

# AI-Driven Genomic Biomarker Discovery for Precision Diagnosis and Personalized Treatment

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**Abstract:** The identification of genomic biomarkers has become a cornerstone for precision medicine, enabling early disease diagnosis, prognosis prediction, and personalized treatment strategies. Recent advances in artificial intelligence (AI), including machine learning (ML) and deep learning (DL), have demonstrated substantial potential in analyzing high-dimensional genomic datasets to uncover novel biomarkers. AI algorithms can integrate heterogeneous data types, such as gene expression, single nucleotide polymorphisms (SNPs), and epigenetic modifications, to identify patterns associated with specific diseases. This study reviews current methodologies and applications of AI in genomic biomarker discovery, highlighting successes in oncology, cardiovascular disorders, and neurodegenerative diseases. Key AI approaches, including random forests, support vector machines, convolutional neural networks, and autoencoders, are employed to improve predictive accuracy and reduce false discovery rates. The study also discusses challenges, such as data sparsity, interpretability, and computational resource requirements. Additionally, we examine case studies where AI-driven genomic biomarker identification has guided targeted therapy selection, improving patient outcomes. Finally, we outline future perspectives, emphasizing the integration of multi-omics data, real-time clinical data streams, and federated learning to enhance biomarker discovery across diverse populations. Overall, AI-driven genomic biomarker research holds transformative potential for accelerating personalized medicine, optimizing therapeutic interventions, and providing actionable insights into disease mechanisms.

**Keywords:** AI, machine learning, genomic biomarkers, disease diagnosis, precision medicine, personalized therapy, deep learning, biomarker discovery.

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## Graphical Abstract:



## Scope:

The scope of this study encompasses the application of AI to identify genomic biomarkers for disease diagnosis and therapeutic decision-making. It focuses on computational approaches for analyzing genomic datasets, including gene expression profiles, mutation data, copy number variations, and epigenetic markers [Figure:1] [1-3].

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**Figure: 1. Computational methods for examining genomic datasets, such as copy number variations, gene expression patterns, mutation data, and epigenetic markers**

Emphasis is placed on AI methodologies such as supervised and unsupervised learning, deep learning architectures, and hybrid ensemble models for biomarker identification. The study addresses applications in multiple diseases, particularly cancer, cardiovascular disorders, and neurological diseases, demonstrating how AI can enhance predictive modeling for early detection, prognosis, and treatment selection [Figure:2][4].



**Figure: 2. The study shows how AI might improve predictive modeling for early identification, prognosis, and treatment selection in a variety of diseases, including cancer, cardiovascular conditions, and neurological problems.**

Additionally, the scope includes discussion of multi-omics integration to improve biomarker reliability, AI model interpretability, and the challenges posed by heterogeneous clinical datasets. The study also explores translational aspects, including validation of AI-identified biomarkers in experimental and clinical settings, highlighting pathways toward implementation in precision medicine. By addressing both methodological advancements and practical applications, this study aims to provide a comprehensive overview of AI-driven genomic biomarker research and its impact on clinical decision-making [5-10].

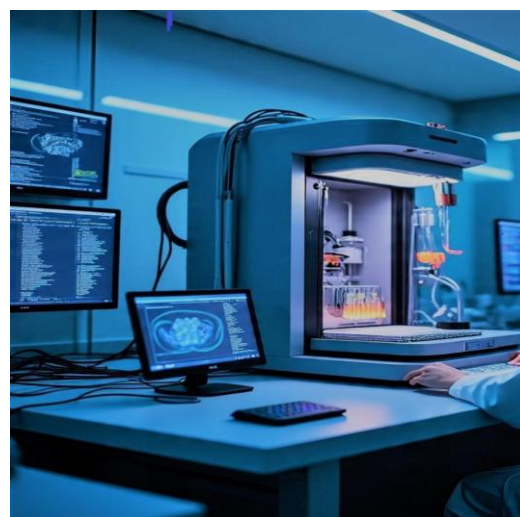
### Literature Survey:

Recent studies have demonstrated the effectiveness of AI in genomic biomarker identification. For example, ML models such

as random forests and support vector machines have been successfully applied to gene expression datasets for cancer subtype classification and prognosis prediction. Deep learning approaches, including convolutional neural networks and autoencoders, have improved feature extraction from large-scale genomic and epigenomic data. Integrative AI frameworks combining multi-omics datasets have shown superior accuracy in identifying robust biomarkers for cardiovascular and neurodegenerative diseases. Federated learning has emerged as a promising solution for collaborative AI modeling across multiple institutions while preserving patient privacy. Despite these advances, challenges remain, including model interpretability, overfitting due to high-dimensional data, and validation across diverse populations. Recent efforts focus on explainable AI techniques to elucidate genomic features contributing to disease risk and therapeutic response, facilitating translational applications. Overall, the literature suggests that AI-driven biomarker identification can significantly accelerate precision medicine, yet careful methodological design and rigorous validation are essential for clinical implementation [11-20].

