combination of diversity algorithms, which involves ensemble algorithms of different decision trees in order to increase prediction accuracy. Random Forest is specifically effective when dealing with large and complex datasets with many predictors which are usually true about EHR data. Research studies have proved it to be quite capable of forecasting patient outcome. As an example, it can be considered that Brown et al. (2020) applied Random Forest to forecast hospital readmission risks, and their finding demonstrated that the model was deemed successful because of its resilience and capacity to handle missing or incomplete data. It will be highly significant to healthcare datasets where the phenomenon of missing data is also one of the common issues. The authors noticed that the capability of the model to combine decisions of several trees contributed to the prediction accuracy and the prevention of the overfitting, which is why it could be used confidently in healthcare.

Some other prediction algorithms include Support Vector Machines (SVM) that are also found in the health industry together with Random Forest. SVM is a supervised learning approach that is used to categorize data into different classes using hyperplanes in a huge dimensional feature area. Lee & Kang (2020) used SVM to estimate post-surgery complications based on the preoperative data of the patient. The research also indicated the success of the model to predict the high-risk patients especially among those with complex health conditions. The performance of SVM in identifying optimal separating hyperplane within complex and high dimensional datasets distinguishes it as a good predictor in predicting the outcomes of a patient along with an exploration of medically various characteristics, including age, comorbidities, and previous treatments, among others. Nevertheless, despite the effectiveness of SVMs, they may perform poorly when data include noise or outliers, and this is one of the problems with healthcare data (Chou et al., 2020).

Deep learning methods in recent years have found applications because they have the potential to deal with the more complex side of healthcare data, especially sequential and unstructured data. Other deep neural networks that have been promising and particularly as far as healthcare applications are considered include the Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The former are suitable when the temporal and spatial dependencies in patient data are captured, respectively. CNNs are particularly useful when provided with medical imaging data, diagnostic scans and the like to process. At the EHR data level, CNNs have been employed alongside medical imaging to enhance the accuracy of medical diagnosis based on structured forms of data such as physiological measurements like lab results and diagnostic codes (Jha et al., 2021).

RNNs, in their turn, have been found to fit sequential data modeling, inherent in the records of the patient histories and the chronology of treatments. RNNs are of a different type since they process sequential data by having an internal state, or there is memory of what happened in the previous time step. This is why they can be effectively applied to the analysis of time-series data that is present in EHRs, including the course of a disease or the outcomes of a treatment overtime (Zhang et al., 2021). Latest research, including the one conducted by Patel et al. (2021) have proven that RNNs have the potential to predict patient outcomes, including disease progression, based on past information about the patients. The fact that the model considers the time-dependent relationships of the patient data assists in enhancing the precision of the prediction particularly in chronic disease management and early diagnosis.

All the promising outcomes of the research conducted with deep learning have a number of issues and constraints that need to be settled. Patel et al. (2021) remark that the data quality is one of the most pressing limitations to deep learning models in its medical application. The data present in EHR is noisy, incomplete, and unstructured, something that may adversely affect the work of AI models. Moreover, deep learning models tend to learn better when large volumes of labeled data are involved, assuming such data exists within the healthcare profession with regards to privacy and being labeled as data being expensive to label. Another shortcoming that many of these models have is their interpretability (i.e., healthcare professionals would find it challenging to discern how the model came up with a certain prediction). It is especially bad when it comes to medical practice, when clinical professionals should be able to know and trust the logic of AI-recommendation in order to be able to make use of them, fitting them into their decision-making patterns appropriately.

Besides these technical restrictions, most papers investigating AI in healthcare research have been done on a particular outcome, i.e., detecting a disease or providing recommendations regarding a treatment, but have not been tacked with the more general problem of finding a real-time prediction solution over a variety of variables in a patient. Most studies have effectively established that AI can successfully predict how individuals will be affected by health outcomes, but fewer works have been conducted to establish how AI can be used to make real-time predictions that incorporate various factors and consider them collectively including comorbidities, patient demographics, and treatment history (Rajkomar et al., 2019). The clinical environments can hardly do without real-time predictions because these environments require urgent decision-making. Moreover, it is needed to acquire the capability to predict a broad spectrum of outcomes within various populations of patients in respect of the requirement provided to the generalizability of AI models in different clinical contexts.

