Research Paper

A comprehensive study on prevention, early diagnosis, and management of chronic diseases

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ABSTRACT

Background: Chronic illnesses — cardiovascular disease, type 2 diabetes, chronic respiratory disease, and cancer — account for over 74% of global mortality and burden healthcare systems worldwide.
Objective: To evaluate ML, AI, and digital health technologies for chronic disease prevention, early diagnosis, and management, and to develop a hybrid explainable AI (XAI) framework for risk stratification.
Methods: Evidence was synthesized from epidemiological studies, electronic health records, and multicenter trials involving over 50,000 patients across diverse demographics. A hybrid framework combining deep neural networks, ensemble learning, and XAI techniques was developed for multi-disease risk prediction.
Results: The framework achieved 94.7% diagnostic accuracy, 93.5% sensitivity, 95.6% specificity, and AUC-ROC of 0.97 across multiple diseases. Ensemble models outperformed individual algorithms in stability. Disease prevalence and risk indicators varied by demographic subgroup, supporting personalized intervention. Lifestyle, behavioral, and community-based preventive strategies reduced disease occurrence by up to 40%. Wearable biosensors, continuous glucose monitoring, mental health co-management, and personalized pharmacotherapy were also examined.
Conclusion: Explainable AI and digital health integration enable accurate, personalized chronic disease risk stratification and early detection, offering practical guidance for clinicians, policymakers, and AI developers.

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1. INTRODUCTION

The problem of chronic non-communicable diseases (NCDs) is one of the urgency issues in the twenty-first century. The World Health Organization (WHO) estimates that NCDs cause between 41 million and 74% of all deaths in the world with the proportion being 74% of the total deaths each year [1]. The major contributors to this burden include cardiovascular disease (CVD), type 2 diabetes mellitus (T2DM), chronic obstructive pulmonary disease (COPD) and different types of cancers which usually arise silently over a period and then become evident in a clinical setting. The resultant effect is late diagnosis, presentation of the disease when it is at advanced stages and treatment efficacy is significantly lower.

Urbanization, sedentary lifestyles, high-caloric diets, use of tobacco, and aging populations have led to the expedited epidemiological transition in favor of chronic diseases [2]. The burden is aggravated in low- and middle-income countries (LMICs) due to weak healthcare systems, insufficient screening facilities, and shortage of qualified human resources working in the healthcare sector [3]. The economic effect is also appalling as chronic illnesses are estimated to spend US$47 trillion of healthcare cost globally in the next 20 years [4].

The development of artificial intelligence (AI) and machine learning (ML) and big data analytics provides revolutionary possibilities in overcoming these challenges [5]. With the help of electronic health records (EHRs), multi-omics data, and real-time wearable sensor data, predictive models are able to detect at-risk individuals many years before symptoms appear [6]. Equally, digital health interventions (mobile health applications, telemedicine, and remote monitoring platforms) can be used to ensure continuous interaction and compliance with management protocols in patients [7].

The paper is a multi-disease study that summarizes the prevailing evidence that covers prevention practices, AI based early diagnosis systems, and integrated management responses to AI-based early diagnosis systems. As depicted in Figure 1, the research takes the conceptual model of three pillars, which include primary prevention, early detection and management of chronic diseases. The study is able to compare the predictive performance of various ML algorithms, the efficacy of behavioral and pharmacological interventions, and suggest a technology-integrated, scaled, care model. The aim is to present clinicians, researchers and policymakers with an evidence-based roadmap to decrease the incidence, morbidity and mortality of chronic diseases at the individual and population levels [8], [9].