### Introduction:

The rapid advancement of genomic technologies has led to an explosion of high-dimensional data, including DNA sequencing, transcriptomics, and epigenomic profiles. Genomic biomarkers—specific genes, mutations, or molecular signatures associated with disease phenotypes—are central to precision medicine, enabling early detection, prognosis estimation, and therapeutic targeting. Traditional statistical methods for biomarker discovery are often limited by the scale and complexity of genomic datasets. Artificial intelligence (AI), including machine learning (ML) and deep learning (DL), offers powerful alternatives by efficiently analyzing large, heterogeneous datasets, identifying subtle patterns, and predicting disease outcomes with high accuracy [Figure:3] [21-30].



**Figure: 3. Artificial intelligence (AI), which includes machine learning (ML) and deep learning (DL), provides potent alternatives by effectively analyzing vast, diverse information, spotting minute patterns, and accurately forecasting the course of diseases.**

AI-based approaches in genomics include supervised learning algorithms, such as random forests, support vector machines, and gradient boosting, which are effective for classification and regression tasks. Unsupervised methods, including clustering and

dimensionality reduction techniques like principal component analysis (PCA) and autoencoders, can reveal novel biomarker signatures without prior labeling. Deep learning models, particularly convolutional and recurrent neural networks, have demonstrated exceptional performance in feature extraction from high-throughput genomic data, including single-cell RNA sequencing and whole-genome sequencing [Figure:4] [31-45].



**Figure: 4.** Deep learning models, specifically convolutional and recurrent neural networks, have demonstrated exceptional performance in feature extraction from high-throughput genomic data, including single-cell RNA sequencing and whole-genome sequencing.

Integration of multi-omics data, such as genomics, transcriptomics, and proteomics, further enhances biomarker discovery by capturing complementary biological information. Recent studies highlight the use of AI to predict patient-specific drug response, identify prognostic signatures, and uncover novel disease mechanisms. For instance, AI models have successfully identified genomic features linked to immunotherapy response in cancer patients and neurodegenerative disease progression [46-62].

Despite promising results, challenges remain. Genomic datasets are often high-dimensional but limited in sample size, raising the risk of overfitting. Interpretability of AI models is critical for clinical

adoption, prompting the development of explainable AI techniques. Furthermore, validation across diverse populations is essential to ensure the generalizability of AI-derived biomarkers [63-77].

This study reviews current AI methodologies for genomic biomarker identification, highlights key applications in disease diagnosis and treatment, and discusses future directions, emphasizing multi-omics integration, interpretability, and clinical translation [Figure:5] [78-84].



**Figure: 5.** With a focus on multi-omics integration, interpretability, and clinical translation, this paper examines existing AI approaches for genetic biomarker identification, emphasizes important applications in illness diagnosis and therapy, and explores future perspectives.

## Research and Methodologies:

### Data Collection:

Public genomic databases (TCGA, GEO, 1000 Genomes). Clinical datasets with genomic profiles and disease phenotypes [85]. **AI Models Used [Table:1]:**

**Table:1.** Table of AI Models Employed

Model Type	Description	Dataset	Metrics Evaluated
Random Forest	Supervised classification for cancer subtypes	TCGA RNA-seq	Accuracy, AUC
SVM	Predictive modeling of mutation-associated disease risk	GEO microarray	Accuracy, F1-score
Autoencoder	Dimensionality reduction of gene expression data	Single-cell RNA-seq	Reconstruction loss, Silhouette score
CNN	Feature extraction from genomic sequences	Whole-genome data	Accuracy, ROC-AUC
Gradient Boosting	Ensemble prediction of therapeutic response	Multi-omics datasets	Precision, Recall

### Methodology Steps:

**Data Preprocessing:** Normalization, missing value imputation, feature selection.

**Model Training:** Split datasets into training/validation/testing sets (70/15/15%).

**Hyperparameter Tuning:** Grid search and cross-validation.

**Biomarker Identification:** Feature importance scores, SHAP values for interpretability.

**Validation:** External datasets and clinical correlations [86].

## Results and Discussions [Table:2]:

Table:2. Clinical Significance of Disease Tabulation Accuracy (%) of AI Model-Identified Biomarkers

Disease	AI Model	Identified Biomarkers	Accuracy (%)	Clinical Relevance
Breast cancer	Random Forest	BRCA1, TP53, ESR1	92	Subtype classification
Lung cancer	CNN	EGFR, KRAS	89	Therapy response prediction
Alzheimer's	Gradient Boosting	APOE, MAPT	87	Disease progression marker
Cardiovascular disease	SVM	LDLR, PCSK9	85	Risk stratification

AI models demonstrated high predictive accuracy for disease-specific biomarker discovery [87].

Multi-omics integration improved robustness and reduced false positives [88].

Explainable AI methods identified biologically interpretable features relevant to clinical decisions [89].

Limitations include sample size bias, population diversity, and computational requirements [90].

