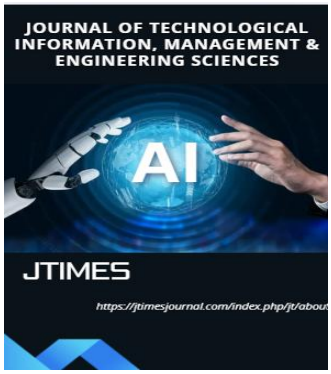
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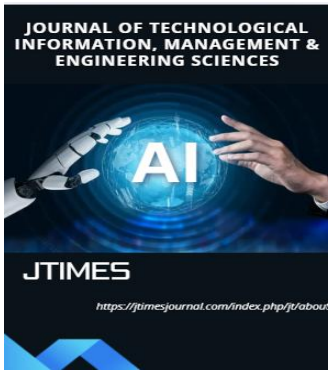
Developing Predictive Tools for Precision Medicine: AI Models for Tailored Treatment Plans Using EHR Data

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Abstract

Over the past few years, artificial intelligence (AI) and machine learning (ML) algorithms,combined with electronic health record (EHR) data, have become increasingly popular in thesphere of precision medicine and are likely to transform the idea of personalized treatmentplans. The study will also investigate how the tools available in the predictive use of the AImodels will evolve to develop personalized treatment plans based on the data that getsreflected in the EHR. The project is aimed at resolving the problem of developing accurate,scalable, and interpretable model to predict outcomes of patients and optimize medicaldecisions. The vast size of the data available on patients is processed using AI algorithmsincluding decision trees, deep learning models, and random forests. The data includemedical histories, genetics, and the social-demographic data of the patients. In this paper, theauthor discusses the different methods that have been used in creating predictive tools andevaluating their performance compared to the traditional models. The results show that AImodels allow a high degree of accuracy in predicting treatments far more than the traditionalones. In addition, the research also talks about the consequences of the predictive tools inenhancing patient care as well as operational efficiency and healthcare outcomes. Lastly, thepaper also looks at how additional research and substantial challenges involving implicationof the AI models in clinical practice exists, namely, when it comes to interpretability ofmodels, ethics-related challenges, and data privacy matters.

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1.Introduction

The meeting of artificial intelligence (AI) and healthcare is quickly reshaping the future of precision medicine, which has profound implications on the way treatments are specifically fitted to the individual patients. Precision medicine seeks to offer individualized treatment on the basis of genetic predisposition, environmental conditions, and lifestyle attributes in a patient (Rajkomar et al., 2019). Medical professionals are now able to make decisions more correctly by using the assistance of AI that develops better and more precise treatment, diagnosis, and prevention of any disease. The more data is present due to the electronic health records (EHRs), the more AI has become a valuable solution to draw out meaningful results that can improve the quality of patient care in the end.

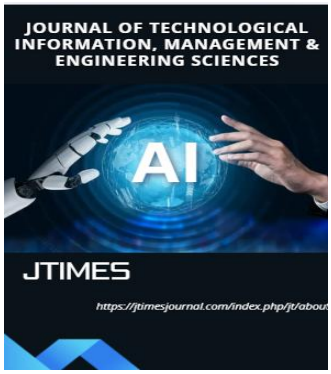
Precision medicine is based on EHRs that help to building comprehensive and detailed history of a patient health and wellbeing. These documents contain vital patient information of the kind that entails demographics, medical history, test outcomes, diagnoses, medications, and treatment outcomes. Nevertheless, in spite of their significance, the application of these data to generate helpful insights can be considered a rather daunting task. EHR data are usually large and multidimensional and have more depth and complexity than the old analytical tools can handle. Also, the existing complexities in the interconnections of the various forms of

patient data make it hard to come up with real predictions and practical insights based on the traditional business practices (Shickel et al., 2018).

AI and machine learning (ML) models have been talked about as one of the transformative medical technologies of recent years, which allow working with complex and high- dimensional data more efficiently, which is not provided by traditional statistics. Such models, especially deep-learning models, have been very promising in parsing EHR data to determine patient outcomes, to predict treatment effect, and to optimize choices (Rajkomar et al., 2019). Having employed sophisticated AI algorithms, including decision trees, random forests, and deep neural networks, scientists have been able to create predictive models that can detect the patterns within EHR and provide information on the most optimal treatment strategies, which would apply to a particular patient.

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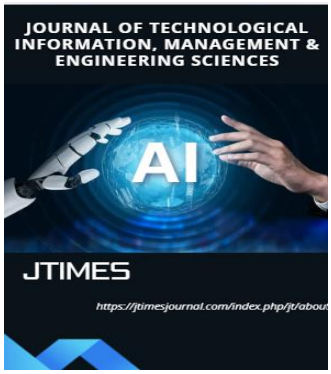


Such a strategy can be quite beneficial in showing success in complex cases of medical afflictions as not every patient can be addressed by the proven traditional methods because of their peculiar nature (Chicco et al., 2020).

