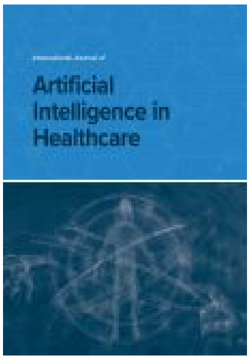

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Machine learning is revolutionising preventive healthcare and patient monitoring: a review

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Machine learning is revolutionising preventive healthcare and patient monitoring: a review

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Abstract: Machine learning (ML) integrated with wearable sensors and biosensors transforms healthcare by enabling continuous patient monitoring and early disease detection. These devices collect real-time vital sign data, including blood pressure, heart rate, and glucose levels, to identify patterns and abnormalities. ML algorithms analyse this data to detect chronic conditions like diabetes and cardiovascular diseases before clinical symptoms appear, reducing hospitalisations, emergency visits, and healthcare costs through a proactive approach. Wearable technology enhances personalised medicine by providing patient-specific health insights and actionable recommendations, such as real-time glucose monitoring to help diabetics adjust their diet and medication based on predictive analytics. Additionally, ML-driven systems assess lifestyle factors like activity levels, stress markers, and sleep patterns to predict potential health risks, improving clinical outcomes while optimising healthcare resource utilisation. AI-powered wearable systems ensure continuous adaptation and enhanced diagnostic accuracy over time. The fusion of ML and wearables is shaping the future of healthcare with a focus on personalisation, prevention, and efficiency.

Keywords: machine learning; ML; artificial intelligence; AI; chronic disease management; telemedicine, remote patient monitoring; RPM.

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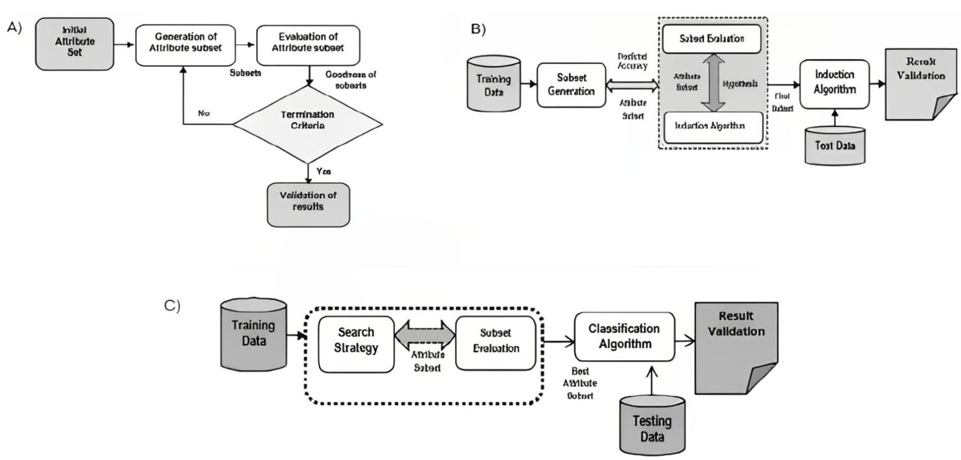
1 Introduction

The integration of artificial intelligence (AI), especially machine learning (ML), has revolutionised medical procedures by enabling personalised medicine tailored to an individual's genetic profile, lifestyle, and medical history (Kononenko, 2001). ML enhances diagnosis, treatment planning, and patient monitoring by detecting complex patterns within large datasets (Shehab et al., 2022; Barragán-Montero et al., 2021). This optimises decision-making and improves healthcare delivery. However, the use of sensitive data such as medical records and genetic information raises significant privacy and data security concerns (Garg and Mago, 2021). Algorithmic bias in ML can also exacerbate healthcare disparities, particularly among marginalised groups. This study investigates current regulatory frameworks protecting patient rights and data privacy. It also examines strategies to mitigate algorithmic risks and promote equitable access to AI-driven personalised medicine. Ensuring ethical and secure implementation is vital to sustaining patient trust and optimising outcomes.

Figure 1 (a) illustrates the process of attribute selection. the attribute selection process wrapper method is represented by (b) for the attribute selection process (c) stands for filter method



Source: Finkelmeyer et al. (2018)

2 Literature survey

The integration of ML in wearable technologies like smartwatches and fitness trackers has revolutionised patient monitoring, enabled real-time health tracking, and shifted healthcare from a reactive to a preventive model. Recent advancements highlight the potential of ML-powered healthcare systems but also reveal critical challenges, particularly in security and privacy. Adversarial attacks can manipulate input data (e.g., medical images, sensor readings) to mislead AI diagnoses, while data poisoning threatens model training through corrupted sources like electronic health records (EHRs), resulting in long-term performance degradation. Additionally, privacy threats such as model inversion and membership inference attacks expose sensitive personal data (Castiglioni et al., 2021. These issues underline the pressing need for secure, trustworthy AI systems in healthcare.

2.1 Personalised and remote healthcare enabled by wearable technologies

Wearable technologies integrated with ML are transforming healthcare by enabling personalised monitoring and remote care. These devices continuously track physiological metrics, facilitating early disease detection – such as obesity, sleep apnea, influenza, and COVID-19 – by recognising subtle anomalies. When combined with genetic and lifestyle data, wearables enhance precision medicine by tailoring treatments. Additionally, their integration with telemedicine platforms allows real-time health monitoring and virtual consultations, especially benefiting rural and underserved areas, with devices like ML-driven ECGs enabling alerts for conditions like arrhythmias (Figure 2) (Samant and Agarwal, 2018).

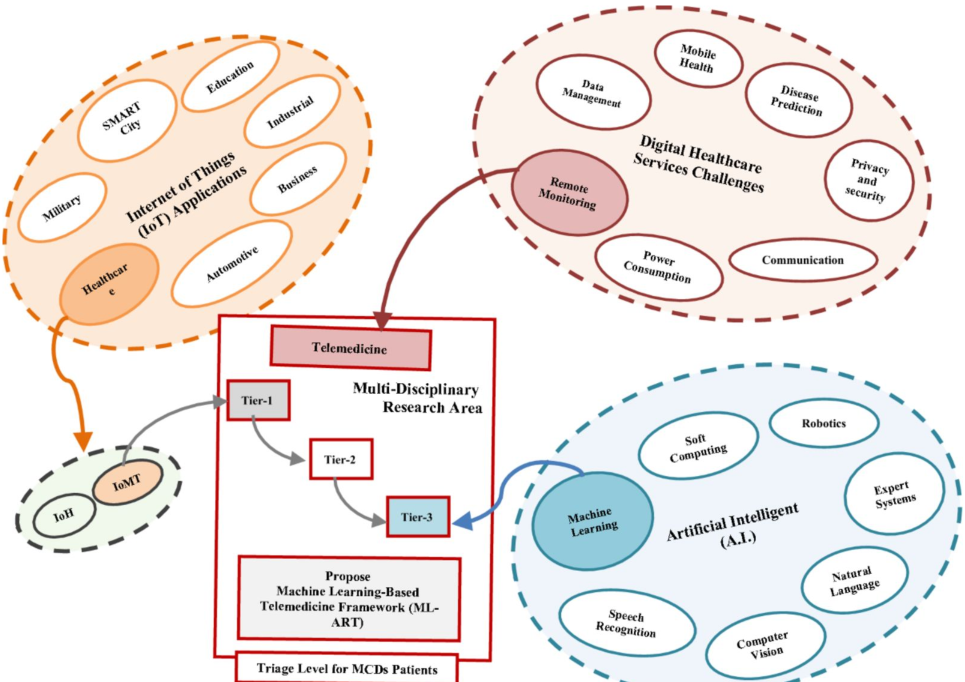
2.2 Bias and fairness in machine learning algorithms

ML is transforming several industries, most notably healthcare, by enabling data-driven decisions and increasing the potential for customised therapies as portrayed in Figure 3. However, concerns about the bias and fairness of these algorithms have drawn a lot of attention due to the potential for harm. Biased algorithms in the healthcare sector can lead to unfair treatment inequalities, unequal access to care, and inaccurate diagnoses (Istepanian and Al-Anzi, 2018). This paper review discusses the causes of bias in ML, how it impacts healthcare outcomes, strategies for mitigating prejudice, and ethical dilemmas that occur when algorithmic decisions are made.