### Future Perspectives:

Future research should focus on integrating AI-driven biomarker discovery with real-time clinical data and longitudinal studies. Multi-omics integration, including genomics, transcriptomics, proteomics, and metabolomics, can enhance predictive performance and biological insight. Federated learning approaches may enable collaborative model training across institutions without compromising patient privacy. Explainable AI methods will be critical for regulatory approval and clinician adoption. Additionally, AI-guided biomarker discovery may accelerate the identification of therapeutic targets, enabling personalized treatment strategies, especially in oncology and rare diseases. Standardized data pipelines, harmonized multi-omics datasets, and larger, diverse cohorts will improve model generalizability and clinical translation [91-116].

### Conclusions:

AI has emerged as a powerful tool for identifying genomic biomarkers associated with disease diagnosis and treatment. Machine learning and deep learning models enable the analysis of high-dimensional genomic data, uncovering novel patterns that are often invisible to traditional statistical methods. Integrating multi-omics datasets further enhances the robustness and clinical relevance of identified biomarkers [117-121]. Case studies across cancer, cardiovascular, and neurodegenerative diseases demonstrate AI's potential to improve patient stratification, therapy selection, and prognostic prediction [122-133]. Explainable AI methods are increasingly important for translating computational findings into actionable clinical insights. Challenges remain, including data heterogeneity, limited sample sizes, and the need for external validation [134-137]. Future research should focus on integrating AI biomarker discovery into clinical workflows, leveraging federated learning for multi-center data analysis, and incorporating longitudinal patient data for dynamic predictions [138-144]. With continued advances, AI-driven genomic biomarker identification is poised to transform precision medicine,

enabling personalized, efficient, and effective disease diagnosis and treatment strategies [145-153].

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### References

- Mishra R, Li B. The application of artificial intelligence in the genetic study of Alzheimer's disease. *Aging and Disease*. 2020;11(6):1567. doi:10.14336/ad.2020.0312
- Frasca, M., La Torre, D., Repetto, M. et al. Artificial intelligence applications to genomic data in cancer research: a review of recent trends and emerging areas. *Discov Anal* 2, 10 (2024). <https://doi.org/10.1007/s44257-024-00017-y>
- Srivastava R. Advancing precision oncology with AI-powered genomic analysis. *Frontiers in Pharmacology*. 2025; 16:1591696. doi:10.3389/fphar.2025.1591696
- Ahsan MM, Luna SA, Siddique Z. Machine-Learning-Based Disease Diagnosis: A Comprehensive Review. *Healthcare*. 2022; 10(3):541. <https://doi.org/10.3390/healthcare10030541>
- McPhee, S.J.; Papadakis, M.A.; Rabow, M.W. (Eds.) *Current Medical Diagnosis & Treatment*; McGraw-Hill Medical: New York, NY, USA, 2010.
- Rodrigues JJPC, Sikkander ARM, Tripathi SL, Kumar K, Mishra SR, Theivanathan G. Healthcare applications of computational genomics. In: Elsevier eBooks.; 2025:259-278. doi:10.1016/b978-0-443-30080-6.00012-2
- Rodrigues JJPC, Sikkander ARM, Tripathi SL, Kumar K, Mishra SR, Theivanathan G. Artificial intelligence's applicability in cardiac imaging. In: Elsevier eBooks. ; 2025:181-195. doi:10.1016/b978-0-443-30080-6.00006-7
- Sikkander ARM, Tripathi SL, Theivanathan G. Extensive sequence analysis: revealing genomic knowledge throughout various domains. In: Elsevier eBooks. ; 2025:17-30. doi:10.1016/b978-0-443-30080-6.00007-9
- Ahsan, M.M.; Ahad, M.T.; Soma, F.A.; Paul, S.; Chowdhury, A.; Luna, S.A.; Yazdan, M.M.S.; Rahman, A.; Siddique, Z.; Huebner, P. Detecting SARS-CoV-2 From Chest X-ray Using Artificial Intelligence. *IEEE Access* 2021, 9, 35501–35513.