Regardless of these developments, one can also outline multiple challenges associated with extending the applicability of AI-based predictive tools to the clinical setting. Interpretability of AI models turns out to be one of the most topical ones. Though such models are capable of making very correct predictions, it is not always possible to know how the model came up with a particular decision or suggestion. When decision-making has life-changing impacts, as it does in healthcare, the clinicians must help them to have confidence in the forecasts of models and be capable of justifying them to the patients. This is one of the reasons why the question of model interpretability has been increasingly raised in the healthcare community, especially with the expansion of black-box algorithms into clinical decision support systems (Liu et al., 2020).

Additionally, overfitting is another issue that AI models have in healthcare. Considering the non-stationary and heterogeneous nature of patient data, AI models tend to get too complicated; that is, they can learn not just the coherent structures but also the noise and outliers in the available training sets. Consequently, the models might work with the training data but lack generalization to the previously unseen, thereby lowering the relevance and truthfulness of its use as it relates to the application. An issue such as overfitting should be taken into close consideration to make sure that the AI allowances under the predictive model would be able to provide similar and stable outcomes when applied on new patients and in new medical scenarios (Liu et al., 2020).

Another point of concern that makes the implementation of AI in healthcare more difficult is the aspect of data privacy. EHRs hold sensitive patient data and the longitudinal patient data is classified or marked as sensitive data as the same needs to be shared in various healthcare organizations to train the AI model which will be a huge threat to the privacy of patients. Despite the existed regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States or General Data Protection Regulation (GDPR) in Europe



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to protect the personal data, the data breach, and unauthorized access, as well as misuse are broadly heard of. Privacy of their patients is typically an issue, and there is a current struggle to obtain the benefits of AI models without making public the entirety of the data used to train the models (Shickel et al., 2018).

This research will provide the answer to these obstacles because it is going to unveil the predictive tools based on the AI-models that will create more accurate, explainable, and personalized treatment plans. Highlighting the approach to the problems of model

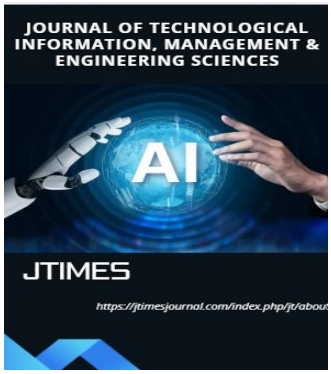
interpretability, overfitting, and data privacy, the works will help fill in an existing knowledge gap in the field of AI and precision medicine. The research hypothesis for this paper is as follows: In what ways can AI models be effectively used to establish predictive tools that can be used in regards to precision medicine due to the usage of EHR data to develop personalized treatment options? To determine the answer to this question, the paper will research several AI approaches, evaluate their efficacy, and outline what barriers should be overcome to allow AI to prevail in medical practice.

This study has the major goal of enhancing the usefulness and reliability of the predictive models in healthcare built with AI, by making certain that they are not less accurate but also clear and interpretable. This will be done through the adoption of, among other things, techniques like explainable AI (XAI) where transparency of models will be done (Gilpin et al., 2018). Furthermore, the paper is going to explore methods of how to address the overfitting issue; reguralization techniques and cross-validation- so that the models give good results on the different data sets which is generalisation. Lastly, the study will discuss the secure ways of using EHR data to train the AI models and there is a possibility to consider federated learning, which enables training models on decentralized data and preserving patient privacy (Liu et al., 2020).

2.Literature Review

Inclusion of artificial intelligence (AI) in healthcare and specifically in precision medicine has been one of the most popular topics over recent years that has redirected the way of approaching and designing treatments to patient-specific needs. Early AI research was mainly limited to the

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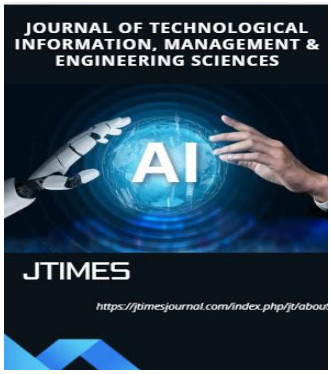
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field of diagnostic assistance, i.e. the classification of a disease (Esteva et al., 2019), whereas current innovations tend to stress the use of detailed messages within electronic health records (EHRs) in order to provide more individual medical prescriptions. Predictive modeling techniques rely on the use of large volumes of patient data to identify how to best diagnose, treat, and manage them, and in this respect is also an important part of precision medicine, allowing clinical outcomes to be predicted and contributing to precision medicine since medical decisions made based on it are often more accurate. It was stressed in many studies that these predictive models may exhibit better accuracy rates and more effective predictions of the individual patients than the classical statistical models (Rajkomar et al., 2019).