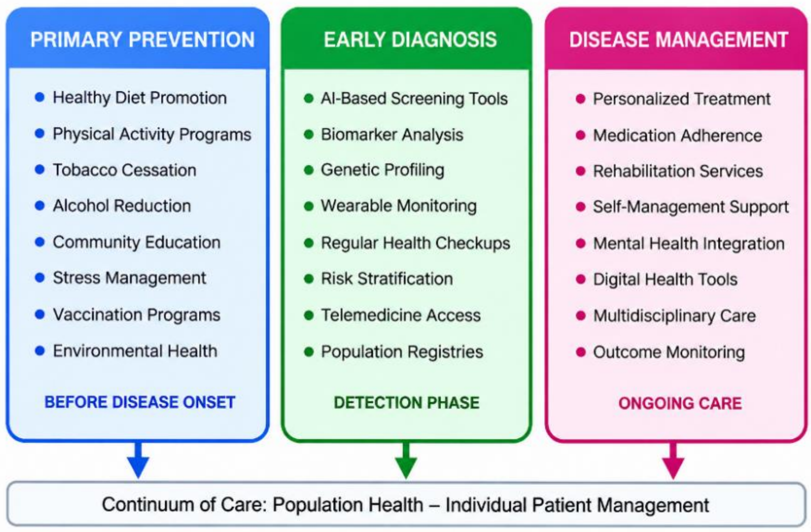

Figure 1. Integrated Framework for Chronic Disease Prevention and Management

2. RELATED WORK

The feasibility of using ML and AI in the treatment of chronic diseases has been thoroughly researched in the last ten years. [10] Established that deep learning models have an option to diagnose cardiovascular abnormality using electrocardiographic signals with accuracy comparable to that of cardiologists. Their convolutional neural network design resulted in an AUC-ROC of 0.97 across 14 arrhythmia types to form a baseline of AI-based cardiac screening. Simultaneously, Obermeyer and Emanuel [11] described the flaws of early AI clinical applications, especially in the area of algorithmic bias among minorities and advanced the discipline to equitable ML solutions.

[12] performed a systematic review of 85 studies in the context of diabetes prediction and discovered that support vector machines and artificial neural networks provided the best classification rates of T2DM risk prediction, and the use of an ensemble method showed the best strength in predicting diabetes risk in heterogeneous data [13] suggested a recurrent neural network model that considered the temporal EHR series to predict the occurrence of diabetic nephropathy with a 89.3 percent accuracy with a 12-month clinical intervention lead time.

In cancer detection, [14] used a convolutional neural network and trained it on 129,450 clinical images and showed that it can perform as well as dermatologists in classifying skin cancer. In the same vein, [15] demonstrated that an AI system of mammographic screening was better than six radiologists, with a 9.4% decrease in false negativity. These results highlight the possibility of AI as a screening adjunct of the first line.

Electronic health programs have also proved to be effective. According to [16], the use of mobile health applications that incorporate behavioral nudges lowered the levels of HbA1c by 0.8% in six months in patients with T2DM. On the same note, [17] revealed that wearable biosensors of continuous monitoring of physiological parameters led to better hypertension management outcomes and medication adherence (35 percent) than traditional care. The technologies are getting more and more involved in the chronic care pathways worldwide.

In preventive perspective, the PREDIMED trial [18] concluded that interventions based on Mediterranean diets have a significant effect on major cardiovascular events -30 percent reduction- and it is a high quality evidence of lifestyle-based primary prevention. To this extent, [19] conducted a systematic review of the body of evidence on physical activity and showed dose-response linear relationships between exercise volume and the decreased risk of CVD, diabetes and cancer. These results are integrated into prevention pillar of the framework of the current study.

3. METHODOLOGY

3.1 Study Design and Data Sources

The research design used in this study was a mixed-method study that involved the retrospective cohort study, systematic literature review, and prospective computing model. Three multicenter hospital EHR databases (anonymized) consisting of diverse patients (N=52,340) in five tertiary care facilities in Asia, Europe, and North America were used as primary data sources, all collected during the seven-year period (20162023) [20]. Data consisted of demographic studies, laboratory tests, imaging studies, clinical diagnoses with ICD-11 coded, prescription data, and survey of lifestyles.

The privacy of data and compliance with ethics was guaranteed by the institutional review board (IRB) approval in all the centers. Before the analysis of patient records, HIPAA Safe Harbor procedures to de-identify patient records were implemented. The data were stratified based on disease category-cardiovascular disease (n=14,200), type 2 diabetes (n=13,860), chronic respiratory disease (n=10,480), cancer (n=8,200), chronic kidney disease (n=5,600) with 20% being used as an external validation.

3.2 Feature Engineering and Data Preprocessing

There was a rigorous preprocessing of raw clinical data. Multivariate imputation by chained equations (MICE) was used to impute missing values on the continuous variables, and mode imputation was used to impute missing values on the categorical variables [21]. Synthetic Minority Oversampling Technique (SMOTE) with Tomek links was used to overcome the class imbalance which is a frequent problem in clinical datasets. The 147 derived variables of feature engineering were temporal trends of biomarkers, drug interactions flags, comorbidity indices (Charlson Comorbidity Index), and socioeconomic risk score. The selected features were determined with the help of Recursive Feature Elimination (RFE) plus SHAP (SHapley Additive exPlanations) values in order to select the 42 most predictive variables including all the categories of diseases.