2.2.1 Bias and fairness in healthcare machine learning

Bias in ML can lead to significant healthcare disparities, with models underperforming for marginalised groups due to biased data, such as in skin cancer detection (dos Santos et al., 2019), resource allocation (Aminizadeh et al., 2023), and ethnic misdiagnoses in medical imaging (Battineni et al., 2019). Addressing these issues demands diverse datasets, fairness constraints, and explainable AI (XAI), while balancing efficiency and justice through regulatory oversight and ethical design (Cuocolo et al., 2020).

Figure 2 The definition of the multi-chronic diseases (MCDS) research field as a multidisciplinary research topic is shown in (a) (b) the triangle-level variation using priority code algorithms for five randomly selected patients (c) the telemedicine framework based on machine learning (ML-TF) (d) is the dataset sample for the x patient (see online version for colours)



(a)

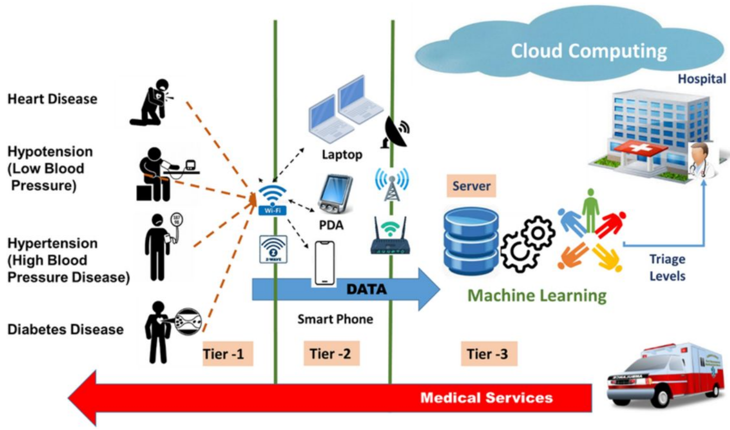
	ST Elivation	R-R	QRS width	Peaks (Heart Rate)	rest?	Paliptation	SH. Breath.	Chest Pain	Raspirotery Rate	Low Blood	High Blood	Mobility	Temprature	Hyperglycemia	Urinate?	Blurred Vision	Extreme Thirst?	Hypoglecemia	Spo2
P-0148	10	20	10	10	10	10	10	10	10	10	10	50	10	95	10	10	10	95	10
P-0848	10	20	50	95	50	50	50	50	10	10	10	50	10	10	10	10	10	10	10
P-1205	10	20	10	10	50	50	50	50	10	70	95	50	10	10	10	10	10	10	10
P-2098	10	20	10	10	10	10	10	10	10	10	10	50	10	70	10	10	10	95	50
P-3212	10	20	10	10	50	50	50	50	95	70	70	50	10	10	10	10	10	50	95

Meidcal Features

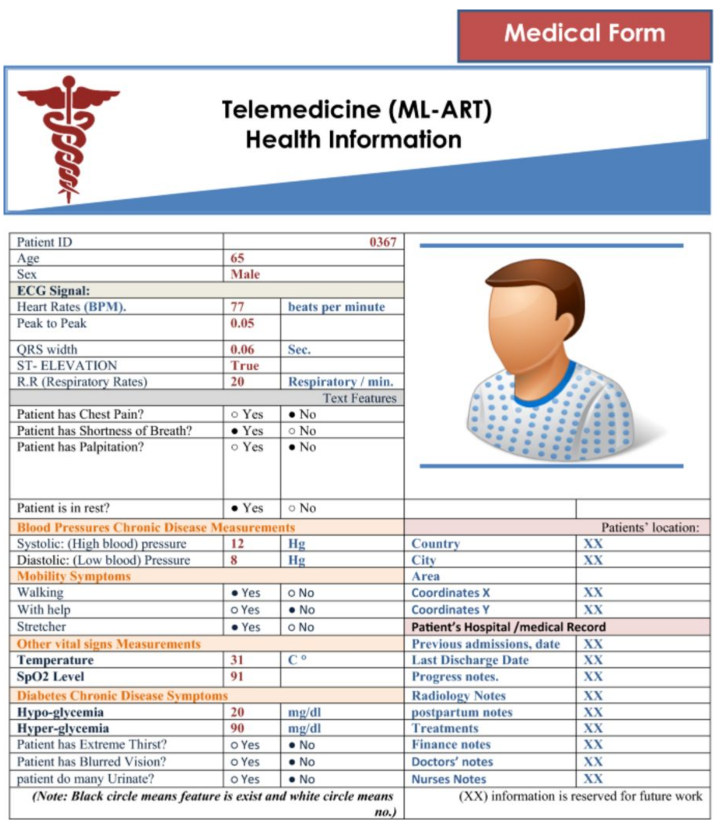
(b)

Source: Finkelmeyer et al. (2018)

Figure 2 The definition of the multi-chronic diseases (MCDS) research field as a multidisciplinary research topic is shown in (a) (b) the triangle-level variation using priority code algorithms for five randomly selected patients (c) the telemedicine framework based on machine learning (ML-TF) (d) is the dataset sample for the x patient (continued) (see online version for colours)



(c)



Medical Form

Telemedicine (ML-ART)
Health Information

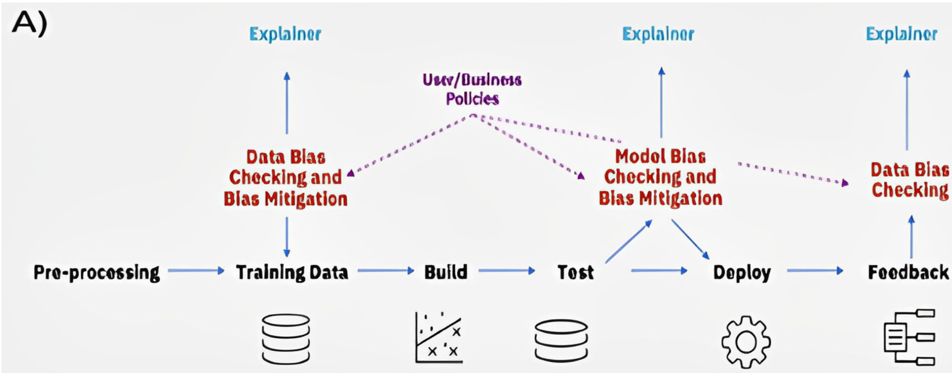
Patient ID	0367	
Age	65	
Sex	Male	
ECG Signal:		
Heart Rates (BPM).	77	beats per minute
Peak to Peak	0.05	
QRS width	0.06	Sec.
ST- ELEVATION	True	
R.R (Respiratory Rates)	20	Respiratory / min.
		Text Features
Patient has Chest Pain?	○ Yes	• No
Patient has Shortness of Breath?	• Yes	○ No
Patient has Palpitation?	○ Yes	• No
Patient is in rest?	• Yes	○ No
Blood Pressures Chronic Disease Measurements		
Systolic: (High blood) pressure	12	Hg
Diastolic: (Low blood) Pressure	8	Hg
Mobility Symptoms		
Walking	• Yes	○ No
With help	○ Yes	• No
Stretcher	• Yes	○ No
Other vital signs Measurements		
Temperature	31	C °
SpO2 Level	91	
Diabetes Chronic Disease Symptoms		
Hypo-glycemia	20	mg/dl
Hyper-glycemia	90	mg/dl
Patient has Extreme Thirst?	○ Yes	• No
Patient has Blurred Vision?	○ Yes	• No
patient do many Urinate?	○ Yes	• No
(Note: Black circle means feature is exist and white circle means no.)		