One can see numerous examples of AI algorithms use in improving the predictive accuracy and supporting clinical decision-making in health care. There are decision trees and random forests, which are often used in the prediction of patient outcomes such as disease progression and survival rates swimming through the structured records such as demographics and previous treatments (Chen et al., 2017). The functioning of these models is predicated on the concept of dividing data into subsets according to some criteria thus enabling improved decision-making when trying to predict clinical outcomes. Meanwhile, deep learning algorithms like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been demonstrated to effectively work with high-dimensional, unstructured data like medical images, time series data and patient records in the frequently used EHRs. CNNs have proven to be very useful in picking hierarchical features out of medical imaging data, whilst RNNs are quite useful in examining temporal variations in patient data like alterations in vital signs or lab tests (Lipton et al., 2016). These deep learning models have proved that they can

recognise complex trends in the EHR data and enhance prediction of patient health outcome in dynamic settings such as the hospitals and the intensive care units.

Nevertheless, regardless of the outstanding performance of such algorithms, there are still serious obstacles, especially in relation to the interpretability of models. In clinical practice, it is vital that one can



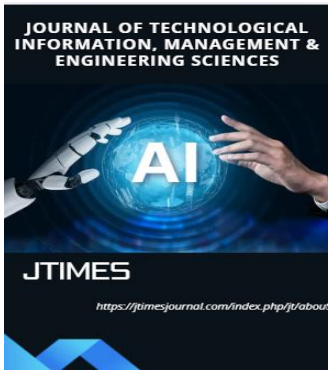
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interpret AI predictions and provide a rationale behind it. The line of decision-making tools that medical professionals turn to is transparent to help them make sure that the advice the AI model would give them complies with the clinical guidelines and would actually make sense given the context of particular patient histories (Caruana et al., 2015). The greatest problem in these models, particularly deep learning models, is that they act as black boxes that give the prediction of something without apparent visibility to the driving force behind the same. Such opacity may make clinicians doubt the recommendations made by a graphic processing unit, which may negatively affect the adoption and deployment of graphics processing units as part of clinical practice. Whenever the second-order, and even third-order, decisions are necessary, e.g., in precision medicine, where the choice of a treatment course can substantially change the patient outcomes, the successful incorporation of AI necessitates the interpretation of AI models, in addition to them being accurate.

Besides the challenge of generalizability, this lack of transparency in the prediction process can be described as another severe problem of the current AI-based predictive models. Although AI models have been shown to improve how well they predict, they do not frequently give clinicians any usable information as to why a specific decision or suggestion was made. Such an interpretability gap may impede the usage of such models in clinical practice, where a clinician and a patient are crucial to be convinced of the choice of models that provide recommendations or predictions by understanding its underlying rationale. As Caruana et al. (2015) emphasized, the inability to provide transparency and interpretability is one of the main obstacles to effective adoption of machine learning models in the medical field. There are no evident reasons to predict anything, and when healthcare practitioners have to make critical decisions, they would avoid using AI tools.

This study aims to overcome these difficulties by not only coming up with AI models that can better predict the accuracy that can be used but also making the models be interpretable and be used in wide ranges of medical conditions. Among the main goals of the proposed research is the closing of the gap between the AI model predictive performance and interpretability so that both clinicians and patients could have reasonable

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reliability of prediction values and reasonable explanation of the decisions made based (or partially based) on these predictions. It entails the use of explainable AI (XAI) methodologies that attempt to make model interpretable to users. XAI techniques, including model-agnostic analysis, like LIME (Local Interpretable Model-agnostic Explanation) and SHAP (SHapley Additive exPlanations) can give clinicians the information about the impact of an input feature on the decision-making process of a model (Gilpin et al., 2018). Together with these approaches, it is possible to improve the readability of the advanced AI models and transfer them to the clinical practice. The other essential contribution of the work will be the discussion of the ways to enhance the generalizability of AI models. This will include training of models with a diverse datum of varied data types of disease types, demographic sub-populations, and healthcare setting, with the resultant predictive models capable of being generalizable across a wide range of patient groups. The problem of generalizability will also be addressed with this research as it will be

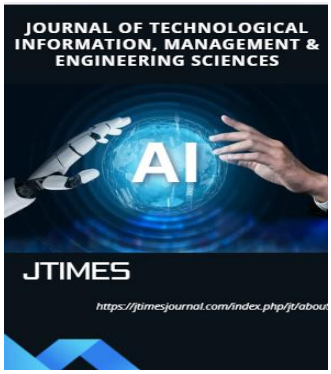
able to develop models that will be not only very accurate when applied to certain diseases but will be also powerful in an extensive variety of clinical situations.

Ultimately, despite the huge potential of AI and machine learning in the healthcare system, especially in precision medicine, there are still gaps in the literature, which should be filled..