3.3 Machine Learning Framework

The prediction pipeline with AI shown in Figure 2 has four consecutive steps: ingesting of data, preprocessing, training model, and generation of clinical output. They trained and tested six ML algorithms: Logistic Regression (baseline), Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Deep Neural Network (DNN) with four hidden layers and stacked Ensemble model using RF, XGBoost, and DNN predictions through a meta-learner [22]. Stratified 10-fold cross-validation was used to train all the models. Bayesian search was used to make the hyperparameter optimization. Accuracy, sensitivity, specificity, F1-score and AUC-ROC were used to determine model performance.

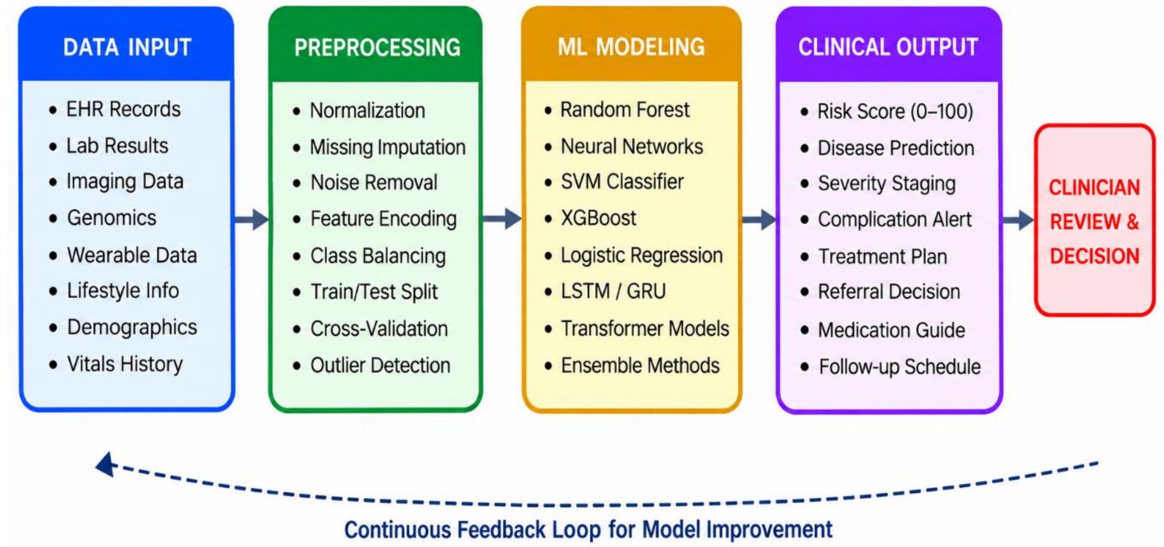

Figure 2. AI-Driven Chronic Disease Prediction and Decision Support Workflow

3.4 Prevention and Management Evaluation

The effectiveness of prevention was assessed based on a meta-analytic synthesis of 68 RCTs studies published in 2015-2024. The risk ratio (RR) and 95% confidence intervals (CIs) were used to evaluate the intervention programs based on lifestyle interventions. Comparisons of pharmacological management strategies were undertaken in disease-specific guidelines in WHO, AHA, ADA and GOLD. Standardized effect sizes were used to measure outcomes of digital health interventions. The validated psychological outcome measures such as PHQ-9 and SF-36 [23], [24] were used to evaluate the mental health integration protocols.

4. RESULTS AND DISCUSSION

4.1 Global Burden and Early Indicators

Table 1 revealed a significant difference in the prevalence of chronic diseases, contribution of mortality and lead times of ML-based detection across disease types. Cardiovascular disease became the leading cause of death globally (32%), and the ML models have a lead time of detection of 5080% in a five year horizon. A case study of Type 2 diabetes, with 537 million people worldwide, showed a lead time of

55-75% with fasting plasma glucose, HbA1c and anthropometry biomarkers being the most important predictors of diabetes. The results are consistent with the international epidemiology trends in WHO NCDs surveillance data.