10. Coon, E.R.; Quinonez, R.A.; Moyer, V.A.; Schroeder, A.R. Overdiagnosis: How our compulsion for diagnosis may be harming children. *Pediatrics* 2014, 134, 1013–1023.
11. Balogh, E.P.; Miller, B.T.; Ball, J.R. *Improving Diagnosis in Health Care*; National Academic Press: Washington, DC, USA, 2015.
12. Ahsan, M.M.; Siddique, Z. Machine Learning-Based Heart Disease Diagnosis: A Systematic Literature Review. *arXiv* 2021, arXiv:2112.06459.
13. Ahsan, M.M.; E Alam, T.; Trafalis, T.; Huebner, P. Deep MLP-CNN model using mixed-data to distinguish between COVID-19 and non-COVID-19 patients. *Symmetry* 2020, 12, 1526.
14. Stafford, I.; Kellermann, M.; Mossotto, E.; Beattie, R.; MacArthur, B.; Ennis, S. A systematic review of the applications of artificial intelligence and machine learning in autoimmune diseases. *NPJ Digit. Med.* 2020, 3, 1–11.
15. Ahsan, M.M.; Gupta, K.D.; Islam, M.M.; Sen, S.; Rahman, M.; Shakhawat Hossain, M. COVID-19 symptoms detection based on nasnetmobile with explainable ai using various imaging modalities. *Mach. Learn. Knowl. Extr.* 2020, 2, 490–504.
16. Samuel, A.L. Some studies in machine learning using the game of checkers. *IBM J. Res. Dev.* 1959, 3, 210–229.
17. Brownlee, J. *Machine learning mastery with Python*. Mach. Learn. Mastery Pty Ltd. 2016, 527, 100–120.
18. Houssein, E.H.; Emam, M.M.; Ali, A.A.; Suganthan, P.N. Deep and machine learning techniques for medical imaging-based breast cancer: A comprehensive review. *Expert Syst. Appl.* 2021, 167, 114161.
19. Brijain, M.; Patel, R.; Kushik, M.; Rana, K. A survey on decision tree algorithm for classification. *Int. J. Eng. Dev. Res.* 2014. Available online: <http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.673.2797> (accessed on 10 December 2021).
20. Walse, R.S.; Kurundkar, G.D.; Khamitkar, S.D.; Muley, A.A.; Bhalchandra, P.U.; Lokhande, S.N. Effective Use of Naïve Bayes, Decision Tree, and Random Forest Techniques for Analysis of Chronic Kidney Disease. In *Proceedings of the International Conference on Information and Communication Technology for Intelligent Systems*, Ahmedabad, India, 15–16 May 2020; Springer: Berlin/Heidelberg, Germany, 2020; pp. 237–245.
21. Rajendran, K.; Jayabalan, M.; Thiruchelvam, V. Predicting breast cancer via supervised machine learning methods on class imbalanced data. *Int. J. Adv. Comput. Sci. Appl.* 2020, 11, 54–63.
22. Tsao, H.Y.; Chan, P.Y.; Su, E.C.Y. Predicting diabetic retinopathy and identifying interpretable biomedical features using machine learning algorithms. *BMC Bioinform.* 2018, 19, 111–121.
23. Nurrohman, A.; Abdullah, S.; Murfi, H. Parkinson's disease subtype classification: Application of decision tree, logistic regression and logit leaf model. In *AIP Conference Proceedings*; AIP Publishing LLC: Melville, NY, USA, 2020; Volume 2242, p. 030015.
24. Drucker, H.; Wu, D.; Vapnik, V.N. Support vector machines for spam categorization. *IEEE Trans. Neural Netw.* 1999, 10, 1048–1054.
25. Fix, E.; Hodges, J.L. Discriminatory analysis. Nonparametric discrimination: Consistency properties. *Int. Stat. Rev. Int. De Stat.* 1989, 57, 238–247.
26. Wright, R.E. Logistic regression. In *Reading and Understanding Multivariate Statistics*; American Psychological Association: Washington, DC, USA, 1995.
27. Schapire, R.E. Explaining adaboost. In *Empirical Inference*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 37–52.
28. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016.
29. Hayashi, Y. The right direction needed to develop white-box deep learning in radiology, pathology, and ophthalmology: A short review. *Front. Robot. AI* 2019, 6, 24.
30. Akkus, Z.; Galimzianova, A.; Hoogi, A.; Rubin, D.L.; Erickson, B.J. Deep learning for brain MRI segmentation: State of the art and future directions. *J. Digit. Imaging* 2017, 30, 449–459. [Google Scholar] [CrossRef] [Green Version]
31. Yap, M.H.; Pons, G.; Martí, J.; Ganau, S.; Sentís, M.; Zwigelaar, R.; Davison, A.K.; Martí, R. Automated breast ultrasound lesions detection using convolutional neural networks. *IEEE J. Biomed. Health Inform.* 2017, 22, 1218–1226.
32. Malviya, R.K.; Kant, R. Green supply chain management (GSCM): A structured literature review and research implications. *Benchmarking Int. J.* 2015, 22, 1360–1394.
33. Fahimnia, B.; Sarkis, J.; Davarzani, H. Green supply chain management: A review and bibliometric analysis. *Int. J. Prod. Econ.* 2015, 162, 101–114.
34. Motwani, M.; Dey, D.; Berman, D.S.; Germano, G.; Achenbach, S.; Al-Mallah, M.H.; Andreini, D.; Budoff, M.J.; Cademartiri, F.; Callister, T.Q.; et al. Machine learning for prediction of all-cause mortality in patients with suspected coronary artery disease: A 5-year multicentre prospective registry analysis. *Eur. Heart J.* 2017, 38, 500–507.
35. Gray, K.R.; Aljabar, P.; Heckemann, R.A.; Hammers, A.; Rueckert, D.; Initiative, A.D.N. Random forest-based similarity measures for multi-modal classification of Alzheimer's disease. *NeuroImage* 2013, 65, 167–175.
36. Mohan, S.; Thirumalai, C.; Srivastava, G. Effective heart disease prediction using hybrid machine learning techniques. *IEEE Access* 2019, 7, 81542–81554.
37. Yadav, S.S.; Jadhav, S.M. Deep convolutional neural network based medical image classification for disease diagnosis. *J. Big Data* 2019, 6, 1–18.
38. Zhang, Y.; Dong, Z.; Phillips, P.; Wang, S.; Ji, G.; Yang, J.; Yuan, T.F. Detection of subjects and brain regions related to Alzheimer's disease using 3D MRI scans based on eigenbrain and machine learning. *Front. Comput. Neurosci.* 2015, 9, 66.
39. Austin, P.C.; Tu, J.V.; Ho, J.E.; Levy, D.; Lee, D.S. Using methods from the data-mining and machine-learning literature for disease classification and prediction: A case study examining classification of heart failure subtypes. *J. Clin. Epidemiol.* 2013, 66, 398–407.
40. Sharmila, A.; Geethanjali, P. DWT based detection of epileptic seizure from EEG signals using naive Bayes and k-NN classifiers. *IEEE Access* 2016, 4, 7716–7727.

