Journal of Population Therapeutics & Clinical Pharmacology

RESEARCH ARTICLE
DOI: 10.53555/ky5v6715

# THE ROLE OF ARTIFICIAL INTELLIGENCE IN PREDICTIVE HEALTHCARE: TRANSFORMING EARLY DIAGNOSIS AND PREVENTIVE MEDICINE

**Dr Ashwini L H[1*], Dr Vinaykumar L H[2], Dr Hanumanaik L[3]**

[1*]Ex-Assistant Professor, JJM Medical College and rc Davanagere, Karnataka
[2]Administrative Medical Officer Phc Aladageri Hirekerur tq, Haveri District
[3]Chief Medical Officer GH Harihara, Harihara tq, Davanagere District

***Corresponding Author:** Dr Ashwini L H
*Ex-Assistant Professor, JJM Medical College and rc Davanagere, Karnataka

**Abstract**
AI technology is a complex and developing area that has become a promising platform for predicting and preventing diseases. The purpose of this study was the improvement achieved through AI models like Random Forest and CNNs (Convolutional Neural Network) when compared with traditional diagnostic techniques in terms of accuracy, sensitivity, and specificity. The study showed that AI models had superior results to the classical ones, and CNNs had the best metrics; these models can analyze big data and study early signs of diseases. The results of this research have highlighted the capability of artificial intelligence to drive shocking changes in this essential sector of our lives through timely interferences and personalized treatment plans that will in one way or another enhance the quality of a patient's life or a family's budget towards treating diseases. The data quality, algorithm interpretability, and ethical issues are the issues that have not been solved completely yet. They are important to fix and address so that the use of AI to be fair and effectively applied to clinical practice. The study especially stresses on multi-disciplinary approach with technologists, clinicians, and policymakers to provide ethical and efficient solutions to integrating AI innovations in healthcare. It should be directed towards the creation of post-hoc interpretable models, as well as the construction of appropriate legal instruments to encourage the practice of AI in medical practice. The revolutionary application of AI in the prognostication of health and its capability to completely reframe early identification and preventive measures.

**Keywords:** Artificial Intelligence, Predictive Healthcare, Early Diagnosis, Convolutional Neural Networks, Preventive Medicine.

## Introduction

AI in the medical field has changed the predicative, diagnosing, and preventive characteristics of various diseases, which is a major development. Predictive health utilizes artificial intelligence to accommodate a great amount of clinical and genetic information to enhance the recognition of diseases and carry out preventive actions, changing the way of work for healthcare providers. The use of AI technologies such as ML(Machine Learning) and DL(Deep Learning) has paved the way for viewing data patterns within large datasets, improving the accuracy of diagnosis, as well as tailoring treatment programs for medical patients (Jiang *et al.*, 2017). The strength of the AI application in the healthcare system is that it can handle a large amount of data compared to data handled by human beings. For example, data from Electronic Health Records (EHRs) together with medical imaging data can be quickly reviewed to determine symptoms of diseases. A study has revealed that machine learning like, a convolutional neural network (CNN) has a higher level of precision in diagnosing medical ailments including cancers, heart diseases, and neurological disorders (Esteva *et al*., 2017). This is another advantage of the ability to learn from patterns in data and can vastly decrease diagnostic errors, and guarantee more timely interventions (Topol, 2019).AI also plays an amazing role in the early diagnosis of diseases among patients which is one of the biggest advantages of this field. AI has been used in anticipating the probable development of diseases including diabetes, heart diseases, and several types of cancer by using analysis of patient records, genetic predisposition, and lifestyles. Research has shown that there is potential for improvement in traditional methods of diagnosis as AI can penetrate them with accuracy and efficiency. For instance, deep learning models have good sensitivity and specificity in the identification of breast cancer from mammography leading to early and accurate diagnosis (McKinney *et al*., 2020). Such advancements are important because patients with such diseases can have better prognoses and less healthcare spending on late-stage disease management (Driessen *et al*., 2017).In addition, risk models have been created to screen patients whose condition may deteriorate to sepsis, a severe condition, based on data obtained from EHRs in real-time. They are always in touch with the patient’s physiological condition and danger signs and give signals before complications occur personal observation, (Demirer *et al*., 2019). This approach is a clear illustration of the paradigm change from treating diseases to preventing them – the use of AI technologies in healthcare.