	Patients' location:
Country	XX
City	XX
Area	
Coordinates X	XX
Coordinates Y	XX
Patient's Hospital /medical Record	
Previous admissions, date	XX
Last Discharge Date	XX
Progress notes.	XX
Radiology Notes	XX
postpartum notes	XX
Treatments	XX
Finance notes	XX
Doctors' notes	XX
Nurses Notes	XX
(XX) information is reserved for future work	

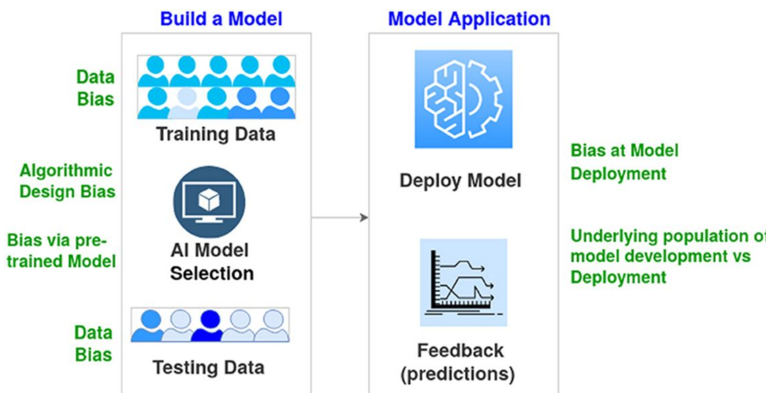
(d)

Source: Finkelmeyer et al. (2018)

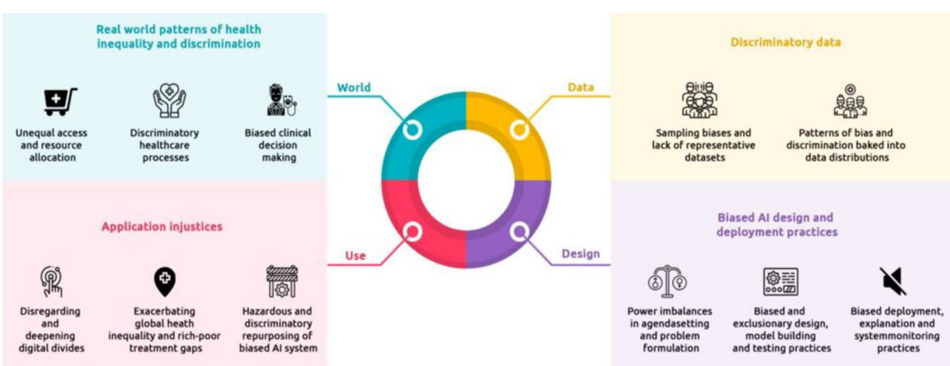
Figure 3 (a) biases in training data (b) biases in model designing (c) biases in development (see online version for colours)



(a)



(b)



(c)

Source: Istepanian and Al-Anzi (2018)

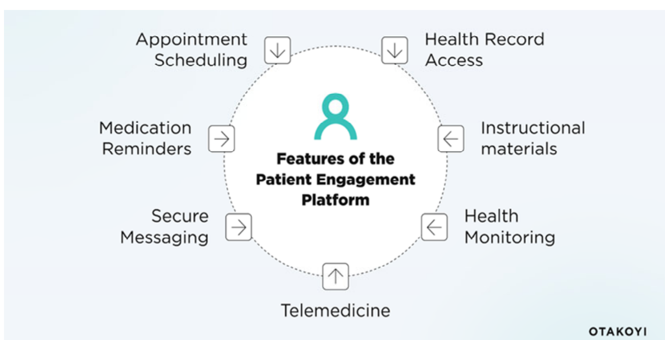
2.3 Informed consent in the era of machine learning

In the healthcare sector, traditional static consent models are challenged by the dynamic nature of AI and ML, which continuously evolve and apply patient data – biometric, behavioural, and genetic – in unforeseen ways (Figure 4). This raises ethical concerns about consent validity for expanding data applications, necessitating dynamic consent models to maintain patient control over data usage over time (Wang et al., 2010).

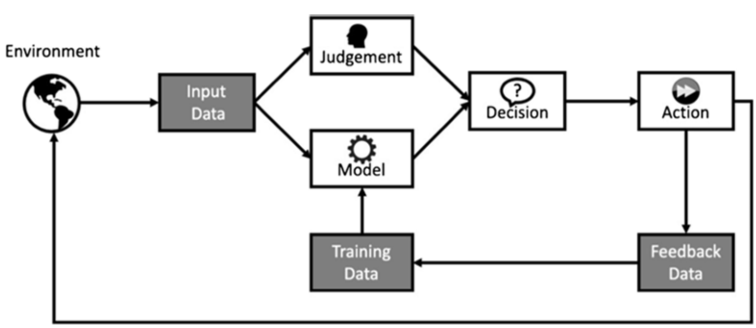
2.3.1 Patient-centred data governance in machine learning healthcare systems

Informed consent in ML-based healthcare must move beyond technical formalities to ensure patients truly understand how their data is collected, processed, and potentially shared with external entities. Deep learning models' lack of interpretability complicates transparency, necessitating simplified communication strategies. Dynamic consent offers a flexible, ongoing model for patient data control, allowing withdrawal or modification of consent over time. However, this approach requires robust digital infrastructure and sustained patient engagement. Healthcare institutions must prioritise clear, accessible communication and real-time consent tools to uphold autonomy and trust in an era of increasing data-driven collaborations and privacy concerns.

Figure 4 (a) Illustrates how ml is used in medical profession to consider patient feedback (Callahan and Shah, 2017) (b) represent feedback loop in ml (Akbulut et al., 2018; Esteva et al., 2021) (c) represents adaptive models used in ml in the field of medical (Mall et al., 2022; Kaplan et al., 2021) (d) represents handling model drift in ml (Rubinger et al., 2023; Alsuliman et al., 2020) (see online version for colours)

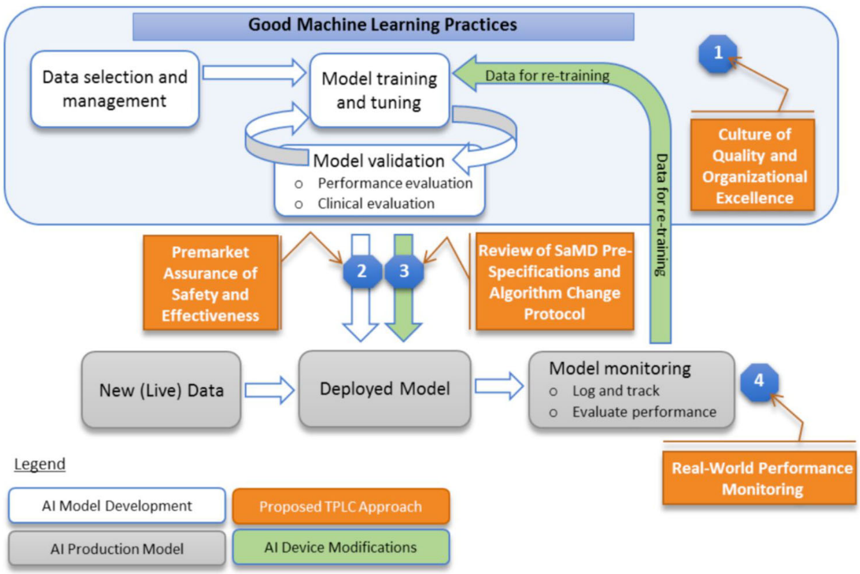


(a)