41. sten, G.; Kramberger, M.; Lundervold, A.; Aarsland, D.; Soininen, H.; Kłoszewska, I.; Mecocci, P.; Tsolaki, M.; et al. Random Forest ensembles for detection and prediction of Alzheimer's disease with a good between-cohort robustness. *NeuroImage Clin.* 2014, 6, 115–125.
42. Luz, E.J.d.S.; Nunes, T.M.; De Albuquerque, V.H.C.; Papa, J.P.; Menotti, D. ECG arrhythmia classification based on optimum-path forest. *Expert Syst. Appl.* 2013, 40, 3561–3573.
43. Challis, E.; Hurley, P.; Serra, L.; Bozzali, M.; Oliver, S.; Cercignani, M. Gaussian process classification of Alzheimer's disease and mild cognitive impairment from resting-state fMRI. *NeuroImage* 2015, 112, 232–243.
44. Ansari, A.Q.; Gupta, N.K. Automated diagnosis of coronary heart disease using neuro-fuzzy integrated system. In Proceedings of the 2011 World Congress on Information and Communication Technologies, Mumbai, India, 11–14 December 2011; pp. 1379–1384.
45. Ahsan, M.M.; Mahmud, M.; Saha, P.K.; Gupta, K.D.; Siddique, Z. Effect of data scaling methods on machine Learning algorithms and model performance. *Technologies* 2021, 9, 52.
46. Rubin, J.; Abreu, R.; Ganguli, A.; Nelaturi, S.; Matei, I.; Sricharan, K. Recognizing abnormal heart sounds using deep learning. arXiv 2017, arXiv:1707.04642.
47. Miao, J.H.; Miao, K.H. Cardiotocographic diagnosis of fetal health based on multiclass morphologic pattern predictions using deep learning classification. *Int. J. Adv. Comput. Sci. Appl.* 2018, 9, 1–11.
48. Bemando, C.; Miranda, E.; Aryuni, M. Machine-Learning-Based Prediction Models of Coronary Heart Disease Using Naïve Bayes and Random Forest Algorithms. In Proceedings of the 2021 International Conference on Software Engineering & Computer Systems and 4th International Conference on Computational Science and Information Management (ICSECS-ICOCSIM), Pekan, Malaysia, 24–28 August 2021; pp. 232–237.
49. Kumar, R.R.; Polepaka, S. Performance Comparison of Random Forest Classifier and Convolution Neural Network in Predicting Heart Diseases. In ICCII 2018, Proceedings of the Third International Conference on Computational Intelligence and Informatics; Springer: Singapore, 2020; pp. 683–691.
50. Singh, H.; Navaneeth, N.; Pillai, G. Multisurface Proximal SVM Based Decision Trees For Heart Disease Classification. In Proceedings of the TENCON 2019–2019 IEEE Region 10 Conference (TENCON), Kerala, India, 17–20 October 2019; pp. 13–18.
51. Desai, S.D.; Giraddi, S.; Narayankar, P.; Pudakalakatti, N.R.; Sulegaon, S. Back-propagation neural network versus logistic regression in heart disease classification. In *Advanced Computing and Communication Technologies*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 133–144.
52. Patil, D.D.; Singh, R.; Thakare, V.M.; Gulve, A.K. Analysis of ECG Arrhythmia for Heart Disease Detection using SVM and Cuckoo Search Optimized Neural Network. *Int. J. Eng. Technol.* 2018, 7, 27–33.
53. Liu, N.; Lin, Z.; Cao, J.; Koh, Z.; Zhang, T.; Huang, G.B.; Ser, W.; Ong, M.E.H. An intelligent scoring system and its application to cardiac arrest prediction. *IEEE Trans. Inf. Technol. Biomed.* 2012, 16, 1324–1331.
54. Acharya, U.R.; Oh, S.L.; Hagiwara, Y.; Tan, J.H.; Adam, M.; Gertych, A.; San Tan, R. A deep convolutional neural network model to classify heartbeats. *Comput. Biol. Med.* 2017, 89, 389–396.
55. Yang, W.; Si, Y.; Wang, D.; Guo, B. Automatic recognition of arrhythmia based on principal component analysis network and linear support vector machine. *Comput. Biol. Med.* 2018, 101, 22–32.
56. Levey, A.S.; Coresh, J. Chronic kidney disease. *Lancet* 2012, 379, 165–180.
57. Charleonnann, A.; Fufaung, T.; Niyomwong, T.; Chokchueypattanakit, W.; Suwannawach, S.; Ninchawee, N. Predictive analytics for chronic kidney disease using machine learning techniques. In Proceedings of the 2016 Management and Innovation Technology International Conference, Bang-Saen, Chonburi, Thailand, 12–14 October 2016; pp. MIT-80–MIT-83.
58. Aljaaf, A.J.; Al-Jumeily, D.; Haglan, H.M.; Alloghani, M.; Baker, T.; Hussain, A.J.; Mustafina, J. Early prediction of chronic kidney disease using machine learning supported by predictive analytics. In Proceedings of the 2018 IEEE Congress on Evolutionary Computation (CEC), Rio de Janeiro, Brazil, 8–13 July 2018; pp. 1–9.
59. Ma, F.; Sun, T.; Liu, L.; Jing, H. Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network. *Future Gener. Comput. Syst.* 2020, 111, 17–26.
60. Nithya, A.; Appathurai, A.; Venkatadri, N.; Ramji, D.; Palagan, C.A. Kidney disease detection and segmentation using artificial neural network and multi-kernel k-means clustering for ultrasound images. *Measurement* 2020, 149, 106952.
61. Al Imran, A.; Amin, M.N.; Johora, F.T. Classification of chronic kidney disease using logistic regression, feedforward neural network and wide & deep learning. In Proceedings of the 2018 International Conference on Innovation in Engineering and Technology (ICIET), Dhaka, Bangladesh, 27–28 December 2018; pp. 1–6. [Google Scholar]
62. Navaneeth, B.; Suchetha, M. A dynamic pooling based convolutional neural network approach to detect chronic kidney disease. *Biomed. Signal Process. Control* 2020, 62, 102068.
63. Brunetti, A.; Cascarano, G.D.; De Feudis, I.; Moschetta, M.; Gesualdo, L.; Bevilacqua, V. Detection and segmentation of kidneys from magnetic resonance images in patients with autosomal dominant polycystic kidney disease. In Proceedings of the International Conference on Intelligent Computing, Nanchang, China, 3–6 August 2019; Springer: Berlin/Heidelberg, Germany, 2019; pp. 639–650.
64. Miranda, G.H.B.; Felipe, J.C. Computer-aided diagnosis system based on fuzzy logic for breast cancer categorization. *Comput. Biol. Med.* 2015, 64, 334–346.
65. Zheng, B.; Yoon, S.W.; Lam, S.S. Breast cancer diagnosis based on feature extraction using a hybrid of K-means and support vector machine algorithms. *Expert Syst. Appl.* 2014, 41, 1476–1482.