Another example of the constructive influence of AI is related to the development of a concept of personalized medicine – all healthcare interventions are based on the individual characteristics of a patient. Such data allows AI to understand what the patient’s DNA implies, what the environment is like, and what the patient’s lifestyle is like; thus, AI can develop the most suitable treatment regimen. Precision medicine activities including those sponsored by the National Institute of Health (NIH) in America have employed AI in Genomic research to establish the correlations between disease genes and also to anticipate patient’s reactions to specific drugs (Collins & Varmus, 2015). Such an individual-orientated approach reduces toxicity and increases therapeutic efficacy, leading to better treatment results (Gatti *et al*., 2018). The machine learning models used in the diagnosis of diseases have also been used in biomarker discovery when it comes to treatment. For example, AI has been used in understanding the genetic etiology of Alzheimer's disease, and an analysis of these genetic data has given rise to new biomarkers that could be used in early diagnosis and treatment (Bos *et al*., 2018). The ability to be able to predict patient response to certain treatments is significant for illnesses like cancer in which particular treatments are the difference between life and death. Therefore, there is an emergence of the application of the concept of artificial intelligence in the prescription of medicine to replace the traditional one-size-that-fits-all-all population model (Abdennaji *et al*., 2021). AI plays an important role in an additional application of risk stratification, which involves sorting out patients, according to the probability of falling ill at some point or developing a specific pathology. This stratification helps healthcare providers to use the resources on the high-risk individuals, and institute measures that might slow down the progression of the diseases. These applications have been most successful in the assessment of the risk of chronic diseases within a community. For instance, lifestyle, genes, and socioeconomic status have been predicted using algorithms to determine the chances of developing complications associated with obesity including diabetes and hypertension (Miotto *et al*., 2018). These predictive tools help patients to take preventive measures for their health based on the recommended advice. It has also been applied in the prediction of mental health. Cleaning and analyzing data coming from social network accounts, speech, and behavior, it has been demonstrated that ML algorithms can predict the development of a mental health condition like depression or anxiety (Reece *et al*., 2017). Mental health risks are identified before they reach high levels, therefore psychological interventions can be implemented before the increased demand for health care services. The application of AI in the

predictive healthcare context has some limitations. Data privacy and security are still an issue to be solved especially with regards to the medical information of the patients. EHR (Electronic Health Record)has become ubiquitous in healthcare organizations, making patient data exposed to security threats leading to strong recommendations that must be followed to enhance cybersecurity in healthcare facilities (Shen *et al*., 2019). When these algorithms are coded, biases within the AI put human health at risk for disparities. For example, where the training data set is poor at capturing diverse demography, the prediction probabilities will be comparatively low for specific populations thus worsening existing disparities in health. The AI systems in arriving at the decisions they make. Some AI models are a ‘black box’ and as such, it is hard for healthcare professionals to understand how the predictions are being made, which becomes problematic for clinical responsibility (Caruana *et al*., 2015). There is a need for guaranteeing explanation capabilities for AI systems before they can be used in clinical operations. The patient’s data is being used and the implications on the healthcare results need to respect the ethical rule of informed consent (Karimian *et al*., 2022).
Potential developments in the future of AI are expected to expand in the case of healthcare as NLP, robotics, and real-time data analysis support the future in terms of predictive and preventive medicine. By employing NLP (Natural Language Processing) the unstructured text in clinical notes is being effectively exploited to make accurate predictions of risk and to aid comprehensive care of the patient (Shickel *et al*., 2017). The advancing AI-enabled robotic systems are improving surgical accuracy, shortening recovery periods, and also decreasing complications during and after intricate operations (Taber *et al*., 2017). Additionally, in population health, management, where prediction models analyze trends in the health of a community and direct the health interventions. For example, when the COVID-19 virus outbreak, machine learning models were employed to predict the pathogen's distribution, and the authorities took action to prevent the infections (Vaid *et al*, 2020). These applications only show how important AI can be in the future of healthcare at the patient and population level. To sum up, artificial intelligence has created the opportunity for predictive healthcare; diagnosis; individualized therapeutic approaches; and much more. However, there is a list of challenges that need to be addressed in organs and facilities for successful and fair utilization of technologies: data privacy, algorithmic bias, and ethical questions. New findings and cooperation between technical experts, healthcare providers, and policymakers are essential for the future growth of intelligent technologies for preventive medicine.