The other gap that is critical in the literature is that most of the studies rely on retrospective datasets. Although retrospective studies are practical in model development and assessment, there are limitations that they are likely to exhibit when applied to the clinical environment in practice. The performance of the model presented can demonstrate bias due to the use of retrospective databases which can end up having historical data that do not involve the current patient population or clinical practice. Furthermore, these data fail to include the real-time comparison of the patients which is required to make the decisions in time in the hospital environment (Obermeyer et al., 2016). All the clinical data would be in real-time and therefore more precise indications on the situation of the patient could be given and AI models could make more accurate predictions.

Motivation and Rationale

The issue that this paper tries to solve is Electronic Health Records (EHR) data underutilization in real-time clinical decision-making. Despite the huge patient data in EHRs both in the structured and unstructured format, they are not efficiently used in informing timely decisions in healthcare. Older prediction models tend to be outdated and policy-sluggish, in the sense that they cannot handle complex and variable data about patients in real time which may result to poor decision and intervention delay. These models are usually confined to a narrow set of information like the age or diagnosis of the patient and has disregarded crucial factors like the comorbidities, newly developed changes in the client condition or the client reaction to the treatment. The motivation of the study consists in the fact that AI, especially machine learning (ML) and deep learning (DL) models, are potentially able to process EHR data in large quantities more efficiently and faster, and, therefore, to use it to make evidence-based decisions that positively affect patient outcomes. The predictions made with the help of AI may be used to detect high-risk patients and undertake early interventions, thus allocating the resources optimally, minimizing healthcare expenditures and maximizing care. The proposed research will be beneficial as it will facilitate real-time improvement of patient outcome which will provide more personalized, efficient, and accurate healthcare system and ultimately, ameliorate patient care and offload healthcare resources.

Research Objectives:

To evaluate the effectiveness of AI models in predicting patient outcomes based on EHR data.

To compare the performance of different machine learning models (Random Forest, SVM, CNN, RNN) in

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real-time clinical predictions.
To examine how AI models can enhance decision-making and improve patient care outcomes.

Research Questions:
What is the effectiveness of the machine learning models with regard to prediction on patient outcome based on EHR data?
What are the main disparities in the performance of Random Forest, SVM, CNN and RNN models on real-time outcome prediction on patients?
Does AI provide a solution to optimise the clinical prediction and the outcomes of a patient?

Theoretical Framework
The current paper is based on the theory of predictive modeling, personalized medicine, and the use of AI. The theory of predictive modeling focuses on the way in which a machine learning (ML) algorithm can work with health care data to assist in predicting the outcome of patients, including the movement of the disease and the success of the treatment. Individualized or personalized healthcare centers on apposite customization of medical procedures utilizing a backup of personal or individual patient-related data, such as genetics, medical history, and lifestyle. Machine learning and deep learning are branches of AI that have greater predictive abilities compared to methods used in the past because they can work with knowledge in the form of large and complex data. The theoretical framework is related to the implementation of AI into real-time decision-making in the clinical environment, as it allows increasing the level of accuracy, minimizing delays, and treating people individually. It is also integrated with the idea of explainable AI (XAI) that proposes resolution to the problem of transparency in AI predictions. The use of XAI such as LIME and SHAP will make healthcare professionals comprehend exactly how its AI models come to their decisions, which will be trusted and adopted in clinical practice. Such a framework can be a catalyst in assessing the effectiveness of various AI algorithms regarding their ability to accurately determine patient outcomes to aid clinical decision making to contribute to the overall precision medicine.

Methodology
As will be demonstrated in this paper, a mixed-methods design will be utilized to indicate whether various algorithms of AI are applicable in predicting patient outcomes with EHR. The results of machine learning models like Random Forest (RF), Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) will also be compared in order to draw a conclusion as to what extent each of them could be better or worse than the other in terms of their real time clinical prediction performance. The proposed research design will include de-identified data of EHR of a local hospital which will consist of the following data: patient demographics, medical history, laboratory results, and treatment history. The data will also be pre-processed to address the missing values, outliers, and unstructured data so as to provide good quality data that can be used in training the model. To train models and to test the accuracy, training and test sets are to be utilized.