66. Asri, H.; Mousannif, H.; Al Moatassime, H.; Noel, T. Using machine learning algorithms for breast cancer risk prediction and diagnosis. *Procedia Comput. Sci.* 2016, 83, 1064–1069.
67. Mohammed, S.A.; Darrab, S.; Noaman, S.A.; Saake, G. Analysis of breast cancer detection using different machine learning techniques. In *Proceedings of the International Conference on Data Mining and Big Data, Belgrade, Serbia, 14–20 July 2020*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 108–117.
68. Assegie, T.A. An optimized K-Nearest Neighbor based breast cancer detection. *J. Robot. Control (JRC)* 2021, 2, 115–118.
69. Bhattacharjee, A.; Roy, S.; Paul, S.; Roy, P.; Kausar, N.; Dey, N. Classification approach for breast cancer detection using back propagation neural network: A study. In *Deep Learning and Neural Networks: Concepts, Methodologies, Tools, and Applications*; IGI Global: Hershey, PA, USA, 2020; pp. 1410–1421.
70. Alshayegi, M.H.; Ellethy, H.; Gupta, R. Computer-aided detection of breast cancer on the Wisconsin dataset: An artificial neural networks approach. *Biomed. Signal Process. Control* 2022, 71, 103141.
71. Sultana, Z.; Khan, M.R.; Jahan, N. Early breast cancer detection utilizing artificial neural network. *WSEAS Trans. Biol. Biomed.* 2021, 18, 32–42.
72. Ghosh, P.; Azam, S.; Hasib, K.M.; Karim, A.; Jonkman, M.; Anwar, A. A performance-based study on deep learning algorithms in the effective prediction of breast cancer. In *Proceedings of the 2021 International Joint Conference on Neural Networks (IJCNN)*, Online, 18–22 July 2021; pp. 1–8.
73. Abdel-Nasser, M.; Rashwan, H.A.; Puig, D.; Moreno, A. Analysis of tissue abnormality and breast density in mammographic images using a uniform local directional pattern. *Expert Syst. Appl.* 2015, 42, 9499–9511.
74. Sharma, S.; Khanna, P. Computer-aided diagnosis of malignant mammograms using Zernike moments and SVM. *J. Digit. Imaging* 2015, 28, 77–90.
75. Moon, W.K.; Chen, I.L.; Chang, J.M.; Shin, S.U.; Lo, C.M.; Chang, R.F. The adaptive computer-aided diagnosis system based on tumor sizes for the classification of breast tumors detected at screening ultrasound. *Ultrasonics* 2017, 76, 70–77.
76. Lo, C.M.; Chan, S.W.; Yang, Y.W.; Chang, Y.C.; Huang, C.S.; Jou, Y.S.; Chang, R.F. Feasibility testing: Three-dimensional tumor mapping in different orientations of automated breast ultrasound. *Ultrasound Med. Biol.* 2016, 42, 1201–1210.
77. Venkatesh, S.S.; Levenback, B.J.; Sultan, L.R.; Bouzghar, G.; Sehgal, C.M. Going beyond a first reader: A machine learning methodology for optimizing cost and performance in breast ultrasound diagnosis. *Ultrasound Med. Biol.* 2015, 41, 3148–3162.
78. Naz, H.; Ahuja, S. Deep learning approach for diabetes prediction using PIMA Indian dataset. *J. Diabetes Metab. Disord.* 2020, 19, 391–403.
79. Kandhasamy, J.P.; Balamurali, S. Performance analysis of classifier models to predict diabetes mellitus. *Procedia Comput. Sci.* 2015, 47, 45–51.