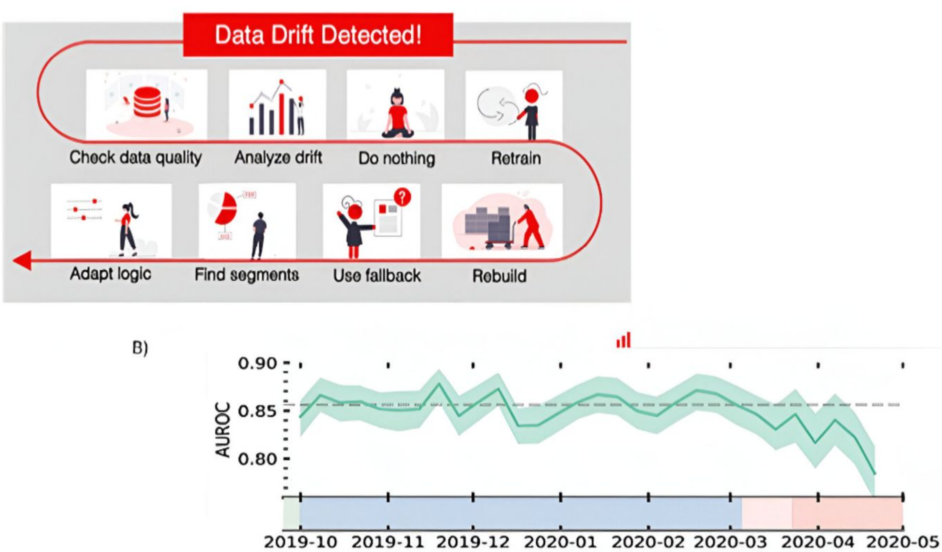


(b)

Figure 4 (a) Illustrates how ml is used in medical profession to consider patient feedback (Callahan and Shah, 2017) (b) represent feedback loop in ml (Akbulut et al., 2018; Esteva et al., 2021) (c) represents adaptive models used in ml in the field of medical (Mall et al., 2022; Kaplan et al., 2021) (d) represents handling model drift in ml (Rubinger et al., 2023; Alsuliman et al., 2020) (continued) (see online version for colours)



(c)



(d)

3 Proposed methodology

Healthcare has been revolutionised by wearable technologies, such as fitness trackers, smartwatches, and medical-grade devices, which allow for continuous patient monitoring. Together with ML, these technologies can provide real-time monitoring, predict potential health issues, and support preventive healthcare actions, all of which can significantly improve patient outcomes (Wang and Summers, 2012). Wearable technology and ML can be integrated with the architecture outlined in this technique to enhance patient monitoring and preventive care. Phases of the process include data collection, feature extraction, cleanup, model building, deployment, and continuous improvement.

3.1 Integrated patient monitoring: data collection, pre-processing, and ML model development

Wearable technologies collect diverse physiological and behavioural data, including heart rate, SpO_2, blood pressure, sleep, and activity, from a wide patient base to train predictive ML models. Data is secured through HIPAA and GDPR-compliant systems, then pre-processed via imputation, outlier removal, and normalisation. Feature engineering involves time – and frequency-domain analysis (e.g., HRV via FFT), supported by RFE and PCA for dimensionality reduction. ML models – random forest, SVM, LSTM, CNN, autoencoders – are trained for classification and anomaly detection. Performance is evaluated using metrics like F1-score and AUC-ROC, with SHAP and LIME offering model explainability (Diwakar et al., 2021; Kumar et al., 2020; Callahan and Shah, 2017).

4 Results and discussion

4.1 Advances in disease diagnosis, detection, and personalised medicine with machine learning

From disease diagnosis to therapy customisation based on patient-specific data, ML is radically changing the healthcare industry. This is a summary of the main areas where ML is advancing patient outcomes:

4.1.1 Medical imaging

ML, especially deep learning, is revolutionising medical imaging by enhancing diagnosis, evaluation, and prognosis across various diseases, as shown in Figure 5 (Ravi et al., 2017). Convolutional neural networks (CNNs) are extensively applied to detect cancerous lesions in organs such as the breast, lung, and skin, with near-radiologist accuracy in mammogram analysis (Hosny et al., 2018). Models like U-Net perform precise semantic segmentation for organ and tumor delineation, aiding surgical and radiotherapy planning (Esteva et al., 2021), while ML also enables disease forecasting and treatment response assessment by analysing large datasets and follow-up images (Kulkarni et al., 2020; Wason, 2018).

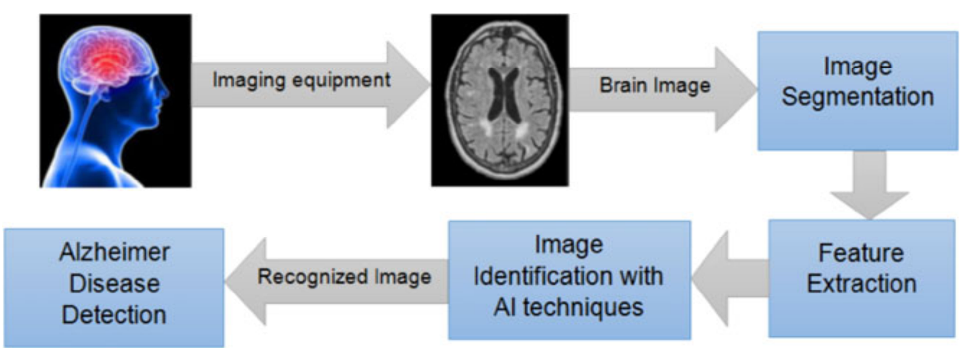
4.1.2 Common ML techniques in medical imaging

CNNs like ResNet, VGG, and U-Net are pivotal in image classification, segmentation, organ localisation, and disease detection (Anaya-Isaza et al., 2021), enhanced by transfer learning using pre-trained models on datasets like ImageNet (Park et al., 2020). generative adversarial networks (GANs) help mitigate data imbalance and boost model training (Khalil et al., 2021), while explainable AI (XAI) methods such as saliency maps, LIME, and SHAP support interpretability for clinical trust (Park et al., 2020; Li. et al., 2021a). Key challenges include access to high-quality labelled data, privacy compliance (Anam et al., 2021), model generalisation across diverse conditions (Alanazi, 2022), and ensuring clinical integration through validation, regulatory approvals, and user-friendly interfaces (Currie et al., 2019; Rana and Bhushan, 2023).

4.2 Pathology

ML is revolutionising pathology by enhancing diagnostic accuracy, streamlining workflows, and supporting personalised treatment. Techniques like CNNs analyse whole slide imaging (WSI) to detect and classify cancerous tissues (Liu et al., 2024; Ruiz et al., 2008), while ML also identifies disease-associated biomarkers through genomic and proteomic data analysis (Zhang et al., 2018; Jara-Lazaro et al., 2010). Outcome prediction using patient data enables tailored therapies (Webster and Dunstan, 2014), and NLP helps integrate unstructured pathology reports with imaging and clinical data (Janowczyk and Madabhushi, 2016; Wang et al., 2019). Furthermore, ML minimises diagnostic inconsistencies and boosts efficiency by automating routine lab tasks and optimising case prioritisation (Gertych et al., 2015; Bhargava and Madabhushi, 2016; Allsbrook et al., 2001; Tolkach et al., 2020).

Figure 5 A flowchart showing how AI approaches are used to identify Alzheimer's disease (a) the process starts with imaging equipment producing brain images, (Li et al., 2021b) and (b) then moves on to image segmentation, feature extraction and (c) AI-assisted identification to identify diseases (Whitmore et al., 2015) (see online version for colours)



4.3 Early disease detection

ML enables earlier diagnosis through genomic data analysis, EHR data patterns, wearable device monitoring, and predictive modelling (Ahuja, 2019; Jiang et al., 2017; Dutta et al., 2021). ML identifies genetic markers for diseases like Alzheimer's, diabetes, and cancers, predicting risk before symptoms appear (Singh et al., 2021; El Houby, 2018). ML analyses EHR data for patterns associated with disease onset, highlighting at-risk individuals for preventive care (Blum and Magill, 2010; Li et al., 2021b). NLP detects early symptoms or family history in clinical notes as depicted in Figure 5, identifying high-risk patients based on subtle clues (Rohokale et al., 2011; Selvaraj and Sundaravaradhan, 2020; Kumar and Devi Gandhi, 2018). ML algorithms monitor real-time data from wearables, detecting early signs of conditions like arrhythmias or diabetes (Whitmore et al., 2015).