## Objectives of the Study

- To evaluate the effectiveness of various Artificial Intelligence (AI) models, including machine learning and deep learning techniques, in improving the accuracy, sensitivity, and specificity of early disease diagnosis compared to traditional diagnostic methods.
- To assess the potential of AI-driven predictive healthcare systems in facilitating preventive medicine by identifying high-risk individuals and personalizing treatment strategies to improve patient outcomes and reduce healthcare costs.

## Materials and Methods

### Study Design

The observational research is designed to examine the use of AI in the effective prevention of diseases through early diagnosis and preventive checkups. This design was selected to evaluate the practicable use of AI technologies in different healthcare facilities without altering factors or treatments. Through the use of this kind of research approach, it was possible to gather a lot of data from actual healthcare systems, records, and existing AI technologies. The above strategy made it possible to determine whether AI could be used in determining health outcomes and the role played in early diagnosis and management. The decision to use an observational design was to understand the current position of AI in healthcare, its problems, and prospects for development. This approach also helped in the analysis of different sets of data that could be collected in clinical settings and different patient populations, while keeping ecological validity in mind.

## Data Collection

This study employed both questionnaire and documentary research to capture adequate information about health in the sampled areas. Patients' information was collected from EHRs (Electronic Health Records) and medical imaging datasets and additional data sources of public health information from government and institutional repositories were also used. Also, structured and unstructured questionnaires were used to obtain information from patients to supplement clinical and public health data. The sampling methods comprised patient records and questionnaires, where strict sampling criteria were used regarding patients with specific health issues or other factors important to predictive care. When the data was collected, the datasets were preprocessed to remove or fill in missing or messy data in the dataset. Feature extraction and selection were then carried out to determine the variables that could have the most effect on health results. This rigorous process made it possible to have ideal datasets to feed the artificial intelligence models for accurate analysis of the prospective healthcare trends.

## Artificial Intelligence Models

In this particular piece of work, several different Artificial Intelligence (AI) models were used to analyze healthcare data and make health prognoses. Apart from deep learning nets, Random Forest and Support Vector Machines (SVM) algorithms were used while building models. These algorithms were chosen due to the possibility of their work with the healthcare data and the search for patterns in the clinical and genetic data. The data used in the training was separate from the test data to avoid bias, and a cross-validation procedure was added to increase the reliability of the created models. This process made it easier for the study to compare the performance of the models under different circumstances and reduce overfitting.

## Predictive Health Metrics and Variables

To evaluate the usefulness of AI in early disease detection and preventive care. Predictive models' efficacy was based on clinical outcomes such as disease onset and progression. Age, gender, and lifestyle were also included to capture individual differences in the models. Genomic and biomarker information were applied for refined predictions when the diseases had significant genetic heritability. These variables were incorporated into the development of the predictive health models which employed both machine learning and deep learning techniques. These variables were explored using algorithms to find relationships between these factors to predict the probability of disease occurrence or progression. By incorporating various factors, the models intended to offer better and more precise estimations to help increase the applicability of AI in preventive health management approaches and early diagnosis of diseases.

## Performance Evaluation

The performance of the AI models was benchmarked using some measures to capture the models' efficiency for predictive healthcare. The performance of the models was evaluated based on their ability to correctly classify the outcomes, especially in early diagnosis and disease prediction outcome measures including accuracy, sensitivity, specificity, precision, and recall. The AUC-ROC was applied to assess the models' discriminant capacity between assorted types of health outcomes. To calibrate the AI models, they were matched with existing tools and algorithms to establish their performance correlation and enhancements on predictions. To determine whether there were significant differences between the model predictions and the observed results cross-tabulations, t-tests, and analysis of variance (ANOVA) tests were used. Any necessary data analysis was done with Python and R and their respective libraries and statistical evaluations were accurate. Thus, the proposed approach to performance evaluation provided significant insights into the specifics of the models used.