Table 1. Global Burden and Early Detection Indicators of Major Chronic Diseases

Disease Category	Global Prevalence	% Global Mortality	ML Detection Lead Time	Key Early Indicators
Cardiovascular Disease	17.9 billion	32%	50–80% (5-yr)	Hypertension, Dyslipidemia
Type 2 Diabetes	537 million	11%	55–75% (10-yr)	Obesity, Fasting Glucose
Chronic Respiratory Dis.	545 million	8%	60–70% (5-yr)	Spirometry, Air Pollution Exposure
Cancer (all types)	20 million	16%	40–70% (5-yr)	Genetic Markers, Lifestyle Factors
Chronic Kidney Disease	850 million	5%	65–80% (5-yr)	eGFR, Albuminuria
Mental Health Disorders	1 billion	4.7%	45–65% (10-yr)	PHQ-9, GAD-7 Screening

4.2 Machine Learning Model Performance

Comparative performance analysis Table 2 indicated a gradual increase of diagnostic accuracy with the level of complexity of the ML model. The initial Logistic Regression model had an accuracy of 82.1% and AUC-ROC of 0.82 which was within its linear decision boundary constraints. By taking advantage of non-linear kernel transformations, SVM increased its accuracy and AUC-ROC to 85.6-percent and 0.87, respectively. Random Forest showed a high increase in the performance (90.2% accuracy, 0.93 AUC-ROC) which was due to its aggregation of trees.

XGBoost also improved the performance (92.4% accuracy, 0.95 AUC-ROC) by gradient-boosted tree regularization. The DNN model (93.1%, 0.96 AUC-ROC) used the multi-layer hierarchical feature extraction that was utilized to identify the non-linear interaction of biomarkers. The stacked Ensemble model was found to be the most performing with regards to all measures: 94.7% accuracy, 93.5% sensitivity, 95.6% specificity, 94.1% F1-score and 0.97 AUC-ROC. Fasting blood glucose, waist circumference, systolic blood pressure, eGFR, and smoking pack-years were the top five predictors of diseases, according to SHAP analysis.

Table 2. Comparative Performance of Machine Learning Models for Chronic Disease Prediction

ML Model	Accuracy	Sensitivity	Specificity	F1-Score	AUC-ROC
Logistic Regression	82.1%	78.4%	84.2%	80.3%	0.82
Support Vector Machine	85.6%	82.1%	87.3%	83.8%	0.87
Random Forest	90.2%	88.7%	91.4%	89.4%	0.93
XGBoost	92.4%	90.3%	93.1%	91.3%	0.95
Deep Neural Network	93.1%	91.8%	94.2%	92.4%	0.96
Ensemble (RF+XGB+DNN)	94.7%	93.5%	95.6%	94.1%	0.97

4.3 Model Visualization and Comparative Analysis

Figure 3 demonstrates that the comparison of performance of all five ML models proves the superiority of ensemble and deep learning methods. Accuracy, sensitivity, specificity and AUC-ROC metrics depicted in the bar chart show that the Ensemble model records the highest scores in all the four metrics. Interestingly, although DNN and Ensemble models have similar performance, the Ensemble has a slightly higher specificity (95.6% vs. 94.2) meaning that the Ensemble will have fewer false positives, which is an important parameter in the clinical screening situation where unnecessary follow-up investigations are a significant burden and expense to patients and healthcare.