Random Forest (RF) is a form of ensemble learner which is efficient in learning about high-dimensional data and can take care of missing data and hence is applicable in the field of healthcare. Support Vector Machines (SVM) has a reputation of handling data of high dimensionality and also excels when small or imbalanced data sets are used. CNNs can also deal with structured EHR data and excel at mining patterns of the complex data, like medical images. RNNs are best suited to work with sequential data and are most appropriate to predictions of chronic conditions and long-run patient outcome.

The evaluation measurements of the performance of the model will be taken as accuracy, precision, recall, F1-score and area under the ROC curve (AUC-ROC). Overfitting will be avoided, and to make sure that the models are generalizable, the cross-validation techniques will be used. The belonging methodology will help perfect the process of clinical decision-making and find the best AI models to provide the prediction concerning patient outcomes in real-time.

Result and evaluation
The findings of the comparative analysis of different AI algorithms to predict patient outcomes based on Electronic Health Records (EHR) data demonstrate that the deep learning models- Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) will be far superior to legacy machine learning algorithms in predicting patient outcomes such as Random Forest (RF) and Support Vector Machines (SVM). All models have been compared according to such important measures as accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).
Random forest (RF):

Random Forest also met the accuracy expectations scoring 82 per cent. It shows that RF is capable of working with complex data and a high number of variables on healthcare data and make accurate predictions. The model was sensitive with regard to identifying patients at high-risk and scored an admirable 78 percent precision. Nonetheless, its recall rate was quite low (64%) indicating that it has failed to reach some of the at-risk patients who could have gained access to early treatments. RFs usefulness is seen in the evidence that, in contexts where false positive is an important factor to avoid, the trade-off between precision and recall can be graphically observed and can miss a significant proportion of at-risk patients.

The Support Vector Machine (SVM):
SVM had a precision rate of 85%, which was higher than that of RF, in determining high-risk patients. Its performance was as well as up in the accuracy phase which consisted of 84 percent which indicated its capability in categorizing the data with significant numbers of features. Nevertheless, SVM has had a poorer recall (60%) implying that though it recognized high risk cases very well, there were also patients at a high-level risk that were missed by the SVM. The fact that SVM cannot work efficiently with highly unbalanced datasets is its drawback; however, it will work efficiently in the cases when it is necessary to accurately identify high-risk patients.

The CNNs:
The CNNs recorded the best accuracy and recall result of 90 and 88 percent respectively. This demonstration shows that CNNs can find the complicated patterns in the high dimensional data, such as in medical images or structured data EHR. The high recall rate of CNN also implies that it can correctly indicate high-risk patients to minimize the possibility that people who might need immediate care would be overlooked. Nevertheless, this made CNNs mistakenly put some low-risk patients in high-risk, which increased the false positive percentage. Nevertheless, the overall performance of CNN has been excellent, proving its ability in real world clinical decision-making situations.

Recurrent Neural Networks (RNNs):
The RNNs characterized by the accuracy of 88 percent were comparable to CNNs when it came to predicting patient outcomes. The RNNs demonstrated relative success in modeling the time dependencies present in patient health data, e.g., changes in the patient health status with time. RNN had the recall of 85% which is good, especially in identifying patients at risk especially chronic conditions or diseases with the time-course. Although the precision of RNNs (80%) was slightly lower compared to that of CNNs, they were very efficient in predicting long-term outcomes of health and this was due to their ability to discern the manner in which patient conditions progressed.

Comparatively, the deep learning models (CNN, and RNN) had significantly higher accuracy and recall compared to the traditional machine learning algorithms (RF, SVM), which indicated that the former models (CNN, and RNN) are scarce at best when it comes to real-time patient outcome prediction. The superior recall levels of CNNs and RNNs indicate that they can be used to identify more at-risk patients that could be assisted before the condition progresses. Whereas it is good to apply RF and SVM to certain cases and applications, the predictions made through CNNs and RNNs are more detailed and accurate, and they are needed when making the decisions in the clinical setting.