Table 1 Survey of machine learning uses in personalised medicine, disease detection, and diagnosis

Aspect	*Key points*
Disease and detection	CNNs (imaging), NLP(notes), anomaly detection → accurate, early results
Personalised care	Drug recommendations, therapy prediction, → tailored, effective treatment
Ml techniques	Deep learning (CNN, RNN), SVM, ensembles, → scalable, data-driven insights
Clinical use	AI Tools, mHealth Apps → real real-time, accessible support
Data and ethics	Imaging, genomics, wearables, privacy, fairness secure, complaint AI

4.4 Personalised medicine

ML plays a pivotal role in personalised medicine by predicting individual treatment responses (Su et al., 2021; Lam et al., 2021), optimising drug dosages (Bozyel et al., 2024; Chinni and Manlhiot, 2024; Nilius et al., 2024), enabling patient subtyping via biomarkers (Oh et al., 2022; Lee and Yoon, 2021), and identifying cancer-related mutations (Field et al., 2021). ML also aids in predicting drug efficacy and adverse reactions using genetic data (Maceachern and Forkert, 2021; Peng et al., 2002) and analysing clinical history for therapy selection (Jarrett et al., 2019). Key challenges include acquiring quality pharmacogenomic data and ensuring model interpretability for clinical use (see Table 1), alongside ethical concerns in genomic data use due to patient privacy (Nayarisseri et al., 2021; Piccialli et al., 2021).

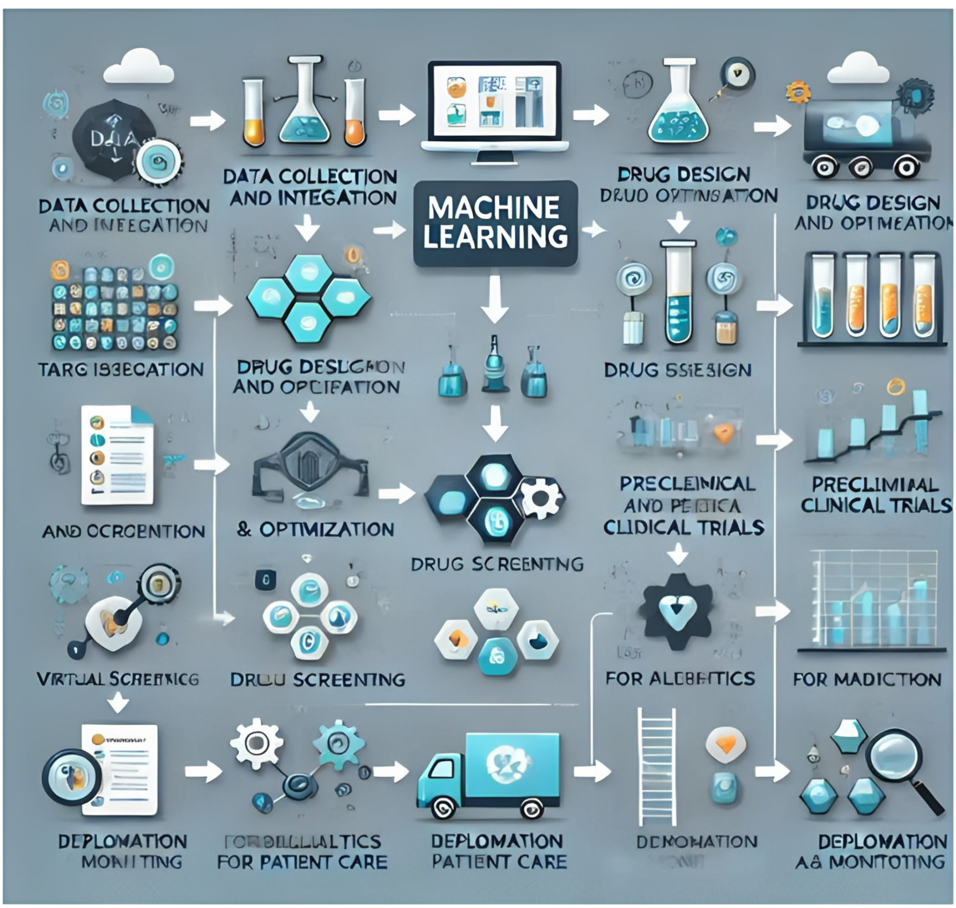
4.5 Machine learning in drug discovery, clinical trials, and efficacy prediction

ML is transforming drug discovery and development by leveraging gene expression, protein interactions, and biological networks for target identification, while using generative models like reinforcement learning and GANs for novel molecule design. ML-driven QSAR models, virtual screening, and predictive analytics using neural networks, random forests, and gradient boosting enhance drug efficacy prediction, repurposing (e.g., COVID-19), clinical trial optimisation (Aziz et al., 2021; Hwang et al., 2016; Varatharajah and Berry, 2022; Hodos et al., 2016; Wong et al., 2019; Réda et al., 2020; Armitage, 1985; Benhenda, 2017; Aliper et al., 2016; Ekins et al., 2019; Borandeh et al., 2021; Elbadawi et al., 2020), and precision medicine, despite challenges in interpretability and data quality (Xu et al., 2021; Awad et al., 2021; Paul et al., 2021; Badwan et al., 2023; Vougas et al., 2019).

4.5.1 Predictive analytics in patient care

Disease onset prediction using ML, as illustrated in Figure 7, enables proactive healthcare by analysing data such as genomics, demographics, and environmental factors (Islam et al., 2018; Weerasinghe et al., 2022). ML models predict hospital readmission risks using EHRs and socio-economic data (Johnston et al., 2019), employing techniques like decision trees, survival analysis, and logistic regression (Taubman et al., 1979; Pines et al., 2013; Kalid et al., 2018). Interpretability tools such as SHAP and LIME ensure transparency by identifying key predictive features (Ahmed et al., 2021; Iranpak et al., 2021; Alanazi et al., 2018; Naseer Qureshi et al., 2020). Integrated within EHR systems, ML-driven alerts support timely interventions (Dahabreh and Kent, 2014; Janke et al., 2016; Chawla and Davis, 2013; An et al., 2023). However, challenges include compliance with HIPAA and GDPR, model bias, need for explainable AI, and integration with existing healthcare infrastructure, as outlined in Table 2.

Figure 6 A flowchart illustrates the primary stages of machine learning in drug discovery, development, and predictive patient care, as well as how they progress (see online version for colours)



Source: Paul et al. (2021), Badwan et al. (2023), and Vougas et al. (2019)

With a focus on target identification, clinical trial optimisation, customised medicine, and regulatory compliance, this table highlights the main areas where ML is used in the different phases of drug research and development as well as in predictive patient care.