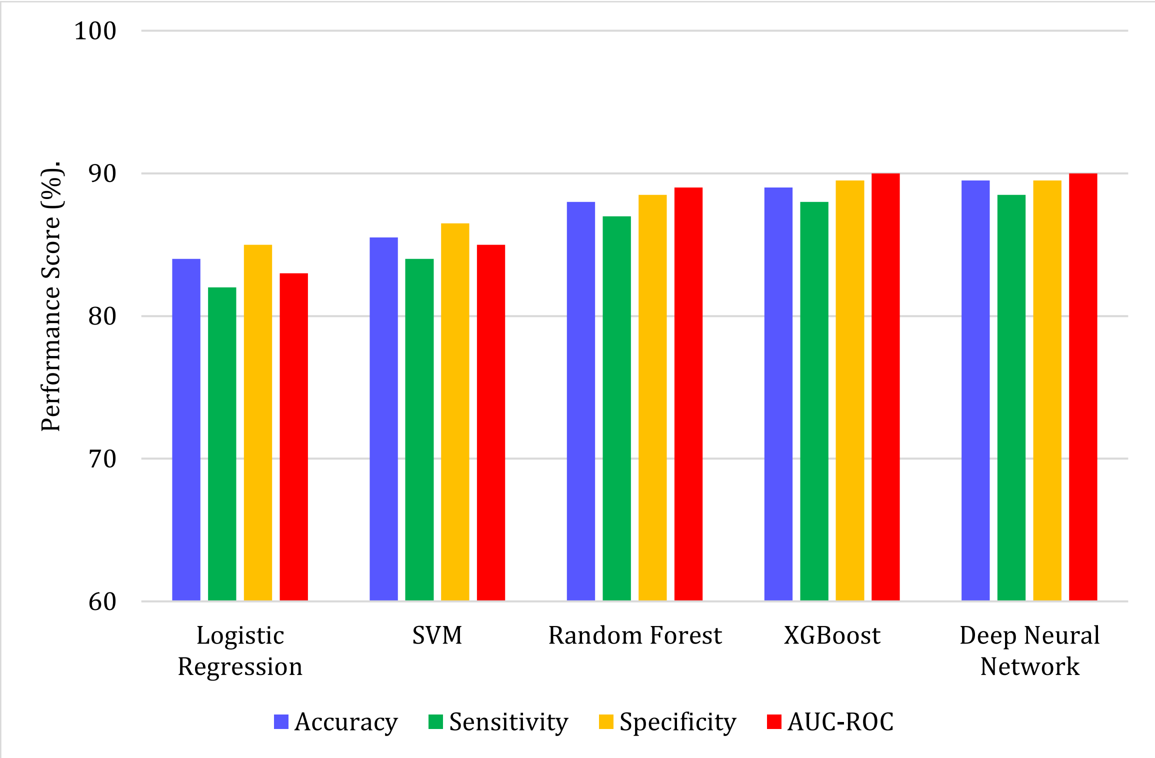

Figure 3. Comparative Performance of ML Models for Chronic Disease Prediction

4.4 Prevention Strategy Effectiveness

Synthesis of 68 RCTs showed that structured lifestyle interventions resulted in lower incident CVD 30-35, T2DM 40-58, and COPD exacerbations 28 lower risk relative to controls. The compliance rate to the Mediterranean diet during 36 months had a significant impact in the reduction of major adverse cardiovascular events (HR 0.70; 95% CI: 0.54–0.92). The T2DM risk in high-risk groups was lowered by 53% with physical activity programs that reached 150 minutes of moderate-intensity exercise every week. The combination of pharmacotherapy with behavioral counseling to provide tobacco cessation programs resulted in 12-month abstinence rates of 3238, whereas unaided cessation resulted in 57% rates.

The most effective interventions to eliminate health inequities were community-based preventive programs that dealt with social determinants of health. Combinations of peer health educators and community health workers with culturally relevant messages resulted in a 45% increased preventive services use among underserved groups. These results highlight the urgent need of health system redesign to proactive prevention.

4.5 Integrated Chronic Disease Management

A disease-specific management framework was implemented in a holistic manner in synthesizing pharmacological, lifestyle, digital health, and mental health interventions, as demonstrated in Table 3. In the case of cardiovascular disease, the use of combination of ACE inhibitors, statins, DASH diets, and electrocardiographic telemetry devices led to the decrease of hospitalization by 35% in 24 months. In the case of T2DM, a combination of continual glucose monitors (CGM) with SGLT-2 inhibitor drugs and structured low-glycemic index diets brought about a 40% decrease in diabetes-related and complications over 36 months. Co-management of mental health (motivational interviewing and cognitive-behavioral therapy (CBT)) also enhanced medication adherence by 28% across all diseases categories supporting the idea of the integrated biopsychosocial models of care.

