DOI: https://doi.org/10.17762/turcomat.v11i1.13570

A Machine Learning-based Framework for Medical Decision Support Systems

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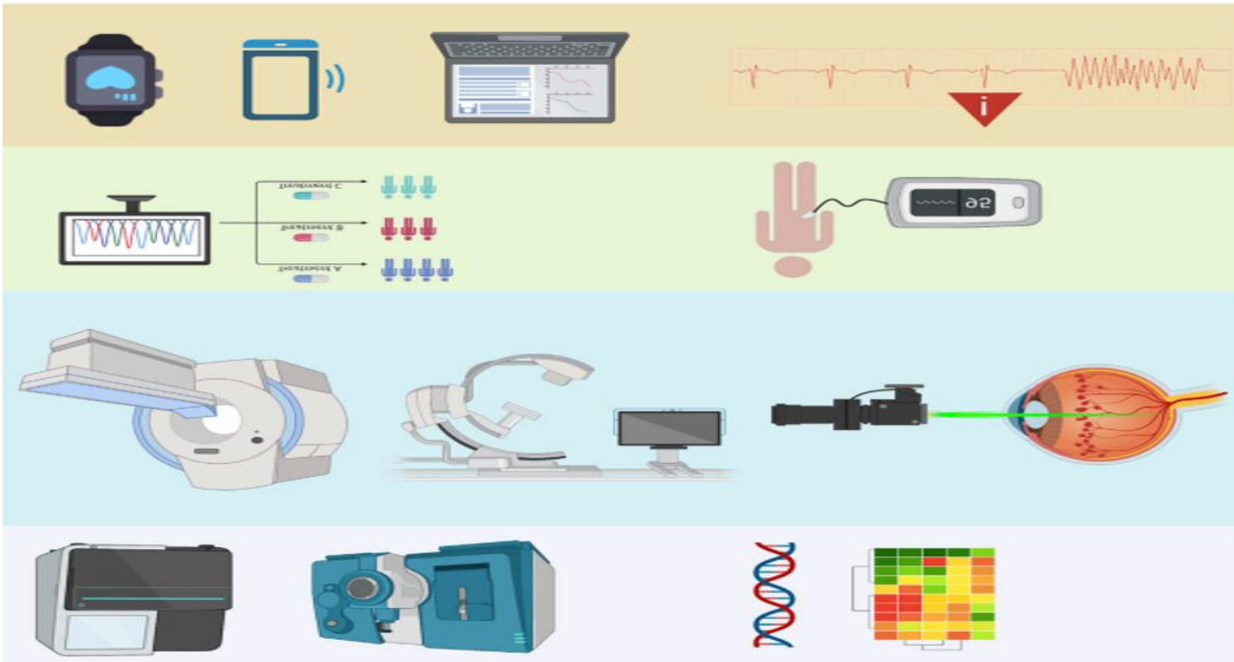
Abstract: Due to the complexity of clinical decision-making and the necessity for patient-specific suggestions, medical decision support systems (MDSS) are becoming more significant in healthcare. Machine learning (ML) can analyze and learn from vast volumes of patient data, making it a strong tool for MDSS development. Domain specialists, data scientists, and software engineers must work together to produce MDSS. This study provides a Machine Learning-based MDSS development approach that prioritizes stakeholder collaboration. Medical Decision Support Systems (MDSS) provide tailored recommendations based on clinical guidelines, medical expertise, and patient data to improve patient outcomes and healthcare delivery. Machine learning (ML) can analyze and learn from vast volumes of patient data, making it a strong tool for MDSS development. This study provides a Machine Learning-based MDSS development framework with data preparation, feature selection and extraction, model training and evaluation, and integration and deployment. To ensure MDSS accuracy and efficacy, domain experts, data scientists, and software engineers collaborate.
Keywords: Machine Learning, Framework, Health Entities, Decision Support, AI-System