Figure 7 Applications of predictive analytics in the medical field: emphasising uses including diagnosis, prognosis, reduced medical expenses, treatment plan formulation, enhanced patient care, clinical decision assistance, remote monitoring, and fewer adverse events (Vougas et al., 2019; Islam et al., 2018; Weerasinghe et al., 2022)

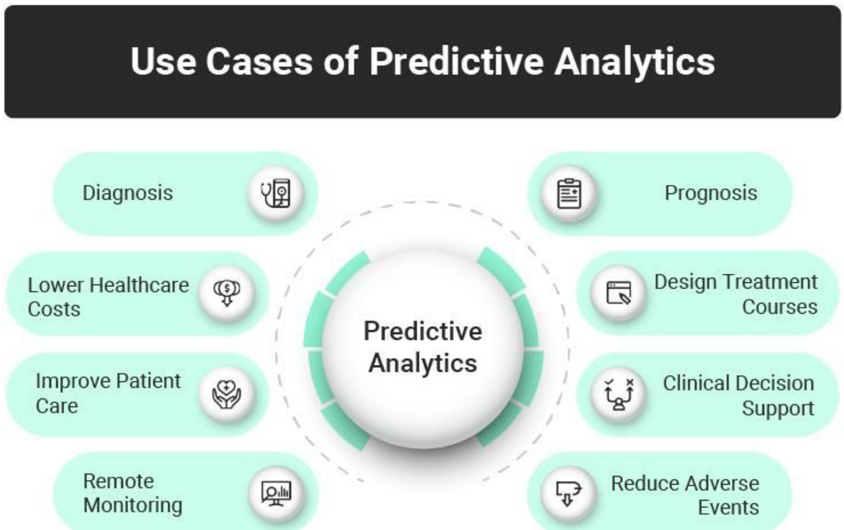


Table 2 Utilising machine learning for predictive patient care and drug development

Area	*ML applications*
Discovery and repurposing	Target-ligand prediction, DL-based structure modelling, drug–disease network inference
Development and formulation	PK/PD modelling, trial design optimisation, biomarker discovery, release profile, and delivery optimisation
Precision medicine and risk strategy	Genotype–phenotype mapping, individualised therapy response, multi-modal risk prediction
Data integration and RWE analytics	Multi-omics + EHR fusion, ML-driven real-world outcome modelling
Regulatory and post-market	Approval likelihood prediction, ML-based AE signal detection for pharmacovigilance

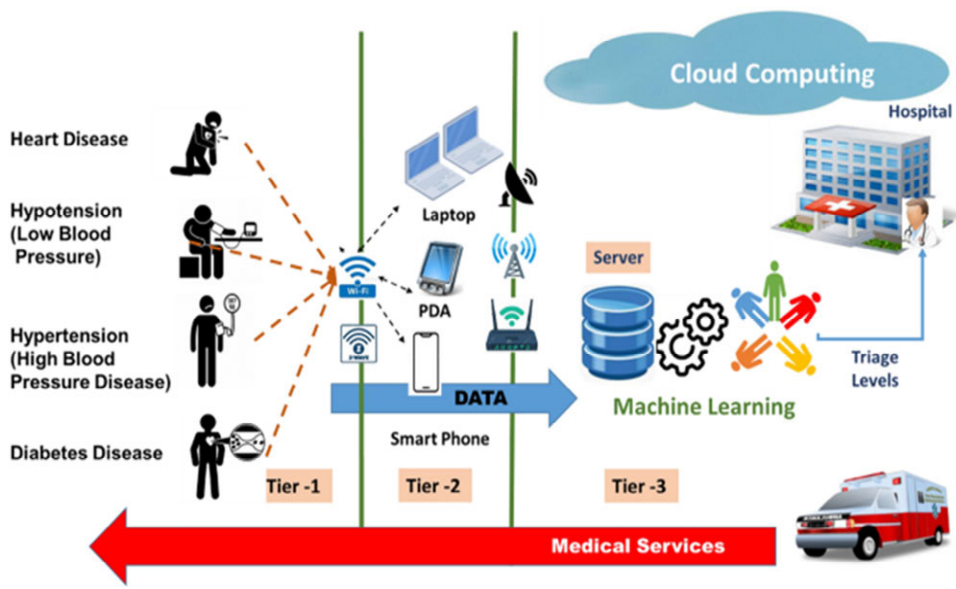
4.6 Machine learning in remote monitoring, wearables, and telemedicine for healthcare

ML transforms healthcare, particularly in remote monitoring, wearables, and telemedicine (Peiffer-Smadja et al., 2020). Through advanced data analysis, ML helps with early diagnosis, personalised care, real-time monitoring, and operational efficiency, especially in chronic disease management and remote care.

4.6.1 Machine learning in chronic disease management and telemedicine

ML plays a transformative role in healthcare by enhancing chronic disease management and enabling efficient telemedicine. ML models analyse patient data to detect risk factors and enable early diagnosis (Tsoukalas et al., 2015; Ansari et al., 2012; Beam and Kohane, 2018). They tailor treatments by segmenting patients based on health and lifestyle, and adaptive algorithms adjust therapies in real-time (Beam and Kohane, 2018; Hinton, 2018; Peiffer-Smadja et al., 2020). Wearables and ML-powered systems offer continuous health monitoring and detect abnormalities to prevent complications (Tsoukalas et al., 2015; Rawson et al., 2019; Macesic et al., 2017). In telemedicine, ML enhances diagnostics through medical image analysis and natural language processing for interpreting symptoms (Santos et al., 2007; Hartvigsen et al., 2018), while predictive models support proactive care (Melendez et al., 2016; Bartz-Kurycki et al., 2018; Mani et al., 2014). ML also personalises treatment (Orhan et al., 2010; Orhan et al., 2010, improves adherence strategies (Tsoukalas et al., 2015; Burdick et al., 2018; McCoy and Das, 2017), and optimises healthcare logistics with sentiment analysis and smart scheduling (Calvert et al., 2016; Johnson et al., 2016; Sim et al., 2001; Revuelta-Zamorano et al., 2016).

Figure 8 Machine learning integration in medical services: a multi-tiered system that collects and transmits data to servers and cloud computing via laptops, cell phones, and wearable technology. predictive analytics, triage levels, and hospital-based decision-making are made possible by applications that monitor heart disease, hypertension, diabetes, and other illnesses (see online version for colours)

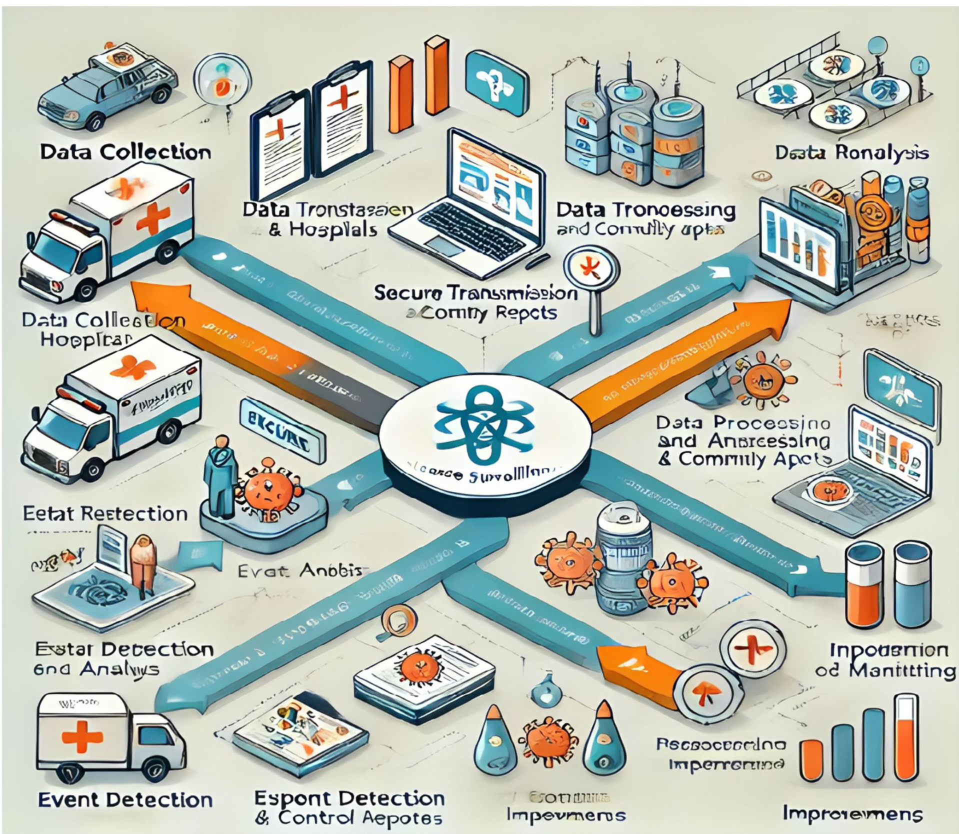


Source: Peiffer-Smadja et al. (2020), Santos et al. (2007), and Hartvigsen et al. (2018)