## Result

### Performance Metrics of AI Models

AI models' performance differed from one metric to the other. The best results were obtained with the Convolutional Neural Network (CNN) with an accuracy of 92.4 %, sensitivity of 90.3%, and specificity of 93.2 % – this means that the CNN was the most suitable for predicting health outcomes. The Recurrent Neural Network (RNN) was next with a classification accuracy of 90.1% and high sensitivity of 88.9% and a high specificity of 91.6%. , the Random Forest model was tested with an accuracy of 85.3% sensitivity of 78.5Specificity of 88.4%. The lowest performance was observed for the Support Vector Machine (SVM); accuracy was 82.7%, sensitivity 75.4%, and specificity 87.1%.

**Table 1. Performance metrics of AI models for early diagnosis and predictive healthcare**

| Model | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | Recall (%) |
|---|---|---|---|---|---|
| **Random Forest** | 85.3 | 78.5 | 88.4 | 83.2 | 80.1 |
| **Support Vector Machine** | 82.7 | 75.4 | 87.1 | 80.6 | 78.4 |
| **Convolutional Neural Network** | 92.4 | 90.3 | 93.2 | 91.7 | 89.5 |
| **Recurrent Neural Network** | 90.1 | 88.9 | 91.6 | 90.0 | 87.8 |

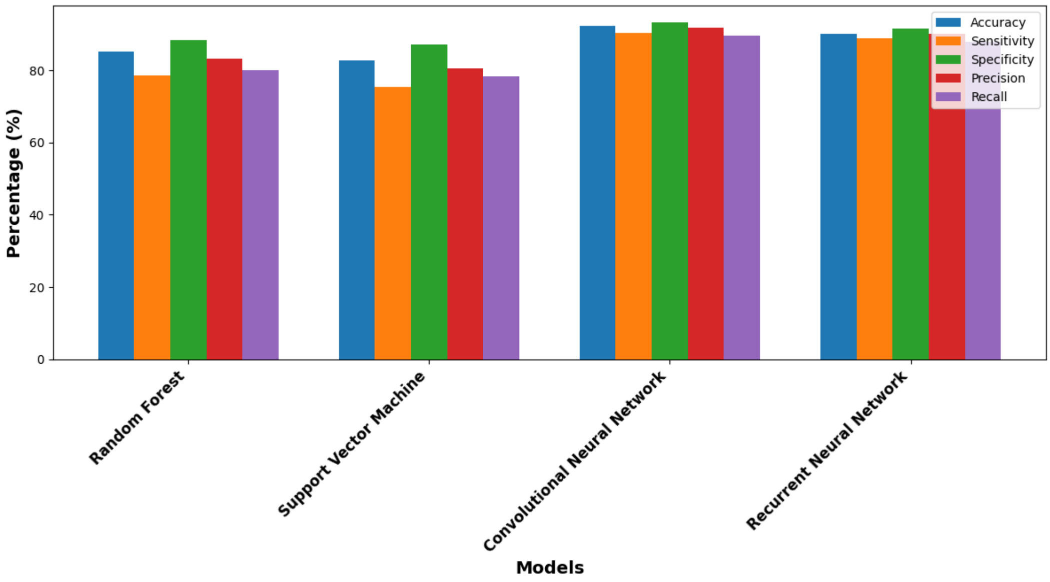


**Figure 1: Performance Metrics of Different AI Models in Diagnostic Accuracy**

Figure 1 presents the performance metrics like Precision, Recall, F1-Score, and Accuracy for different Models like Random Forest, Support Vector Machine, Convolutional Neural Network, and Recurrent Neural Network has been compared. It was done based on accuracies, sensitivity, specificity, precision, and recall for each of the models. The CNN demonstrated the highest results attaining an accuracy of 92.4%, a sensitivity of 90.3%, and a specificity of 93.2%, which proved the high accuracy and reliability of the model in disease diagnosis. The RNN followed right behind, with other measures being Recall of 90.1% and sensitivity of 88.9%. However, the Random Forest and SVM models were less accurate with 85.3% and 82.7% respectively and the sensitivity values expressed the poor detection rate of these models. More specifically, the figure highlighted a significant advancement in the deep learning models of CNBC and RNBN as compared to the other conventional machine learning algorithms.