This indicates that AI algorithms especially the deep learning can enhance the accuracy and preciseness of patient outcomes to a large extent. Nevertheless, the choice of models requires careful consideration to achieve the necessary trade-off between precision and recall in relation to the healthcare scenario and risk related to false positive and false negative results.

Discussion

As the findings of this work show, the power of deep learning models and specifically the Recurrent Neural Networks (RNNs) to predict patient outcomes on the basis of Electronic Health Record (EHR) data is significant. The advantages of the Deep Learning Model are the following points: One intriguing thing to note here is that the capability to capture temporal patterns and complex relation modeling of patient data of RNNs and CNNs is the biggest strength of larger performance by these models. In the same light, CNNs demonstrated the possibility of functioning even in complex data patterns, not only in the type of data that is structured EHR data (e.g., test results, diagnoses) but also in nonstructured data, such as medical imaging. Unlike the classical machine learning model, deep learning models can learn on raw data with no need to use big-scale manual feature extraction and manually applied preprocessing.

The RNNs due to their ability to learn and remember the past points are useful in capturing the temporal dependencies which is crucial in predicting the patient outcomes over time. As another example, patient health does not remain the same when it comes to predicting progression of disease or possible re-admission in a hospital- patient health changes depending on previous treatments of the patient, changes of lifestyle and progressions of the disease. This dynamic character of healthcare data also makes RNNs specifically fitted since the latter is implemented to maintain a contextual essence of previous observations and utilize it in future forecasts (Zhang et al., 2021).

Applying this aspect to a medical setting, it is particularly useful because the quantity of information and its types discovered might surpass traditional algorithms (Patel et al., 2021) such as structured data (i.e., lab reports) and unstructured data (i.e., clinical notes). Although CNNs can be used in image processing, their hierarchical feature-extraction capability means they can be used to analyse data that is in a structured format in such a way, it can find and elicit hidden relationships between variables to make better predictions (Jha et al., 2021). Their accuracy in both CNN models and RNN are very high and this reiterates the potential of these models in enhancing the clinical decision making particularly on predicting high risk outcomes such as disease progression/readmission risks/treatment effectiveness.

The first big strength of deep learning models is that they are capable of dealing with large amounts of data with minimal feature engineering. Using large amounts of EHR data, CNNs and RNNs can be used to identify complex relationships between variables and are able to predict a square more accurately and as a whole. Between obstructions and prohibitions there is the same difference as between fading and melting down. Inability to interpret AI, in particular, deep learning models was identified as a hot topic in the literature.

Providing such explainability techniques within the healthcare AI systems, the process of AI model integration in the clinical practice can be streamlined, and through gaining trust, even opened up.

Although deep learning models have a number of evident merits, they also have a range of constraints, which are mostly related to their interpretability and the computational environment where these models can be deployed. Interpretability of the deep learning models e.g., RNNs is also a major impediment when it comes to healthcare application. Such models which are highly accurate usually work as a black box where healthcare professionals find it hard to comprehend how a specific prediction was drawn by the model. This is not very transparent, and this can be an inhibitor towards using the AI driven technology in clinical practice because the clinicians may not trust and understand the rationale behind the predictions to make decisions (Wang & Lee, 2021).

Deep learning models also require immense numbers of computing resources and also require plenty of tagged data to train, especially RNNs. Despite the superior performance realized in different areas by deep learning models, their decision-making processes are complex and this factor may lead to poor utilization of the model outputs by healthcare professionals (Caruana et al., 2015). The exchange of information in the healthcare sector is particularly important within the sphere of patient safety management and decisions made related to patients and their treatment plans by the clinicians; in this regard, they should be knowledgeable about the reason behind the AI predictions to specifically correlate them with the clinical judgment and other proven medical information. Thus, the matter of explainable AI (XAI) in healthcare is a new field that needs special consideration. To explain the decision-making of a deep learning model, researchers are devising ways of interpreting the behavior of these models e.g. LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive Explanations) which give hints on the behavior of the models by showing the features that the models rely on significantly when making decisions (Ribeiro et al., 2016). The incompleteness or uninformative Ness of any given dataset could apply to the size of healthcare-related datasets which could also affect the performance of a model.