4.7 Public health and disease surveillance

ML is transforming public health and disease surveillance by enabling rapid, data-driven responses to emerging health challenges, as portrayed in Figure 9, and improving the efficiency of healthcare delivery (Li et al., 2020). Below is a comprehensive overview of ML's applications in public health and disease surveillance:

Figure 9 Flowchart illustrating the process of disease and public health monitoring (Li et al., 2020) (see online version for colours)



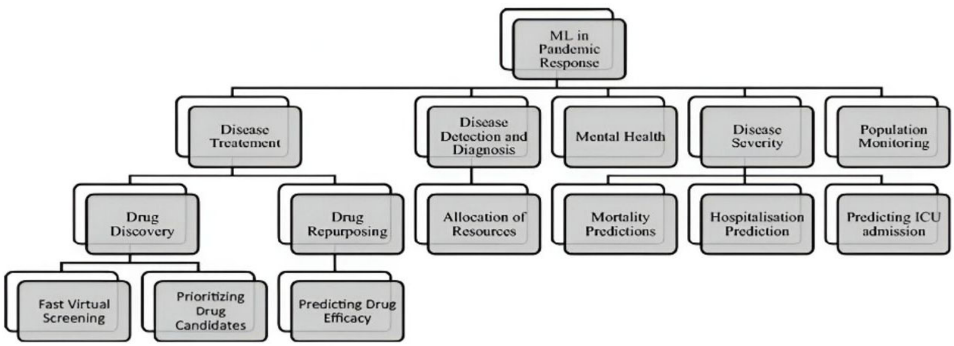
4.7.1 Pandemic responses

ML plays a critical role in pandemic response by supporting disease modelling using SEIR and agent-based models with mobility data (Di Martino et al., 2014), enabling early warnings through NLP on news and health records (Shinkareva et al., 2011) and forecasting ICU/PPE needs while optimising vaccine delivery (Buchweitz et al., 2012; Parisot et al., 2018; Verhoeven et al., 2018). ML aids diagnostics via image analysis of chest X-rays/CT scans (Serda et al., 2013; Abraham et al., 2017) and enhances PCR/antigen test accuracy (Heinsfeld et al., 2018; Yang et al., 2010). In drug discovery, ML models like AlphaFold expedite protein structure prediction and drug screening ; Kassam et al., 2013; Shirer et al., 2012; Wang et al., 2022; Schipul et al., 2012).

Additionally, ML strengthens health communication by analysing public sentiment and misinformation (Craddock et al., 2009; Finkelmeyer et al., 2018) and improves contact tracing and outbreak monitoring using mobility analytics (Behzadi et al., 2007; Hong et al., 2019).

With a focus on important topics like disease treatment (drug discovery, drug repurposing), disease detection and diagnosis (allocation of resources), mental health, disease severity (hospitalisation and ICU admission predictions), and population monitoring, the chart illustrates the use of ML in pandemic management. Fast virtual screening, ranking drug candidates, estimating therapeutic efficacy, predicting mortality, and other specific tasks are among them.

Figure 10 Role of machine learning (ML) in pandemic response



Source: Shirer et al. (2012), Wang et al. (2022) and Schipul et al. (2012)

Table 3 ML in healthcare: micro summary

Area	*Focus*	*Techniques*	*Data*	*Impact*
Diagnosis, treatment, and drug delivery	Accurate detection, personalised care, optimised drugs	CV, NLP, DL, RL, generative models	EHRs, imaging, genomics, clinical trials	Faster diagnosis, tailored therapy, efficient drug R&D
monitoring and public health	Remote care, outbreak tracking	Wearables, time-series, anomaly, and cluster detection	IoT, telehealth, community reports	Proactive care, early alerts, better policies

4.7.2 Health data analysis

ML enhances health data analysis (Franco et al., 2013) by leveraging algorithms to assess medical history, genetics, and lifestyle factors for disease risk prediction (Shirer et al., 2012; Cao et al., 2021; Plitt et al., 2015). CNN-based image analysis supports radiologists in detecting anomalies in X-rays, MRIs, and CT scans (Vincent et al., 2008). Personalised treatment is achieved through ML by analysing genetic and lifestyle data (Mohammadian Rad et al., 2018), while clustering algorithms identify patient subgroups for optimised care (Bauer and Just, 2015). ML accelerates drug discovery by predicting drug-target interactions and repurposing drugs (de Wilde et al., 2017). Wearable tech enables real-time health monitoring and alerts using ML (Di Martino et al., 2014; Shinkareva et al., 2011), and NLP simplifies clinical documentation and diagnostics (Cherkassky et al., 2006; Kana et al., 2009). Predictive modelling and survival analysis improve patient management, resource planning, and clinical trial optimisation (Altman and Bland, 1994; Mahmud et al., 2021; Pereira et al., 2009; Hjelm et al., 2014; Heinsfeld et al., 2024; Gowri et al., 2024). However, challenges include data privacy, HIPAA/GDPR compliance, bias mitigation, and the need for interpretable AI models in critical healthcare decisions (Table 3).

5 Results and discussion

Wearable technology combined with ML has transformed healthcare by enabling real-time health monitoring, early disease detection, and personalised care. Devices like fitness trackers and medical-grade sensors gather physiological data, which ML models analyse to forecast health risks and support chronic illness management (e.g., diabetes, hypertension). Privacy concerns are mitigated through data encryption, differential privacy, and federated learning, while regulations like GDPR and HIPAA safeguard sensitive patient data. Fairness-aware learning and diverse datasets are used to reduce biases in ML diagnostics. Challenges such as data accuracy, sensor faults, and compliance with privacy norms persist. Future work suggests integrating blockchain and IoT for enhanced security and reliability. ML-powered remote patient monitoring (RPM) supports telemedicine by reducing hospital visits and improving access. To ensure clinical trust, improving interpretability, adaptive models, and real-time feedback mechanisms is essential.

6 Conclusions

The integration of wearable technology and ML is revolutionising healthcare by enabling real-time health data collection, early disease detection, and personalised treatment plans. This shift from reactive to preventive care supports chronic condition management and enhances overall healthcare quality. ML algorithms analyse large datasets from wearables to predict health risks and deliver actionable insights to both patients and professionals. However, concerns around algorithmic bias, data privacy, and security must be addressed through strict regulatory compliance and ethical standards. Future progress in cybersecurity, model adaptability, and collaborations with blockchain and IoT may further enhance the reliability and impact of these technologies.

7 Limitations and future scope

Notwithstanding its advantages, ML-driven wearables have issues with security, privacy, and data accuracy. Problems that can impact the dependability of ML algorithms include environmental noise, human compliance, and sensor errors. Valid data analysis is essential for efficient health monitoring. Given that wearables collect confidential medical data, worries around data security and privacy are especially important (Nayyar et al., 2021). To protect patient data, strong privacy-preserving methods and compliance with laws like GDPR are required. Future advancements in ML-driven wearables will concentrate on increasing the range of physiological factors that can be monitored, strengthening data security, and personalising and optimising ML models. Blockchain, AI, and the internet of things (IoT) will all be integrated with wearable technology to transform patient monitoring and preventive healthcare.