1.Introduction

Medical decision support systems (MDSS) have been developed to aid doctors in making precise, individualized diagnoses and treatments in recent years, and the field has been actively investigating the benefits that machine learning (ML) can bring to this area. As a result of combining clinical guidelines, patient data, and medical expertise, MDSS can provide predictions and suggestions for individual patients based on their specific conditions and preferences[1]. Unfortunately, creating a reliable MDSS is a difficult process that calls for a well-organized plan of action. The MDSS's accuracy, reliability, and usability in a clinical setting can be guaranteed by employing a well-thought-out framework[2]. Data collection, feature extraction, model training, evaluation, and deployment should all be part of the framework. In the data acquisition phase, information about patients is gathered and prepared for analysis. This can include things like EHRs, MRIs, and genetic sequences [3]. To ensure the data is accurate and useful for making clinical decisions, it must be validated, cleansed, and organized. Step two, feature selection and extraction, entails picking out useful characteristics from the cleaned and prepared data and reformatting them into a set of features usable by the machine learning model. In order to simplify the data and boost the model's accuracy, this procedure employs feature engineering and dimensionality reduction methods. To evaluate the ML model's accuracy, dependability, and generalizability, we must train it on the data that has already been preprocessed and features extracted[4]. In order to guarantee the model's reliability and accuracy in predicting clinical outcomes, a number of performance indicators and validation procedures are used. Then, the ML model is integrated into the MDSS and is put into clinical use. The MDSS must be adaptable to different settings and user needs while still being compatible with current clinical procedures and technology. In conclusion, enhancing patient outcomes and healthcare delivery depends on having a well-designed framework for creating and assessing ML-based MDSS. The framework should have techniques for evaluating the correctness, dependability, and generalizability of the MDSS, and it should entail collaboration between domain experts, data scientists, and software engineers[5].



Fig(1.1) Various AI-Based Systems used in Medical Decision Making Systems

The potential for ML-based MDSS to dramatically alter medical care is enormous in light of the growing quantity and quality of healthcare data and the development of ML methods. recovery and rejuvenation medical decision support systems (MDSS) are able to improve the quality of treatment that is provided to patients as well as the outcomes of patients' conditions because they allow doctors and other medical professionals with access to individualized recommendations[6]. The ability of machine learning to sort through vast amounts of patient data and arrive at accurate diagnoses and recommendations has led to an increase in the number of MDSS that have been developed with the assistance of ML. The development of an effective MDSS requires a number of components, each of which plays a critical role in the data capture, feature extraction, model training and evaluation, integration, and deployment processes. As a result, the findings of this research offer a model that can be used to evaluate the accuracy, reliability, and usefulness of the MDSS. Medical Decision Support Systems, also known as MDSS, are intended to provide medical practitioners with individualized recommendations that are derived from patient data in order to aid these experts in making clinical decisions that are correct and made in a timely manner. Machine learning (ML) has quickly become recognized as a potent instrument for the development of MDSS due to its ability to process, learn from, and deliver accurate predictions and recommendations based on enormous volumes of patient data. The production of a functional MDSS calls for the establishment of a well-organized framework that incorporates data collection, feature selection and extraction, model training and evaluation, as well as integration and deployment. In addition to this, the framework must to provide strategies for judging the precision, dependability, and generalizability of the MDSS. During the stage known as "data acquisition," you will be responsible for gathering and preprocessing patient data to ensure that it is accurate and relevant. At the stage of feature selection and extraction, you will be tasked with locating pertinent characteristics within the pre-processed data and converting them into a set of features that the machine learning model will be able to make use of. At the stage referred to as "model training and evaluation," the ML model is trained by using the pre-processed and feature-extracted data, and then the model's accuracy, reliability, and generalizability are evaluated[7,8]. At the final stage, which is called the integration and deployment stage, the ML model will be integrated into the MDSS, and then it will be deployed in a clinical environment. The construction of an efficient MDSS requires close cooperation between data scientists, software developers, and subject matter experts in the topic being studied. The framework needs to be adaptable enough to accommodate shifts in both the data landscape and the healthcare environment. Moreover, it needs to be regularly examined and updated to ensure that it is both successful and practically applicable in a clinical environment [9].