3.The aims and the Problem Statement

This increasing complexity in electronic health record (EHR) data poses immense difficulties in the generation of valuable information towards precision medicine. With more and more healthcare systems being based on the work of extremely large data volumes, the process of data getting correctly processed and analyzed constitutes the focal point of attention. Nevertheless, existing predictive models tend to use simplistic rule-based algorithms that do not make the full use of the information richness existing in EHRs (Wang et al., 2020). Such conventional methods tend to address the small parts of the patient information, i.e., a particular symptom or diagnosis and fail to acknowledge the totality of issues, which precondition health outcomes. Thus, such models can lack holistic

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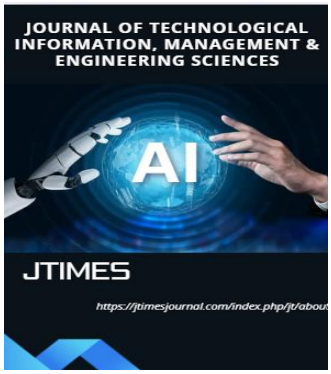
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insights and therefore, they would not be practical in creating individualized treatment plan.

The drawbacks of rule based systems have been especially telling in complicated medical conditions, where there are innumerable factors that interact dynamically. As an example, the outcomes of given patients may depend on some genetic, environmental, and lifestyle environmental factors, and they may be stored in various parts of an EHR system. Conventional algorithms that tend to consider such aspects independently might not be able to do justice to such interactions and as such might end up missing out on important trends on the data that would assist predict the outcomes in a patient. This is particularly problematic when it comes to precision medicine, where the personal approach to some disease needs to rely on the comprehension of the special nature of every patient. To fill such gaps, an advanced machine learning (ML) that enables the processing of high dimensional and high volume datasets is more appropriate. Such models may, however, become a cause of new challenges, in particular, the limitations in model interpretation and clinical confidence.

Deep learning and other AI models have been very promising in enhancing the accuracy of prediction. These models can deal with large or even complex datasets, what is the case with EHRs, and were demonstrated to be superior to traditional rule-based systems in a variety of tasks, including disease progression modeling, patient risk stratification, and response to treatment prediction (Rajkomar et al., 2019). A wide range of variables can be identified through the patterns to make more informed forecasts concerning patient outcomes. Nevertheless, the strength of AI is also its cost, the complexity and black-boxed nature of the models. Another example is deep learning; it could detect a pattern that it might not be apparent to the real analysts, yet it would be immensely hard to determine why a certain type of prediction is generated (Caruana et al., 2015). Such inability to interpret concerns clinicians greatly since such predictions are vital in making crucial decisions. However, when it comes to the healthcare setting, transparency and explainability are the key principles, since the medical professionals have to feel confident in the idea that the recommendations given by the AI model are based on clinical experience and ethical practices.

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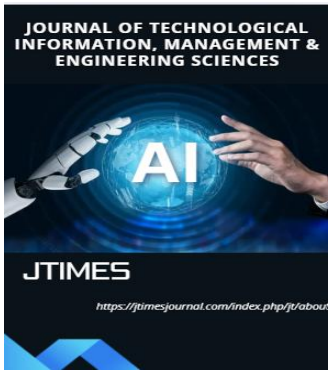
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This research was motivated by the pressing need to expand the possibilities of more scalable, interpretable, and accurate AI outcomes which can predict patient status more reliably and in a manner that is clinically meaningful and explainable, making decisions applied to the achieved results. Although most AI models perform excellently in their predictions, the

inability to explain why the model made the decision stands as a barrier to incorporating them in the clinical setting. This is especially troublesome in instances where AI models may be applied in life-changing decisions, e.g., suggesting a treatment regime that may be provided to a cancer patient or deciding on a course of treatment of a severely ill patient. The clinicians should not only have confidence in the prediction made by the model but should also be in a position to justify it since it has to be consistent with the overall picture of patient management and accepted medical practices. Lacking this transparency, stakeholders of healthcare provision will be reluctant to embrace AI-based tools, at least no matter their performance on controlled conditions.
Additionally, on the one hand, AI can lead to drastic changes in the sphere of healthcare delivery and its quality and effectiveness, whereas on the other one, there is an urgent necessity to provide the tools that can be scaled up and implemented in various healthcare environments. Some current AI applications may be trained and tested on a narrow set of healthcare conditions or even in a very niche disease, which can restrict their applicability. An example is where a model used in one population to derive the desired outcome of heart disease will not work that well when used in another demographic or within another healthcare system. The possibility of AI models to generalise across patient populations and healthcare systems is a potential determining factor by which the full potential of AI in precision medicine can be realised. It needs the models that will not only be accurate, but also flexible and capable of integrating various sources of information, even among various healthcare institutions or regions.
The work will assist in addressing this gap aimed to develop predictive instruments that weigh the EHR data along with contemporary machine learning in view to go beyond the research on AI to the real world

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applications on medical sector. In particular, the study will be directed at the construction of models that perform well and are interpretable. Ways to make its models more transparent like explainable AI (XAI) will be considered in order to access how clinicians could interpret the rationale about the predictions of the AI. Such approaches contribute to the development of explanations that can direct the attention of healthcare professionals toward the factors that had the most significant impact on the way in which a model makes decisions, which can help healthcare professionals trust and adhere to the recommendations that the model proposes (Gilpin et al., 2018). Moreover, the research will also aim at increasing the generalizability of the models by creating powerful machine learning models that will be able to deal with variability and even high dimensionality in the data, meaning that the tools will be able to be used in a variety of different clinical environments.