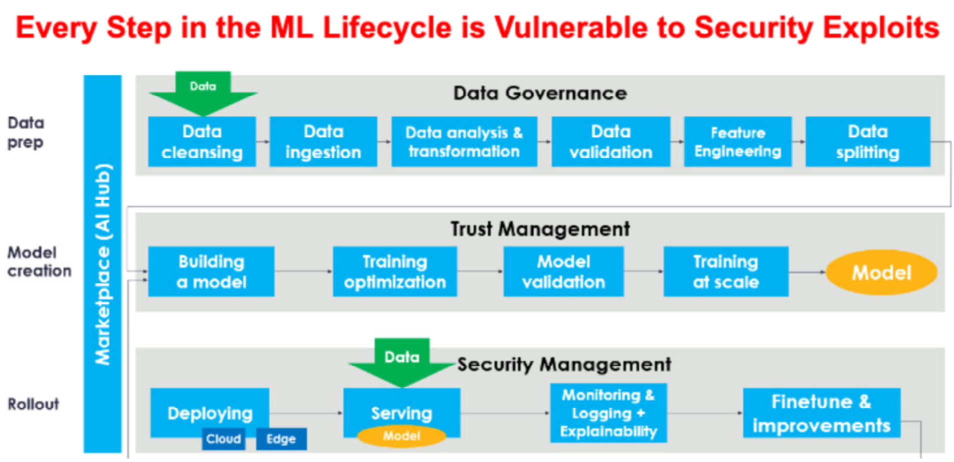
7.1 Data security risks in machine learning-driven medicine

ML in healthcare enables personalised medication, diagnosis, and treatment by leveraging sensitive data such as behavioural, biometric, and genomic information. However, it introduces cybersecurity risks like data poisoning, adversarial attacks, and other cyber threats. This article explores cybersecurity solutions, evaluates compliance standards, examines the impact of breaches on public trust, and highlights key limitations of ML-driven medicine.

7.2 Vulnerabilities in ML systems

Numerous attacks can jeopardise ML systems, jeopardising the security of the data they analyse as well as the model's accuracy, as depicted in Figure 11.

Figure 11 Represents vulnerabilities in machine learning systems (Samant and Agarwal, 2018; Nayyar et al., 2021; Castiglioni et al., 2021) (see online version for colours)

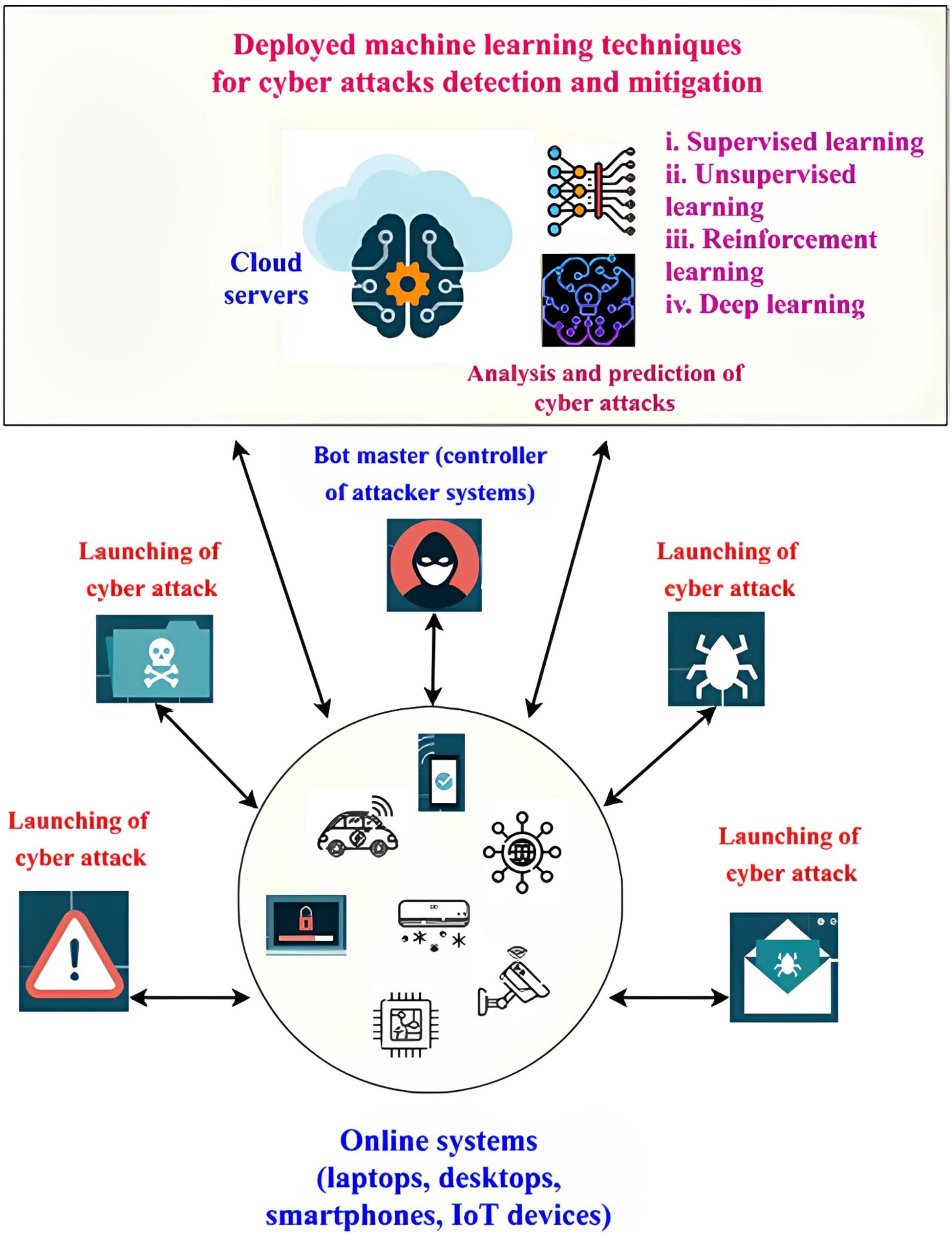


Healthcare AI systems face critical security and privacy threats, including adversarial attacks that manipulate inputs like medical images, data poisoning of EHRs that degrade model accuracy, and privacy inference techniques such as model inversion and membership inference attacks that risk patient confidentiality (Castiglioni et al., 2021). These vulnerabilities can result in misdiagnoses, unsafe treatments, and severe privacy breaches if not properly mitigated.

7.3 Cybersecurity measures

To lessen the security risks associated with ML in the healthcare sector, as shown in Figure 12, numerous cybersecurity strategies are being employed. These measures are meant to protect both the sensitive data that ML models use and the integrity of the models themselves.

Figure 12 Demonstrates how to perform a range of tasks using machine learning (see online version for colours)



Source: Nayyar et al. (2021), Castiglioni et al. (2021), and Kaur et al. (2018)

Ensuring data security and privacy is critical in healthcare ML systems. Encryption methods such as AES and RSA are commonly used to protect data at rest and in transit, while homomorphic encryption enables computations on encrypted data. Secure communication protocols like TLS, MFA, VPNs, and private cloud environments help prevent unauthorised access (Kaur et al., 2018). Additionally, privacy-preserving techniques like differential privacy and federated learning enhance patient confidentiality. Differential privacy adds noise to data to protect identities, while federated learning enables decentralised model training without sharing raw data (Winkler-Schwartz et al., 2019). These approaches collectively ensure secure and confidential AI deployment in healthcare.

7.3.1 Security compliance standards

In both the US and Europe, regulations like HIPAA and GDPR aim to safeguard patient data in ML-driven healthcare systems. HIPAA mandates access controls and encryption for EHRs, but struggles with evolving threats like adversarial attacks and model inversion. GDPR emphasises consent, data minimisation, and anonymisation – principles central to federated learning and differential privacy – yet faces difficulties anonymising complex data types like genetic information. Meanwhile, regulatory frameworks like FDA and CE Marking ensure software-based medical device safety but often lag behind the cybersecurity demands of adaptive ML models. Public trust is fragile; data breaches in personalised medicine can erode patient confidence, diminish ML system efficacy, and expose healthcare institutions to legal and reputational risks.

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