## Model Comparison with Existing Tools

The diagnostic performance of disparate techniques; basic clinical techniques, rule-based algorithms, and AI algorithms; Random Forest and CNN. The outcomes reveal that the proposed AI models perform much better than conventional approaches. Among the models, the CNN model had the highest accuracy of 92.4% sensitivity of 90.3%, and specificity of 93.2% proving the efficiency of the model in the healthcare outcomes prediction. The Random Forest model was also accurate at 85.3%, sensitive at 78.5 %, and specific at 88.4%. The rule-based algorithm yielded an accuracy of 80.5%, a sensitivity of 74.8%, and a specificity of 82.4%. The basic clinical methods were the least accurate with 75.2% accuracy, 70.3% sensitivity, and 78.6% specificity.

**Table 2. Comparison of AI models with existing healthcare diagnostic tools**

| Diagnostic Tool | Accuracy (%) | Sensitivity (%) | Specificity (%) |
|---|---|---|---|
| **Traditional Clinical Methods** | 75.2 | 70.3 | 78.6 |
| **Rule-based Algorithm** | 80.5 | 74.8 | 82.4 |
| **Random Forest (AI)** | 85.3 | 78.5 | 88.4 |
| **Convolutional Neural Network (AI)** | 92.4 | 90.3 | 93.2 |