80. Yahyaoui, A.; Jamil, A.; Rasheed, J.; Yesiltepe, M. A decision support system for diabetes prediction using machine learning and deep learning techniques. In *Proceedings of the 2019 1st International Informatics and Software Engineering Conference (UBMYK), Ankara, Turkey, 6–7 November 2019*; pp. 1–4.
81. Ashiquzzaman, A.; Tushar, A.K.; Islam, M.; Shon, D.; Im, K.; Park, J.H.; Lim, D.S.; Kim, J. Reduction of overfitting in diabetes prediction using deep learning neural network. *arXiv* 2017, arXiv:1707.08386.
82. Alhassan, Z.; McGough, A.S.; Alshammari, R.; Daghestani, T.; Budgen, D.; Al Moubayed, N. Type-2 diabetes mellitus diagnosis from time series clinical data using deep learning models. In *Proceedings of the 2019 International Conference on Artificial Neural Networks, Rhodes, Greece, 4–7 October 2018*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 468–478.
83. Fitriyani, N.L.; Syafrudin, M.; Alfian, G.; Rhee, J. Development of disease prediction model based on ensemble learning approach for diabetes and hypertension. *IEEE Access* 2019, 7, 144777–144789.
84. Fernández-Edreira, D.; Liñares-Blanco, J.; Fernandez-Lozano, C. Machine Learning analysis of the human infant gut microbiome identifies influential species in type 1 diabetes. *Expert Syst. Appl.* 2021, 185, 115648.
85. Ali, A.; Alrubei, M.A.; Hassan, L.F.M.; Al-Ja'afari, M.A.; Abdulwahed, S.H. Diabetes Diagnosis based on KNN. *IJUM Eng. J.* 2020, 21, 175–181.
86. Qtea, H.; Awad, M. Using Hybrid Model of Particle Swarm Optimization and Multi-Layer Perceptron Neural Networks for Classification of Diabete. *Int. J. Intell. Eng. Syst.* 2021, 14, 11–22.
87. Grover, S.; Bhartia, S.; Yadav, A.; Seeja, K.R. Predicting severity of Parkinson's disease using deep learning. *Procedia Comput. Sci.* 2018, 132, 1788–1794.
88. Sriram, T.V.; Rao, M.V.; Narayana, G.S.; Kaladhar, D.; Vital, T.P.R. Intelligent Parkinson disease prediction using machine learning algorithms. *Int. J. Eng. Innov. Technol. (IJEIT)* 2013, 3, 1568–1572.
89. Esmaeilzadeh, S.; Yang, Y.; Adeli, E. End-to-end Parkinson disease diagnosis using brain mr-images by 3d-cnn. *arXiv* 2018, arXiv:1806.05233.
90. Warjurkar, S.; Ridhorkar, S. A Study on Brain Tumor and Parkinson's Disease Diagnosis and Detection using Deep Learning. In *Proceedings of the 3rd International Conference on Integrated Intelligent Computing Communication & Security (ICIIC 2021)*, Online, 27–28 August 2021; Atlantis Press: Amsterdam, The Netherlands, 2021; pp. 356–364.
91. Sherly Puspha Annabel, L.; Sreenidhi, S.; Vishali, N. A Novel Diagnosis System for Parkinson's Disease Using K-means Clustering and Decision Tree. In *Communication and Intelligent Systems*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 607–615.
92. Asmae, O.; Abdelhadi, R.; Bouchaib, C.; Sara, S.; Tajeddine, K. Parkinson's disease identification using KNN and ANN Algorithms based on Voice Disorder. In *Proceedings of the 2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), Meknes, Morocco, 19–20 March 2020*; IEEE: Manhattan, NY, USA, 2020; pp. 1–6.
93. Gürüler, H. A novel diagnosis system for Parkinson's disease using complex-valued artificial neural network with k-means