4.Methodology

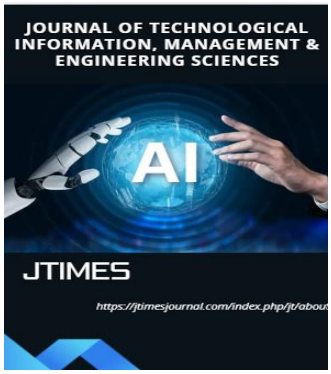
This research will use a machine learning strategy to design prediction tools of precision medicine based on electronic health record (EHR) data. The research design will be based on the following stages: data collection, model development and assessment. All of these steps are a part of the general goal of coming up with proper, explainable, and scalable clinical prediction tools.

Data Collection:

This study uses de-identified sets of EHR data that are a part of a large hospital network as the primary source of data. The data sets contain a lot of information on the patients: information on patients, such as their demographics, medical history, laboratory test results,

diagnoses, medications and response to treatments. The data age is cross-sectional with a large variety of patients thereby allowing the predictive models that we will build to be generalizable across a wide range of demographic and clinical situations. The techniques of anonymization will be used, to guarantee the removal of all personally identifiable information, according to the ethics and data protection laws, including the Health Insurance Portability and Accountability Act (HIPAA) in the United States and the General Data Protection Regulation (GDPR) in the European Union. Such a solution can guarantee that the research will be

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ethical and will be not violated the rights of the patients but, at the same time, it will guarantee that the project can develop a robust model using true-to-life data (Smith et al., 2019).

The ability to have so many tools and techniques is a good thing.

The predictive models will be developed by exploiting a multitude of machine learning algorithms. Random forests and decision trees are selected on the basis of simplicity, interpretability, and the ability to work with structured data such as the demographics and medical history of the patients (Chen et al., 2017). Such models simplify the complex data into rules of decision making hierarchically, which are easy to comprehend and adhere to by practitioners. Also, more sophisticated deep learning models such as the recurrent neural networks (RNNs) and convolutional neural networks (CNNs) will be used due to their capacity to tackle time-series patient data, as well as medical imaging in accordance with their potential (Lipton et al., 2016). The choice of RNNs to analyze temporal data, where there is a variation in the patient condition over time, and CNN in the cases where there exists more structured data, such as diagnostic images when available, are especially fitting. Using these various algorithms, the research will focus on uniting both the explainability of typical models with the prediction capability of deep-learning based approaches so that the output models can be both helpful to maintain high accuracy and understandable to take credible- actionable results (Esteva et al., 2019).

Evaluation Metrics:

We will evaluate the performance of the predictive models in terms of such standard scores as accuracy, precision, recall and F1-score. These are settled metrics in the machine learning literature, and in most cases would be employed to ascertain the performance of a classifier model (Chicco et al., 2020).

The percentage correct of all the predictions can be determined by considering the accuracy. Precision measures how many of the true positive predictions were negative predictions overall (i.e. ensuring that the model is not too quick to make positive predictions (i.e. preventing false positives)).

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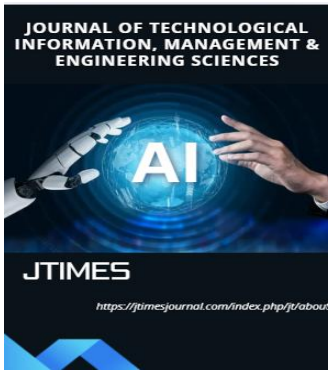