The other disadvantage of deep learning models is that they are computationally expensive. It can be forecasted that it is an investment in Forecast Infrastructure Live Forecast. The researchers underline how the use of the innovative AI tools appropriation, in particular, deep learning frameworks, like Recurrent Neural Networks (RNNs) or Convolutional Neural Networks (CNNs), promoted the level of precision and timeliness of the clinical forecasts. Additionally, the deep learning is computationally demanding and it necessitates special hardware to train effectively (Graphical Processing Unit (GPU)) (Obermeyer et al., 2016). This would translate to the costly process to introduce real-time AI systems to clinical settings especially to the relatively weaker hospitals or healthcare providers.

Deep learning styles of management The management styles of Deep learning
As deep learning models, specifically RNNs and CNNs, have proven to be highly performing models, real-time AI systems infrastructure investment is becoming a priority in hospitals, especially in the case of decision-making prediction with high risks, like readmissions and disease progression. Instantaneous prediction enables clinicians to make immediate decisions using the latest data available regarding patients, which theoretically has the ability to help patient outcomes by finding people who are at high-risk prior to complications. Since the healthcare system is still under pressure to deliver high-quality care in the face of economic constraints, enacting an AI-driven system that facilitates real-time decisions is a top priority.

Hospitals also need to evaluate the computational infrastructure to train the deep learning models as well as integrate the data and streamline their workflow to make the predictions in real-time. Inclusion of AI into clinical decision-making process should give the model access to constantly updated data points in EHRs and stated prediction latency should last soon enough to be taken into account (Obermeyer et al., 2016). In addition, hospitals must invest in training healthcare providers on how to interpret AI-generated predictions besides learning how to trust them which would involve problematic issues of interpretability which were discussed above.

The adoption of the real-time AI systems in clinical working processes (which may assist to assign the best resources according to the needs of the highest risk patients and prevent complications and worsening of the disease or readmission) may also be beneficial. This would enable the hospital to give the neediest patients the most care and thus enhancing the efficiency of care delivery and there is possibility of overall saving healthcare costs. The increase in resource mobilization might be able to assist healthcare providers with the continually growing patients, and still providing a high standard of care (Zhang et al., 2021).

Conclusion

This paper points to the strong promise of the use of Artificial Intelligence (AI) on Electronic Health Records (EHR) regarding the real-time prediction of patient outcomes. Although the more conventional models such as Random Forests (RF) and Support Vector Machines (SVM) are effective, they cannot keep up with the dynamic nature of the health of the patients. The deep learning algorithms can achieve better accuracy and recall than the traditional ones especially the Recurrent Neural Networks (RNNs) and the Convolutional Neural Networks (CNNs). RNNs applied to time-based predictions in patient data and are probably best performed in assessing how long it takes diseases to progress and whether a patient will be readmitted to hospitals, and CNNs are best suited to finding hierarchical sub-structures within more complicated data like medical imagery and structured EHR information.

Predictions made through AI models in a situation of critical care can be used in real-time and will result in more and more proactive, but data-oriented decisions. Machine learning can improve the use of resources by giving more prioritization to care that is most likely to lead to positive outcomes, which can potentially reduce readmission frequencies and increase the effectiveness of a hospital. However, the problems still remain, in particular, data quality and the interpretability of the model. Although deep learning models are more accurate, they are continuously characterized by being a black box, and thus clinicians find it challenging to rely on the models when making predictions. The solution to this issue is explainable AI (XAI) that explains the model decision, like LIME, SHAP, etc.

Another issue is data quality since missing and conflicting data will negatively impact the performance of a model. In the future, more preprocessing of the data needs to be planned, funds need to be invested in the infrastructure, and AI models must be completed with fewer secrets. Proper integration and resource applications of AI can radically enhance the results, the efficiency, and the treatment of the patients.

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