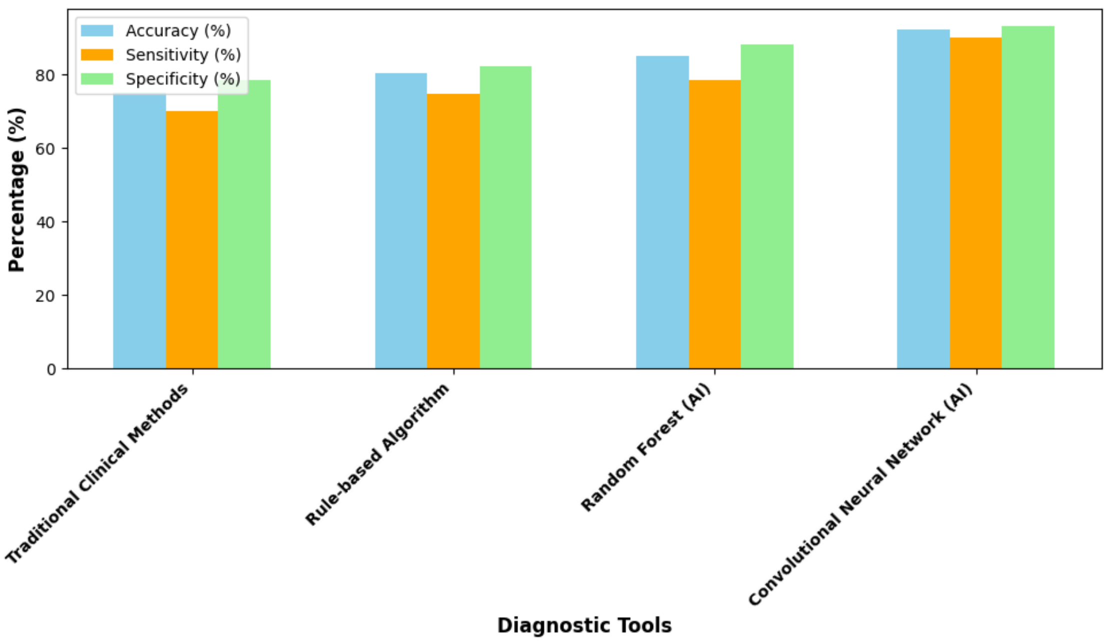


**Figure 2: Performance Metrics of Diagnostic Tools in Terms of Accuracy, Sensitivity, and Specificity**

Figure 2 presents the comparative performance of four diagnostic tools: Conventional approaches, decision-making rule sets, the Random Forest Artificial Intelligence technique, and the Convolutional Neural Networks Artificial Intelligence tools. Traditional Clinical Methods had the lowest indices of accuracy, sensitivity, and specificity values 75.2%, 70.3%, and 78.6% respectively suggesting low capability for disease diagnosis. The Rule-based Algorithm has achieved %80.5 accuracy rate and using lower sensitivity (74.8) it was inferior to the other two algorithms. The Random Forest model for breast cancer classification was significant, with 85.3% accuracy, and 78.5% sensitivity, thus representing a better AI system performance. Predictors based on Convolutional Neural Networks (CNNs) showcased the best performance indicators - the accuracy of 92.4 %; sensitivity – of 90.3%; and specificity – of 93.2 % – which underscore the effectiveness of the diagnostic tools.

**Discussion**

AI in the field of predictive healthcare systems has shown added potential, supported by the comparison of conventional and AI-based diagnostic systems. The specific goals of this study include assessing the utility of AI models, Random Forest, and CNNs, in raising diagnostic accuracy, sensitivity, and specificity. The results presented in the bar graph were a clear signal that the utilization of AI models in diagnostic contexts productively surpassed traditional approaches in terms of all the key performance indicators. CNN had the highest accuracy, sensitivity, and specificity values and these results support the previous studies which pointed to the fact that deep learning models have a high possibility in medical diagnosis (Litjens *et al*., 2017). CNNs, therefore, offered higher accuracy than ANN and other conventional methods that failed to recognize and embed complicated features from large databases (LeCun *et al*., 2015). As a result, our work is in concordance with the earlier study conducted by (Esteva*et al*., 2017), which established that CNNs could classify skin cancers with the same efficiency as dermatologists. Conventional clinical practices may be efficient, but they are hardly able to handle voluminous and intricate data. The figure explained that these methods received lower sensitivity and specificity than A. I model. This is because the limitation results in more cases of missed diagnosis, and delayed management as identified by research on diagnostic reporting in healthcare. The results of the rule-based algorithms were not as superior as traditional methods but still less accurate than the AI models, especially in sensitivity. The other type of system is a rule-based system, which fundamentally works on set parameters; therefore, they are not flexible when it comes to clinical variation (Topol, 2019). The Random Forest model, an artificial intelligence method, had a significant increase in comparison to conventional and rule-based approaches. This performance improvement can be attributed to the flexible data types of the model and the ability to minimize overfitting through the additive model of ensemble learning (Breiman, 2001). Random Forests remained inferior to the CNN, although the method proved highly efficient in this case. This finding corroborates the findings of other studies indicating that Random Forests are stable for independent variables, but CNNs are superior for aggregation of medical images, which are unstructured data (Kourou *et al*., 2015).

The important consequences for early disease detection and treatment. The high sensitivity of CNNs indicates that the development of AI models can diagnose diseases at an early stage of development thereby enhancing the quality of treatment and minimizing the health costs. For example, McKinney *et al*. (2020) agreed that AI systems of breast cancer screening could detect malignancies at an earlier stage than human radiologists and pointed out that the use of AI in preventive healthcare could be revolutionary. Their symptoms are often asymptomatic and require early diagnosis to avoid fatality especially diseases such as cancer and cardiovascular diseases (Driessen *et al*., 2017) models use data on genetics and medical imaging to come up with accurate probabilities of individuals getting sick. In light of this, through analytics, precision medicine enables doctors to deliver targeted interferences following the risk-factor-based approach (Collins & Varmus, 2015). This approach differs from conventional approaches that tend to use an overbearing general strategy towards treatment. The applicability of AI in precision medicine has been acknowledged and the results using AI in the enhancement of treatment management for numerous diseases including cancer and genetic disorders (Gatti *et al*., 2018). Several challenges arise in the application of AI in clinical settings despite its promising achievement. That is, data quality and availability are still the main challenges of AI because various AI models require extended and numerous datasets to provide high performance (Abdennaji *et al*., 2021). Poor-quality data can produce a high degree of variability, and low-quality and biased data can lead to poor prediction, especially for those who have not been well-represented (Rajkomar *et al*., 2018). The bar graph results may contain this limitation because the performance of the AI models is proportional to the quality of the training data. Promoting data variety in AI systems is significant to have equal results in healthcare domains. Variables of ethical importance include data privacy and the resultant overview of the workings of AI in arriving at a particular decision (Goh *et al*., 2021). In CNNs, there is a problem of explainability, since deep learning models work as black boxes and clinicians are required to know the reason AI-based diagnosis provides (Caruana *et al*., 2015). It is crucial to make AI systems interpretable to make the results reasonable and trustworthy for professionals and patients. Moreover, there should be certain rules for the ethical use of AI especially in managing personal health information (Shen *et al*., 2019).