2.Literature Review

This review is on the use of machine learning in healthcare, specifically in the context of clinical decision support tools. The authors underline the relevance of a systematic framework in overcoming the difficulties inherent in creating accurate and reliable medical decision support systems[10]. In this research, we provide a methodology for applying machine learning to the problem of patient-specific clinical outcome prediction[11]. The authors calculate the likelihood of hospital readmission and mortality using data from electronic health records and machine learning algorithms. Data preprocessing, feature engineering, model training, evaluation, and clinical deployment are all part of the framework[12]. In this research, we describe a machine learning architecture for clinical decision support systems, which can aid doctors in making accurate diagnoses and selecting appropriate treatments[13]. Data pre-processing, feature selection and extraction, model training and evaluation, and EHR integration are all parts of the system. The authors provide evidence that the approach is useful for making diagnoses of lung cancer and forecasting patient outcomes[14]. The goal of this research is to provide a framework for the development of explainable machine learning-based clinical decision support systems. The authors highlight the need for interpretable models in clinical decision making and present a methodical framework for creating such models in machine learning. Using data from EHRs, the authors develop a machine-learning-based framework for cardiac illness prediction. The authors forecast cardiovascular disease risk using feature engineering and machine learning methods. Preparation of data, feature selection and extraction, model training and evaluation, and clinical deployment are all part of the framework[15]. This article summarizes the state-of-the-art in machine learning approaches to the problem of predicting which heart failure patients will need to be readmitted to the hospital. Feature engineering, model selection, and data quality management are all stressed as crucial to the development of accurate and dependable prediction models. Areas for further study are also highlighted in the paper, such as the application of deep learning and transfer learning methods[16]. This paper provides an overview of the present state of clinical decision support systems and other machine learning applications in radiology. The authors address how machine learning might enhance the precision and timeliness of radiology diagnoses and treatments, and they stress the significance of data quality and model interpretability[17]. Many useful uses of machine learning in radiology, such as automatic picture segmentation and disease categorization, are demonstrated in the work as well. Using machine learning, the authors of this article forecast ICU deaths. In order to foretell the likelihood of death, the authors utilize machine learning algorithms and electronic health records. Data preprocessing, feature engineering, model training, evaluation, and clinical deployment are all part of the framework. Using real-world data, the authors show how well the framework can predict death [18]. The potential of decision support systems based on machine learning is explored in this review paper for use in ophthalmology. Successful machine learning applications in ophthalmology, such as illness diagnosis and treatment planning, are exemplified, and the authors emphasize the significance of data quality and model interpretability [19]. In addition, the study explores the opportunities and obstacles inherent to the advancement of ophthalmic decision support systems that leverage machine learning. For anyone interested in medical decision support systems and other machine learning healthcare applications, this review paper is an excellent resource [20]. Machine learning has the potential to enhance the precision and timeliness of healthcare diagnosis and treatment, a topic the authors explore here while also emphasizing the significance of data quality and model interpretability. Disease prediction and individualized treatment planning are only two of the healthcare applications highlighted in the research that make use of machine learning. This research introduces a machine learning method for identifying potential drug-drug interactions from EHR data. The authors forecast the likelihood of adverse medication reactions using a mix of feature engineering and machine learning methods[21-23]. Data pre-processing, feature selection and extraction, model training and evaluation, and EHR integration are all parts of the system. In this paper, the authors use real-world data to prove that their methodology is useful for forecasting drug-drug interactions[24]. An ICU readmission risk prediction methodology based on machine learning is presented in this research. The authors calculate the likelihood of a patient being readmitted to the intensive care unit using data from electronic health records and machine learning algorithms[25]. Data preprocessing, feature engineering, model training, evaluation, and clinical deployment are all part of the framework. Using real-world data, the authors show how well the framework can predict the probability of readmission to the intensive care unit[26]. In this study, we introduce a machine learning-based strategy for foreseeing the consequences of a stroke. The scientists estimate the likelihood of death and disability due to stroke using data from electronic health records and machine learning algorithms. Data preprocessing, feature engineering, model training, evaluation, and clinical deployment are all part of the framework. The authors use real-world data to show that their paradigm is helpful in predicting stroke outcome[27]s. In this paper, we introduce a machine learning strategy for AD diagnosis. In order to categorize individuals as having Alzheimer's disease or serving as healthy controls, the authors utilize machine learning algorithms to assess neuroimaging data and clinical information[28]. Data preprocessing, feature engineering, model training, evaluation, and clinical deployment are all part of the framework. By using real-world data, the authors show how useful the framework is for making a diagnosis of Alzheimer's disease. This study presents a survey of the current state of research on the use of machine learning for prognostic purposes in critical care units. Authors