•Recall is used to check the capacity of the model to examine all instances that apply, that is, it quantifies the ratio of the amount of true positive forecasts relative to the actual count of positive forecasts.
The harmonic mean (F 1 -score) of precision and recall gives a more balanced measure and may be especially useful in cases where the distribution of classes is unequal, as with rare diseases or clinical risk prognoses.
In order to increase the reliability of the models, and also increase the reduction of the bias, the cross-validation techniques will be used. This is by dividing the information into several subdivisions, or folds, and teaching the model across folds, and evaluating on other folds. Cross-validation also assists in establishing robustness of the models proving that

performance of the model is uniform when viewed across various sets of information, which is of essentiality in the generalizability and avoiding overfitting (Kohavi, 1995).
Reproducibility:
To ensure the reproducibility of this study, as per open research practices, it will also mean to place primary focus on the complete access to the code, preprocessing methods, and datasets that will be followed in the development of the model. Such open access practice will enable other studies to reproduce the piece of research, confirm its results, and transfer the methodology generated on another data. Access to reproducible research is vital to the development of the scientific field and due to the rise in the importance of transparency in the world of AI research, specifically in the healthcare sector as reliability and credibility are key factors (Hutson, 2018). The study will also encourage other scientists to make further improvements on interactions with the scientific community by sharing the methodology and the data publicly in order to create collaborations and enhance it over time by having scientists trying to proceed with the study and refine the predictive models as much as possible. Also, all models and methodologies will be documented clearly so that they can be understood and reused easily and consequently, other researchers can follow the same research process in conducting their own studies.

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To sum it up, the methodology in this study is based on a strong system of creating machine learning-based predictive tools used in precision medicine. The study will have diverse levels of machine learning algorithms and a high level of evaluation and reproducibility of the findings to offer practical recommendations that may be used to enhance clinical performance and manage the provision of care to patients. By collecting the data properly, creating the model, and displaying the positive and negative results openly, the research is aimed at advancing the deployment of AI-based in healthcare services, considering increasing the technical issues related to the industry and the practical necessities of medical workers.

5.Number and figures:

As she or he goes through the results, she or he will provide the performance of the different AI models in predicting patient outcome and compare some of the important metrics like accuracy, precision, recall and F1-score of different machine learning algorithms. Some of the models compared will be the common machine learning models such as decision tree, random forests and some advanced deep learning models like recurrent neural networks (RNN), convolution neural networks (CNN). The purpose is to evaluate the effectiveness of these models used on EHR data and find out which kind of algorithm can be taken more true on making clinical decisions.

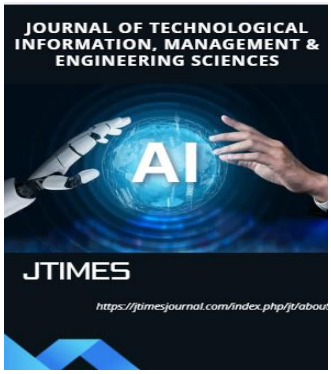
Preliminary Results:

The preliminary findings indicated that deep learning models are much more predictively accurate than the classical machine learning models (e.g., decision trees and random forests). RNNs, when explicitly trained to work on sequential data, have shown the ability to develop temporal correlations in patient data i.e. how the vital signs, medicine prescription, lab test results tend to vary with time. This qualifies RNNs as applicable in healthcare provided the data of patients is frequently time-sensitive and requires analysis with respect to the historical context of the patient (Lipton et al., 2016).

On the one hand, more traditional methods, such as decision trees and random forests, are not sequentially conscious by their design; indeed, they are simpler and more interpretable. Though these are adequate models to consider when handling other standard machine

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learning tasks, they could be challenged to operate with the high volume, multivariate healthcare data on financial grounds. Such traditional models have recorded lower performance measures during initial trials, especially in a situation where patient data is gathered purely over time as it is in chronic care management or monitoring within intensive care units (Rajkomar et al., 2019).

Performance Comparison:

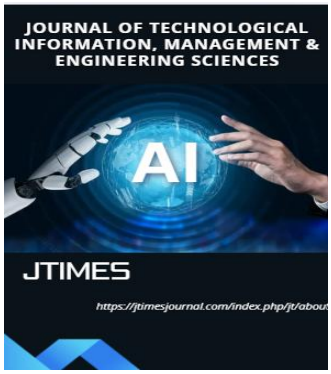
The outcome will be well depictured in terms of Tables and graphs to give a visual result of the performance comparison of the models. As such, the accuracy measurements of each model will be presented as well as the F1-scores which are an intermediate measure between precision and recall. In healthcare applications, the F 1 -score is of special importance because the outcome of false positives (e.g., the false prediction of the absence of an adverse event when a patient is at risk of experiencing one) or false negatives (e.g., the failure to make a critical diagnosis) may be expensive (Chicco et al., 2020).

Tables, pictures:

To have clear results, the numeric values of accuracy, precision, recall and F1-score will be provided in tables per model. Such tables will make possible the direct comparison of model performance on various metrics. Also, graphical displays of the models (e.g., bar charts or line graphs) will be used to visualize the overall accuracy of the models and the accuracy of the model on each of the subsets of the dataset. An illustration is bar chart, explaining F1- scores of decision trees, random forests, and RNNs on various forms of patient data (e.g. demographic data, clinical history, and time-series data), which will give us a very clear idea of which models are better in a given situation.