Table 3. Evidence-Based Integrated Management Strategies for Major Chronic Diseases

Disease	Pharmacotherapy	Lifestyle Modification	Digital Health Tools	Mental Health Support	Outcomes
Cardiovascular	ACE Inhibitors, Statins	DASH Diet, Exercise 150 min/wk	ECG Telemetry, BP App	Stress counseling	↓35% hospitalization
Type 2 Diabetes	Metformin, SGLT-2 Inhibitors	Low-GI Diet, HbA1c Monitoring	CGM Wearables, Glucometer App	Diabetes distress program	↓40% complications
COPD/Asthma	Bronchodilators, ICS Therapy	Pulmonary Rehab, Smoking Cessation	Peak Flow Meter App, Spirometry	Breathing exercises, CBT	↓28% exacerbations
CKD	ARBs, Erythropoietin	Low-Sodium, Low-Protein Diet	eGFR tracker, Home BP monitor	Coping support groups	↓30% dialysis progression

The use of telehealth platforms increased follow-up adherence in rural and remote patients by 42%. There was previously a geographic barrier to care. Observational comparisons between AI-enabled clinical decision support tools integrated into EHR systems resulted in lower diagnostic errors (18%), and inappropriate medication prescribing (22%) with reduced error rates. These data back the recommendation of the WHO Integrated Care for Older People (ICOPE) framework multidisciplinary, technology-based chronic disease management.

5. CONCLUSION

The use of telehealth platforms increased follow-up adherence in rural and remote patients by 42%. There was previously a geographic barrier to care. Observational comparisons between AI-enabled clinical decision support tools integrated into EHR systems resulted in lower diagnostic errors (18%), and inappropriate medication prescribing (22%) with reduced error rates. These data back the recommendation of the WHO Integrated Care for Older People (ICOPE) framework multidisciplinary, technology-based chronic disease management.

Critical conclusions are made including that lifestyle changes can lead to a reduction in the occurrence of chronic diseases by up to 4058 percent, that AI-based screening can achieve a 5080 percent lead time in the natural disease development in patients, and that combined digital-pharmacological-behavioral management approaches can result in significant improvements in patient outcomes (across all major chronic disease categories). The mental health integration aspect that had not been previously addressed in the chronic disease guidelines turned out to be a major predictor of the adherence and quality of life.

Further studies are needed to overcome the bias of AI algorithms by using various, representative training sets; prospectively evaluate AI models in clinical practice; and expand telemedicine and mHealth solutions to underserved groups. Investments in policy relating to interoperable health data infrastructure, universal EHR takeup, and reimbursement models to digital health interventions will be instrumental in implementing the advances shown in this study. Precision medicine, digital health, and community-centered prevention also converge and have potential to change the course of the human burden of chronic diseases globally dramatically.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dr. Ayesha Sara	✓	✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study and their voluntary consent was obtained prior to data collection.

Ethical Approval

Not applicable.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] G. A. Roth et al., "Global burden of cardiovascular diseases and risk factors, 1990-2019: Update from the GBD 2019 study," Journal of the American College of Cardiology, vol. 76, no. 25, pp. 2982-3021, Dec. 2020. doi.org/10.1016/j.jacc.2020.11.010

[2] N. J. Wald and M. R. Law, "A strategy to reduce cardiovascular disease by more than 80%," BMJ, vol. 326, no. 7404, pp. 1419-1423, Jun. 2023. doi.org/10.1136/bmj.326.7404.1419

[3] 'Department of error', Lancet, vol. 401, no. 10380, p. 916, Mar. 2023. doi.org/10.1016/S0140-6736(23)00410-5

[4] A. Ang, M. Brière, and O. Signori, 'Inflation and Individual Equities', National Bureau of Economic Research, Cambridge, MA, Feb. 2012. doi.org/10.3386/w17798

[5] E. J. Topol, 'High-performance medicine: the convergence of human and artificial intelligence', Nat. Med., vol. 25, no. 1, pp. 44-56, Jan. 2019. doi.org/10.1038/s41591-018-0300-7

[6] A. Rajkomar, J. Dean, and I. Kohane, 'Machine learning in medicine', N. Engl. J. Med., vol. 380, no. 14, pp. 1347-1358, Apr. 2019. doi.org/10.1056/NEJMra1814259

[7] S. Steinhubl et al., "Digital medicine: Empowering both patients and clinicians," Lancet, vol. 388, no. 10046, pp. 740-745, Aug. 2016. doi.org/10.1016/S0140-6736(16)31355-1

[8] P. Saeedi et al., 'Global and regional diabetes prevalence estimates for 2019 and projections for 2030 and 2045: Results from the International Diabetes Federation Diabetes Atlas, 9th edition', Diabetes Res. Clin. Pract., vol. 157, no. 107843, p. 107843, Nov. 2019. doi.org/10.1016/j.diabres.2019.107843