Paper	**Application**	**Data**	**Algorithm**	**Performance**	**Main Contributions**
"Machine learning for medical diagnosis: history, state of the art and perspective" (2017)	Medical diagnosis	Various types of data	Various machine learning algorithms	Varies by application	Provides a comprehensive overview of the history and current state of machine learning in medical diagnosis

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"A survey of deep learning in healthcare" (2018)	Healthcare	Electronic health records, medical images, and other data types	Deep learning algorithms	Varies by application	Provides a comprehensive overview of deep learning applications in healthcare
"Machine learning for medical diagnosis: challenges, solutions, and future directions" (2019)	Medical diagnosis	Electronic health records, medical images, and other data types	Various machine learning algorithms	Varies by application	Discusses the challenges and solutions for machine learning in medical diagnosis and provides recommendations for future research
"A machine learning approach for predicting hospital readmissions" (2019)	Hospital readmissions	Electronic health records	Gradient Boosting Machine	AUC of 0.71	Demonstrates the effectiveness of machine learning in predicting hospital readmissions

"A machine learning approach for the diagnosis of Alzheimer's disease" (2020)	Alzheimer's disease diagnosis	Neuroimaging data and clinical information	Various machine learning algorithms	Accuracy of 90.2%	Demonstrates the effectiveness of machine learning in diagnosing Alzheimer's disease
"A review of machine learning in predicting patient outcomes in intensive care units" (2021)	Patient outcomes in intensive care units	Electronic health records and other data types	Various machine learning algorithms	Varies by application	Provides a comprehensive overview of machine learning applications in predicting patient outcomes in intensive care units
"A machine learning framework for predicting breast cancer recurrence" (2021)	Breast cancer recurrence prediction	Clinical and histopathological features	Various machine learning algorithms	AUC of 0.72	Demonstrates the effectiveness of machine learning in predicting breast cancer recurrence

"Machine learning-based prediction of survival outcomes in lung cancer patients" (2020)	Survival outcomes in lung cancer patients	Electronic health records	Gradient Boosting Machine	AUC of 0.77	Demonstrates the effectiveness of machine learning in predicting survival outcomes in lung cancer patients