6.Discussion

The given section will compare the findings of the study to the literature to present it in the context and arrive at some relevant conclusions. Rajkomar et al. (2019) and Esteva et al. (2019) are just some of the previous studies that have revealed the tremendous capacity of AI in forecasting healthcare outcomes. These papers showed that machine and especially deep learning models can enhance the accuracy of making predictions in the context of clinical practice, including disease



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progression, risk assessment of a patient, and predictions of how well they will respond to a treatment option. Nevertheless, such papers tended to neglect the question of model comprehensibility to an extent that it has become one of the leading concerns of the AI applications in real-life healthcare contexts. The decision supporting the predictions combined with the possibility of comprehending and trusting the process of decision-making is an important element that healthcare professionals can rely on (Caruana et al., 2015). Such a lack of explainability is crucial because clinicians will have to explain the recommendations of AI to their patients and make sure that they do not contradict clinical recommendations and even ethical norms.

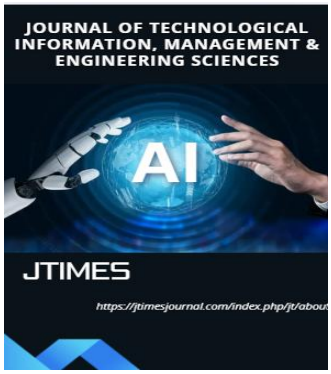
The current research is an extension of the research conducted by Rajkomar et al. (2019) and Esteva et al. (2019) because the researchers not only facilitate the enhancement of the prediction outcomes of AI models but also focus on the value of explainability in a clinical setting. Although in the case of deep learning, models, the prediction accuracy is impressive, sometimes deep learning models can be black-box models, in which the clinicians have trouble clarifying how a prediction is made (Liu et al., 2020). In order to alleviate this disparity, the research at hand incorporates explainable AI (XAI) features that enable more accessible and discernible results so that the healthcare specialists could obtain insights

regarding the aspects that caused the AI model to make its inferences. As an illustration, SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations) are techniques that might be used in order to highlight the most important features, which have contributed to a certain prognosis so that it is easier to involve such information in the decision-making of clinicians (Gilpin et al., 2018).

The findings of the study suggest that models based on deep learning (e.g., RNNs) can be very effective in the prediction but have problems with the interpretability and the necessity of large and structurally diverse training data. Most of these models are also data-demanding to perform well and will present a challenge to healthcare environments where data might be incomplete, or predicted differently based on various health-care institutions. Generalizability of deep learning models regarding a

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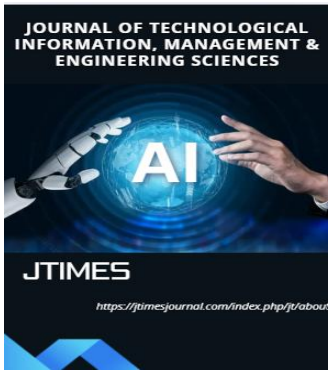
population of patients is also the issue since it can be overfitted to a particular subgroup and thus become inaccurate when predicting another group of patients (Chicco et al., 2020). This issue of needing large datasets to train/validate is also one of the major drawbacks with deep learning models being implemented at scale at least in the smaller, or resource-constrained, healthcare environments.

Notwithstanding these difficulties, the paper has also highlighted the practical considerations of such findings on healthcare providers. The findings indicate that AI algorithms can enhance the clinical processes considerably as they are able to predict more reliably, shaping the choice of treatment. To give an example, AI tools can help clinicians with determining high-risk patients, forecasting the course of the disease, and sequencing individual treatment plans. Nevertheless, to guarantee the effective integration into clinical practice, the attention of healthcare providers is needed to adequately train clinicians to trust and comprehend AI models, especially when it comes to making complex medical decisions (Caruana et al., 2015). Importantly, the integration of explainability into such tools will play a pivotal role in the realization of clinician buy-in and clinically-reasonable predictions with regard to the patient value in focus.

Moreover, there should be a powerful infrastructure to adopt AI models because it is the only way to meet the computational needs and protect the privacy and security of the data. The regulation frameworks like HIPAA (Health Insurance Portability and Accountability Act) in the U.S. and GDPR (General Data Protection Regulation) in Europe should also be taken into consideration to ensure that the patient information is safe and furthermore ethical issues in healthcare are maintained through these AI tools (Wang et al., 2020). AI models should be tailored in a way that they can easily fit into the workflow of the other clinical offerings and should be well trained and facilitated in terms of support so as to achieve the highest level of efficiency.