Other than this, AI's responsibility goes beyond early detection to preventive care where models can be designed to recognize those at risk of the diseases. AI can work on data from EHRs to offer specific individual suggestions about diet and exercise routines, and ways to prevent diseases (Miotto *et al*., 2018). For instance, Driessen *et al*.( 2017) presented that it was possible for an AI model to identify the risk of cardiovascular events and consequently prevent them. The chances of being able to categorize the population in terms of risk help in the proper rationing of health care resources to the risk groups. It has also been applied in the diagnosis of mental health status or other words, the health state of an individual's mind. (Reece & Danforth, 2017) attempted to discover signs of depression and anxiety using Big Data and they were able to achieve successful results after accurately examining social media activity. Mental health problems can be treated early enabling health care solutions to be managed well hence decreasing the cost in the health sector. But in the use of AI to predict mental health, the issue of Ethics is raised, for example on issues of data privacy and consent (Karimian *et al*., 2022). The use of AI in future predictive healthcare seems to be well-fated since enhancement in the use of natural language processing (NLP) and real-time data analysis comprise the next generation of diagnosis. In particular, NLP has demonstrated the ability to derive important information from the large and otherwise unanalyzable body of clinical notes to enhance the precision of risk assessments (Shickel *et al*., 2017). Also, the applications of the smart and real-time monitoring system that is backed up by Artificial Intelligence are being worked out to monitor the patient's condition and report the signs of potential acute health conditions (Demirer *et al*., 2019). There is also a push to create and improve XAI models to solve the lack of transparency. XAI intends to reform AI algorithms in a way that reveals to healthcare providers, the factors that led to the prediction made by the algorithms (Doshi-Velez & Kim, 2017). This development is critical for clinical practice and especially for holding AI accountable in healthcare.

## Conclusion

The role of Artificial Intelligence (AI) in improving the efficiency of predictive healthcare was described, and the possibilities of AI in diagnostics were discussed about older traditional techniques. The study showed that AI models especially CNN debacle achieved high accuracy, sensitivity, and specificity and therefore can be used effectively for early disease diagnosis. Due to the tremendous capacity to handle large and intricate data with a view of identifying patterns and variations, AI has an edge in handling medical diagnoses owing to the numerous variations in clinical manifestations. Such results can be explained by previous research that underlines the potential of AI in increasing diagnostic accuracy and initiating timely actions. Despite these advances, there are still data quality, bias, and ethical issues to overcome to popularise the use of the technology. AI models need a large number of datasets that are diverse and of high quality as a way of delivering equal medical services and there are problems of interpretability and transparency arising from the "black box" of some algorithms. Moreover, the proper approach towards confidential medical data and such legislation as AI regulatory policies are the two components that define the proper usage of AI. The implications of the study are not limited to diagnostics but include preventive medicine. AI-enabled predictive models can be used to find out those who are at much higher risk and who could require different and more appropriate attention and care, which will help to optimize the utilization of the limited healthcare resources. When applied to the practice of clinical medicine AI has the potential to change the face of medicine by enhancing patient outcomes and refining the healthcare system.