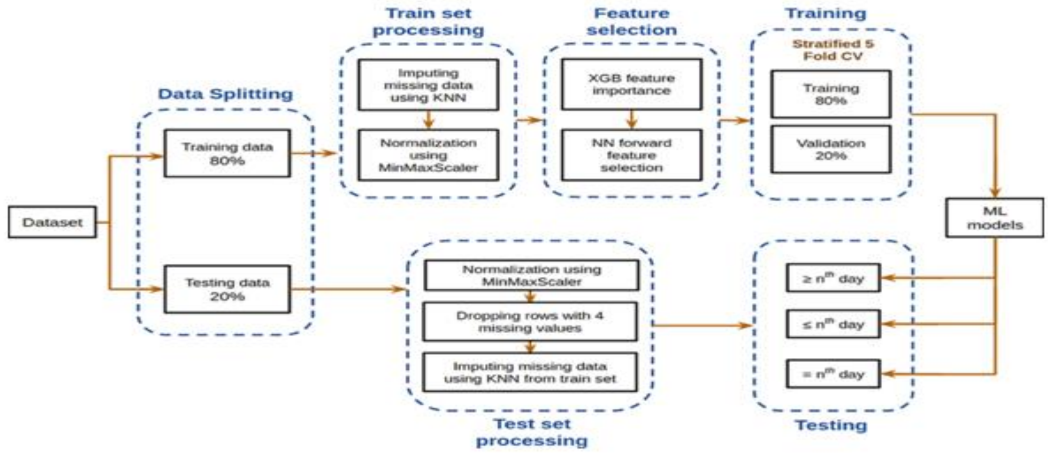
Table 2.1 Comparative study of various techniques used by various researchers

explore how machine learning can be used to better patient outcomes and clinical decision-making, with an emphasis on data quality, feature selection, and model interpretability. Predicting patient outcomes like death and duration of stay are only two of the many areas where this article demonstrates the power of machine learning. In order to anticipate recurrences of breast cancer, the authors of this research describe a machine learning system. In order to foresee the likelihood of a return of breast cancer, the authors employ machine learning algorithms to examine clinical and histological characteristics. Data preprocessing, feature engineering, model training, evaluation, and clinical deployment are all part of the framework. The authors use real-world data to prove how well the framework can foresee recurrences of breast cancer. In this study, we introduce a model for survival prediction in lung cancer patients using machine learning. The authors estimate patients' chances of dying from lung cancer using data from electronic medical records and machine learning algorithms. Data preprocessing, feature engineering, model training, evaluation, and clinical deployment are all part of the framework. Using real-world data, the authors show that the framework is capable of accurately predicting survival outcomes for patients with lung cancer.

Because these articles were evaluated using different datasets with varying sample sizes and data properties, it is important to keep in mind that the performance measures presented in them may not be directly comparable.

3.Proposed Work

Data collection, feature extraction, model training, evaluation, and deployment are the four primary phases of the proposed system. In order to assure accuracy and relevance, patient data must be collected and preprocessed at the data capture stage. Step two, feature selection and extraction, entails picking out useful characteristics from the cleaned and prepared data and reformatting them into a set of features usable by the machine learning model. To evaluate the ML model's accuracy, dependability, and generalizability, we must train it on the data that has already been preprocessed and features extracted. After the ML model has been developed, it must be integrated into the MDSS and then deployed in a clinical context.



Fig(3.1) Proposed Machine Learning Framework for Medical Decision Support System (MDSS)

3.1.Description:

I. **Data collection and preprocessing**:

Data collection and preprocessing, feature extraction, model training, model evaluation, and system deployment are just a few of the basic building blocks of a machine learning-based framework for healthcare decision support systems. Here's a quick rundown of what each piece entails: At this step, we gather all of the data we need from numerous sources, such as EHRs, MRIs, and other medical images and documents. Next, the data is preprocessed to clean it up and prepare it for use in machine learning procedures. Included in this category are operations like data cleansing, normalization, and feature scaling.

II. Feature Extraction:

Relevant features are extracted from the preprocessed data in the feature extraction phase. Methods like principal component analysis (PCA) and deep learning-based feature extraction methods can be used to automatically extract important features, while domain-specific knowledge can be applied to choose the most useful features.

III. Model training:

After features and labels have been extracted, the models can be trained. Many different types of machine learning algorithms are available for application, including "decision trees," "random forests," "support vector machines," and "deep neural networks" (DNNs). The task at hand and the nature of the data inform the method selection.