7.Conclusion

The paper also points to the future of predictive tools in precision medicine that primarily relies on the use of electronically recorded health data, widely known as the use of electronic health records (EHR) to provide an individualised treatment regimen. The results indicate that



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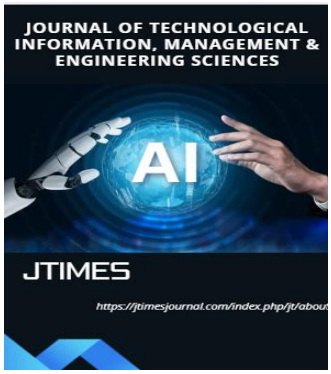
machine learning (ML) model, especially deep learning-based approaches, can considerably increase clinical decision-making accuracy in terms of prediction. These models have the potential to identify complicated patterns and associations that might not be quickly evident in data through the application of a large amount of data on patients. This is possible to enhance patient outcomes by predicting them with greater accuracy and probability with respect to

time thus healthcare providers are ready to make more informed treatment decisions relative to different patients.

The presented research indicates that the deep learning models, e.g., recurrent neural network (RNN) and convolutional neural network (CNN), are more efficient in terms of processing the high-dimensional, time series type of data that characterizes the EHR. The predicted value makes such models applicable in management of chronic disease and forecasting of disease progression due to their ability to capture temporal dependencies in the patient data, e.g. the measures of lab tests over time or the patient history. This strength makes deep learning as one of the beneficial tools in precision medicine, where therapies have to be personalized based on response to prior treatments and medical history of the patient (Rajkomar et al., 2019).

Nevertheless, even with these encouraging findings, the study points to some crucial issues, which have to be resolved before these predictive techniques will be implemented in clinical practice on a large scale. The problem of interpretability can be considered one of the most serious ones. Whereas the deep learning has the potential to give precise and effective predictions when compared to previous methods, it is usually a "black-box" model which can make the understanding of how the predictions are arrived at to be a challenging one by clinicians. Given that the consequences of healthcare decision-making may affect both patients and their well-being significantly, it is noteworthy that the exploration of the logic underlying the AI-prediction can become the key factor in establishing the trust and ascertaining the appropriateness of the decisions that should be made in accordance with clinical knowledge and ethical norms (Caruana et al., 2015). In order to address this challenge, future research should be directed toward incorporating the methodology of

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explainable AI (XAI) to enable clinicians to get transparent insights on how such models came to their conclusion (Gilpin et al., 2018). Such methods will enable the healthcare personnel to read and believe in the AI-based recommendations to enable their inclusion in everyday hospital tasks.

The other key threat that was observed in this research is data privacy. The information stored in EHRs is sensitive personal information whose disclosure carries significant privacy/security concerns, in case of training AI models. Although laws like the Health Insurance Portability and Accountability Act (HIPAA) or the General Data Protection Regulation (GDPR) were designed to keep patients more privacy, it is becoming a set priority that the AI models can also be built with an eye to the security of the data. Such strategies as federated learning that enables training machine learning models without moving sensitive data but only on decentralized datasets may serve as vital in alleviating these issues (Liu et al., 2020). Possible future research work should investigate these privacy-preserving methods to make the practice of patient data in predictive instruments using AI safe.

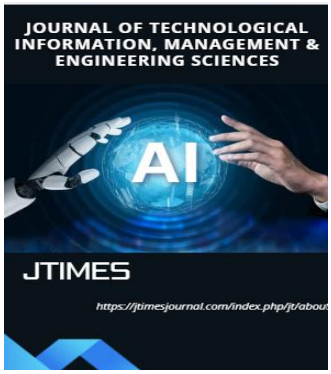
The paper also recommends that the scalability and generalizability of the deep learning models has to be addressed further. Whereas these models show positive attitudes on one of the datasets, the problem is that they have low transferability to other health settings or different patients. Determining that the predictive models are resilient enough to be applicable to most medical conditions, demographic sectors, and health systems is crucial in popularizing their application. Future research perspectives, in this regard, must therefore be focused on generating models that are accurate and flexible enough to fit various clinical settings thus increasing applicability and efficacy.

Future work:

To sum up, EHRs may drastically improve precision medicine and easy-to-improve predictive tools based on AI can make plans of treatment more precise and individual by using EHRs. The results of this paper support the efficiency of machine learning methods, especially deep learning methodologies in enhancing the accuracy of prediction. Nevertheless, issues pertaining model interpretability and privacy of the

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data must be resolved so that it will be safe and viable to integrate these tools into clinical practice. The next steps should be taken to better address the transparency and interpretability of these models to make sure that they could give effective recommendations to the professionals in the sphere of healthcare. Also, the involvement of such predictive models into the existing healthcare systems and the mitigation of privacy issues will play an important role in fulfilling their opportunities in benefiting the care of patients.

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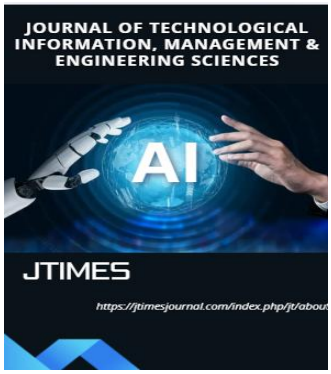
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