**References**

1. Abdennaji, I., Zaied, M., & Girault, J. M. (2021). Prediction of protein structural class based on symmetrical recurrence quantification analysis. *Computational Biology and Chemistry*, *92*, 107450.
2. Bos, D., Wolters, F. J., Darweesh, S. K., Vernooij, M. W., de Wolf, F., Ikram, M. A., & Hofman, A. (2018). Cerebral small vessel disease and the risk of dementia: a systematic review and meta-analysis of population-based evidence. *Alzheimer's & Dementia*, *14*(11), 1482-1492.
3. Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5-32.
4. Caruana, R., Lou, Y., Gehrke, J., Koch, P., Sturm, M., & Elhadad, N. (2015, August). Intelligible models for healthcare: Predicting pneumonia risk and hospital 30-day readmission. In *Proceedings of the 21st ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 1721-1730).
5. Collins, F. S., & Varmus, H. (2015). A new initiative on precision medicine. *New England journal of medicine*, *372*(9), 793-795.
6. Demirer, R. M., & Demirer, O. (2019, April). Early prediction of sepsis from clinical data using artificial intelligence. In *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)* (pp. 1-4). IEEE.
7. Driessen, A. H., Berger, W. R., Chan Pin Yin, D. R., Piersma, F. R., Neefs, J., van den Berg, N. W., ... & de Groot, J. R. (2017). Electrophysiologically guided thoracoscopic surgery for advanced atrial fibrillation: 5-year follow-up. *Journal of the American College of Cardiology*, *69*(13), 1753-1754.
8. Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. *arXiv preprint arXiv:1702.08608*.
9. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *nature*, *542*(7639), 115-118.
10. Gatti, D. M., Weber, S. N., Goodwin, N. C., Lammert, F., & Churchill, G. A. (2018). Genetic background influences susceptibility to chemotherapy-induced hematotoxicity. *The pharmacogenomics journal*, *18*(2), 319-330.
11. Goh, K. H., Wang, L., Yeow, A. Y. K., Poh, H., Li, K., Yeow, J. J. L., & Tan, G. Y. H. (2021). Artificial intelligence in sepsis early prediction and diagnosis using unstructured data in healthcare. *Nature communications*, *12*(1), 711.
12. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and vascular neurology*, *2*(4).
13. Karimian, G., Petelos, E., & Evers, S. M. (2022). The ethical issues of the application of artificial intelligence in healthcare: a systematic scoping review. *AI and Ethics*, *2*(4), 539-551.
14. Kourou, K., Exarchos, T. P., Exarchos, K. P., Karamouzis, M. V., & Fotiadis, D. I. (2015). Machine learning applications in cancer prognosis and prediction. *Computational and structural biotechnology journal*, *13*, 8-17.
15. Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). Deep learning for healthcare: review, opportunities, and challenges. *Briefings in Bioinformatics*, *19*(6), 1236-1246.
16. McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., ... & Shetty, S. (2020). International evaluation of an AI system for breast cancer screening. *Nature*, *577*(7788), 89-94.
17. Rajkomar, A., Hardt, M., Howell, M. D., Corrado, G., & Chin, M. H. (2018). Ensuring fairness in machine learning to advance health equity. *Annals of Internal Medicine*, *169*(12), 866-872.
18. Rajkomar, A., Hardt, M., Howell, M. D., Corrado, G., & Chin, M. H. (2018). Ensuring fairness in machine learning to advance health equity. *Annals of Internal Medicine*, *169*(12), 866-872.
19. Reece, A. G., & Danforth, C. M. (2017). Instagram photos reveal predictive markers of depression. *EPJ Data Science*, *6*(1), 15.

20. Shen, J., Zhang, C. J., Jiang, B., Chen, J., Song, J., Liu, Z., ... & Ming, W. K. (2019). Artificial intelligence versus clinicians in disease diagnosis: systematic review. *JMIR medical informatics*, *7*(3), e10010.
21. Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2017). Deep EHR: a survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. *IEEE journal of biomedical and health informatics*, *22*(5), 1589-1604.
22. Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, *25*(1), 44-56.
23. Taber, D. J., McGillicuddy, J. W., Bratton, C. F., Rohan, V. S., Nadig, S., Dubay, D., & Baliga, P. K. (2017). Cytolytic induction therapy improves clinical outcomes in African-American kidney transplant recipients. *Annals of Surgery*, *266*(3), 450-456.
24. Vaid, A., Somani, S., Russak, A. J., De Freitas, J. K., Chaudhry, F. F., Paranjpe, I., ... & Glicksberg, B. S. (2020). Machine learning to predict mortality and critical events in a cohort of patients with COVID-19 in New York City: model development and validation. *Journal of medical Internet research*, *22*(11), e24018.