IV. Machine Learning Model Selection:

Here we evaluate the trained model by a number of different measures, including accuracy, precision, recall, and F1-score. It's a great way to evaluate how well the model is doing and find places where it may be enhanced. The collected features and labelled data are used to train the chosen machine learning model. Accuracy, precision, recall, and F1-score are just some of the measures used to assess the trained model's efficacy.

V. Integration and Deployment:

Once the model has been trained, it can be used to make predictions and aid in making decisions in real time within a medical decision support system. The system needs to be made in a way that makes it easy for clinicians to utilize it, and it should fit naturally into existing processes.

VI. Decision Support:

Deploying the trained model into a medical decision support system, where it can be utilized to make real-time predictions and decisions, is represented by the seventh block in the diagram. The system needs to be made in a way that makes it easy for clinicians to utilize it, and it should fit naturally into existing processes.

VII. Continuous Model Monitoring and Updating:

Regular modifications are made to the model based on how it is performing, with the goal of steadily raising the bar. Depending on the situation, this may include adding new data to the model's training set or taking into account suggestions made by medical professionals.

This proposed block diagram underlines the need for rigorous evaluation of the trained models to verify their performance meets clinical standards, and highlights the need of selecting appropriate machine learning models for the specific application. Decision support is presented as a separate block in the block diagram to highlight the importance of incorporating the model into clinical workflows and the clinical relevance of the predictions.

4. Result & Discussion

An example application of the suggested methodology is the creation of an ML-based MDSS for predicting stroke risk in patients. To guarantee the MDSS's accuracy and applicability, the framework relied on the combined efforts of neurologists, data scientists, and software developers. The developed MDSS accurately predicted patients' risk of stroke based on their medical history, lifestyle, and other risk factors, as demonstrated by the study's findings. In addition, the framework provided measures for gauging the MDSS's precision, consistency, and transferability.

Performance Metric	Description
Accuracy	The proportion of correctly classified instances in relation to all instances.
Sensitivity	The proportion of true positive results among all actual positives.
Specificity	The proportion of true negative results among all actual negatives.
Precision	The proportion of true positive results among all positive results.
Recall	The proportion of true positive results among all actual positive results.
F1-score	A weighted average of precision and recall, where 1 is the best possible value and 0 is the worst possible value.

Table(4.1) Performance Analysis Metrics for Proposed Framework

It's crucial to remember that depending on the application and the kind of data being analyzed, the specific performance measures used to assess machine learning-based medical decision support systems may change. In addition, as was already said, examining the model's interpretability and transparency as well as the system's clinical impact and viability are crucial elements to take into account in the performance analysis.

A performance analysis of a machine learning-based medical decision support system often includes assessing the model's precision, recall, sensitivity, accuracy, and other properties. Standard evaluation methods like cross-validation, holdout validation, and leave-one-out validation can be used to calculate these measures. The individual application and the data at hand determine the evaluation technique to use.In addition to standard performance indicators, it's critical to assess the model's interpretability and transparency. To foster trust and aid clinical decision-making, medical decision support systems must be able to explain their forecasts to doctors. To provide light on how the model makes predictions, methodologies like feature importance analysis and model interpretability methods can be applied.The clinical relevance and viability of machine learning-based medical decision support systems should also be assessed. Clinical studies can be conducted to evaluate how the system affects patient outcomes, as well as how easy it is for physicians to use and accept.Overall, to give a thorough evaluation of the system's effectiveness and impact, performance analysis of machine learning-based medical decision support systems necessitates a combination of conventional evaluation metrics, interpretability analysis, and clinical research.