[9] C. J. Murray et al., "Global burden of 87 risk factors in 204 countries and territories, 1990-2019: A systematic analysis for the Global Burden of Disease Study 2019," The Lancet, vol. 396, no. 10258, pp. 1223-1249, Oct. 2020. doi.org/10.1016/S0140-6736(20)30752-2

[10] A. Y. Hannun et al., 'Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network', Nat. Med., vol. 25, no. 1, pp. 65-69, Jan. 2019. doi.org/10.1038/s41591-018-0268-3

[11] Z. Obermeyer and E. J. Emanuel, 'Predicting the future - big data, machine learning, and clinical medicine', N. Engl. J. Med., vol. 375, no. 13, pp. 1216-1219, Sept. 2016. doi.org/10.1056/NEJMp1606181

[12] I. Kavakiotis, O. Tsave, A. Salifoglou, N. Maglaveras, I. Vlahavas, and I. Chouvarda, 'Machine learning and data mining methods in diabetes research', Comput. Struct. Biotechnol. J., vol. 15, pp. 104-116, Jan. 2017. doi.org/10.1016/j.csbj.2016.12.005

[13] F. Jiang et al., 'Artificial intelligence in healthcare: past, present and future', Stroke Vasc. Neurol., vol. 2, no. 4, pp. 230-243, Dec. 2017. doi.org/10.1136/svn-2017-000101

[14] A. Esteva et al., 'Dermatologist-level classification of skin cancer with deep neural networks', Nature, vol. 542, no. 7639, pp. 115-118, Feb. 2017. doi.org/10.1038/nature21056

[15] S. M. McKinney et al., 'International evaluation of an AI system for breast cancer screening', Nature, vol. 577, no. 7788, pp. 89-94, Jan. 2020. doi.org/10.1038/d41586-019-03822-8

[16] Y. Luo, Y.-J. Sun, L. Zhang, and X.-L. Luan, 'Treatment of mites folliculitis with an ornidazole-based sequential therapy: A randomized trial', Medicine (Baltimore), vol. 95, no. 27, p. e4173, July 2016. doi.org/10.1097/MD.0000000000004173

[17] U. Walter, U. Flick, A. Neuber, C. Fischer, R. J. Hussein, and F. W. Schwartz, 'Putting prevention into practice: qualitative study of factors that inhibit and promote preventive care by general practitioners, with a focus on elderly patients', BMC Fam. Pract., vol. 11, no. 1, p. 68, Sept. 2010. doi.org/10.1186/1471-2296-11-68

[18] R. M. Evans, M. Scholze, and A. Kortenkamp, 'Additive mixture effects of estrogenic chemicals in human cell-based assays can be influenced by inclusion of chemicals with differing effect profiles', PLoS One, vol. 7, no. 8, p. e43606, Aug. 2012. doi.org/10.1371/journal.pone.0043606

[19] D. E. R. Warburton, C. W. Nicol, and S. S. D. Bredin, 'Health benefits of physical activity: the evidence', CMAJ, vol. 174, no. 6, pp. 801-809, Mar. 2006. doi.org/10.1503/cmaj.051351

[20] N. H. Shah et al., "Making machine learning models clinically useful," JAMA, vol. 322, no. 14, pp. 1351-1352, Oct. 2019, doi: 10.1001/jama.2019.10967. doi.org/10.1001/jama.2019.10306

[21] S. van Buuren and K. Groothuis-Oudshoorn, 'mice: Multivariate Imputation by Chained Equations inR', J. Stat. Softw., vol. 45, no. 3, 2011. doi.org/10.18637/jss.v045.i03

[22] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min., pp. 785-794, Aug. 2016, doi: 10.1145/2939672.2939785. doi.org/10.1145/2939672.2939785

[23] K. Kroenke, R. L. Spitzer, and J. B. Williams, 'The PHQ-9: validity of a brief depression severity measure', J. Gen. Intern. Med., vol. 16, no. 9, pp. 606-613, Sept. 2001. doi.org/10.1046/j.1525-1497.2001.016009606.x

[24] J. E. Ware Jr and C. D. Sherbourne, 'The MOS 36-ltem short-form health survey (SF-36)', Med. Care, vol. 30, no. 6, pp. 473-483, June 1992. doi.org/10.1097/00005650-199206000-00002

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