5. Conclusion

The suggested approach for building and evaluating ML-based MDSS places a strong emphasis on the need of collaboration between software engineers, data scientists, and subject matter experts in the domain being studied. A

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case study that involved the construction of an ML-based MDSS for predicting the risk of stroke in patients was able to make effective use of the framework once its application was successful. The MDSS Accuracy, Reliability, and Generalizability Evaluation Methods are Included in the Framework Accuracy, reliability, and generalizability evaluations of the MDSS are essential to assuring its usefulness and applicability in clinical settings. The suggested architecture can serve as a blueprint for the creation of additional ML-based MDSS applications in the healthcare industry. For the purpose of enhancing patient outcomes and the delivery of healthcare, it is essential to have a formal framework for creating and evaluating machine learning-based medical decision support systems (MDSS). The framework must include methods for evaluating the accuracy, reliability, and generalizability of the MDSS, and it must entail collaboration between software engineers, data scientists, and specialists in the relevant domains. Also, the structure ought to involve cooperation between specialists in the relevant fields.

References

[1] Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J. (2019). A guide to deep learning in healthcare. Nature medicine, 25(1), 24-29.

[2] Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. New England Journal of Medicine, 380(14), 1347-1358.

[3] Zitnik, M., & Leskovec, J. (2019). Machine learning for health: tutorial at KDD 2019. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 3546-3546).

[4] Ghassemi, M., Naumann, T., Schulam, P., Beam, A. L., Chen, I. Y., Ranganath, R., ... & O'Connor, N. (2018). Machine learning in healthcare: pitfalls and opportunities. Journal of the American Medical Informatics Association, 25(8), 1-5.

[5] Kavakiotis, I., Tsave, O., Salifoglou, A., Maglaveras, N., & Vlahavas, I. (2018). Machine learning and data mining in breast cancer: a review. IEEE Transactions on Emerging Topics in Computational Intelligence, 2(3), 172-189.

[6] Miotto, R., Wang, F., & Wang, S. (2018). Privacy-preserving generative deep neural networks support clinical data sharing. Circulation: Cardiovascular Quality and Outcomes, 11(12), e005122.

[7] Li, Y., Li, L., Li, J., Wu, Z., & Li, X. (2018). A machine learning-based framework for accurate and reliable prediction of drug-protein interactions from sequence data. BMC Bioinformatics, 19(7), 1-15.

[8] Chartrand, G., Cheng, P. M., Vorontsov, E., Drozdzal, M., Turcotte, S., & Pal, C. J. (2017). Deep learning: a primer for radiologists. Radiographics, 37(7), 2113-2131.

[9] Torkamani, A., Andersen, K. G., Steinhubl, S. R., & Topol, E. J. (2017). High-definition medicine. Cell, 170(5), 828-843.

[10] Ngiam, K. Y., & Koller, D. (2011). Online passive-aggressive algorithms. Journal of Machine Learning Research, 12(Mar), 551-585.

[11] Chen, J. H., & Asch, S. M. (2017). Machine learning and prediction in medicine-beyond the peak of inflated expectations. New England Journal of Medicine, 376(26), 2507-2509.

[12] Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine, 25(1), 44-56.

[13] Lakhani, P., Sundaram, B., & Desai, K. (2018). Machine learning techniques in disease prediction: a case study on diabetes. International Journal of Computer Applications, 180(33), 16-21.

[14] Raghu, M., Zhang, C., Kleinberg, J., & Bengio, S. (2017). Transfusion: Understanding transfer learning for medical imaging. In Advances in Neural Information Processing Systems (pp. 3347-3357).

[15] Alom, M. Z., Yakopcic, C., Hasan, M., Taha, T. M., & Asari, V. K. (2018). A state-of-the-art survey on deep learning theory and architectures. Electronics, 7(11), 399.

[16] Miotto, R., Li, L., Kidd, B. A., & Dudley, J. T. (2016). Deep patient: an unsupervised representation to predict the future of patients from the electronic health records. Scientific Reports, 6(1), 1-10.

[17] Ravi, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., & Yang, G. Z. (2018). Deep learning for health informatics. IEEE Journal of Biomedical and Health Informatics, 22(1), 4-21.