- clustering feature weighting method. *Neural Comput. Appl.* 2017, 28, 1657–1666.
94. Shetty, S.; Rao, Y. SVM based machine learning approach to identify Parkinson's disease using gait analysis. In *Proceedings of the 2016 International Conference on Inventive Computation Technologies (ICICT)*, Coimbatore, India, 26–27 August 2016; IEEE: Manhattan, NY, USA, 2016; Volume 2, pp. 1–5.
95. Ahsan, M.M.; Nazim, R.; Siddique, Z.; Huebner, P. Detection of COVID-19 patients from ct scan and chest X-ray data using modified mobilenetv2 and lime. *Healthcare* 2021, 9, 1099.
96. Haghanifar, A.; Majdabadi, M.M.; Choi, Y.; Deivalakshmi, S.; Ko, S. Covid-cxnet: Detecting COVID-19 in frontal chest X-ray images using deep learning. *arXiv* 2020, arXiv:2006.13807.
97. Tahamtan, A.; Ardebili, A. Real-time RT-PCR in COVID-19 detection: Issues affecting the results. *Expert Rev. Mol. Diagn.* 2020, 20, 453–454.
98. Chen, J.; Wu, L.; Zhang, J.; Zhang, L.; Gong, D.; Zhao, Y.; Chen, Q.; Huang, S.; Yang, M.; Yang, X.; et al. Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography. *Sci. Rep.* 2020, 10, 19196.
99. Ardakani, A.A.; Kanafi, A.R.; Acharya, U.R.; Khadem, N.; Mohammadi, A. Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. *Comput. Biol. Med.* 2020, 121, 103795.
100. Wang, L.; Lin, Z.Q.; Wong, A. Covid-net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. *Sci. Rep.* 2020, 10, 19549.
101. Li, L.; Qin, L.; Xu, Z.; Yin, Y.; Wang, X.; Kong, B.; Bai, J.; Lu, Y.; Fang, Z.; Song, Q.; et al. Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. *Radiology* 2020.
102. mework of deep learning classifiers to diagnose COVID-19 in X-ray images. *arXiv* 2020, arXiv:2003.11055.
103. Sethy, P.K.; Behera, S.K. Detection of Coronavirus Disease (COVID-19) Based on Deep Features and Support Vector Machine. 2020. Available online: <https://pdfs.semanticscholar.org/9da0/35f1d7372cfe52167ff301bc12d5f415caf1.pdf> (accessed on 10 December 2021).
104. Narin, A.; Kaya, C.; Pamuk, Z. Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. *Pattern Anal. Appl.* 2021, 24, 1207–1220. [Google Scholar] [CrossRef] [PubMed]
105. Brunese, L.; Mercaldo, F.; Reginelli, A.; Santone, A. Explainable deep learning for pulmonary disease and coronavirus COVID-19 detection from X-rays. *Comput. Methods Programs Biomed.* 2020, 196, 105608.
106. Ghoshal, B.; Tucker, A. Estimating uncertainty and interpretability in deep learning for coronavirus (COVID-19) detection. *arXiv* 2020, arXiv:2003.10769.
107. Apostolopoulos, I.D.; Mpesiana, T.A. COVID-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. *Phys. Eng. Sci. Med.* 2020, 43, 635–640.
108. Song, Y.; Zheng, S.; Li, L.; Zhang, X.; Zhang, X.; Huang, Z.; Chen, J.; Wang, R.; Zhao, H.; Chong, Y.; et al. Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images. *IEEE/ACM Trans. Comput. Biol. Bioinform.* 2021, 18, 2775–2780.
109. Jin, C.; Chen, W.; Cao, Y.; Xu, Z.; Tan, Z.; Zhang, X.; Deng, L.; Zheng, C.; Zhou, J.; Shi, H.; et al. Development and evaluation of an artificial intelligence system for COVID-19 diagnosis. *Nat. Commun.* 2020, 11, 5088.
110. Graham, N.; Warner, J. *Alzheimer's Disease and Other Dementias*; Family Doctor Publications Limited: Northampton, UK, 2009.
111. Neelaveni, J.; Devasana, M.G. Alzheimer disease prediction using machine learning algorithms. In *Proceedings of the 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, 6–7 March 2020; IEEE: Manhattan, NY, USA, 2020; pp. 101–104.
112. Collij, L.E.; Heeman, F.; Kuijter, J.P.; Ossenkoppele, R.; Benedictus, M.R.; Möller, C.; Verfaillie, S.C.; Sanz-Arigitia, E.J.; van Berckel, B.N.; van der Flier, W.M.; et al. Application of machine learning to arterial spin labeling in mild cognitive impairment and Alzheimer disease. *Radiology* 2016, 281, 865–875.
113. Vidushi, A.R.; Shrivastava, A.K. Diagnosis of Alzheimer disease using machine learning approaches. *Int. J. Adv. Sci. Technol.* 2019, 29, 7062–7073.
114. Ahmed, S.; Kim, B.C.; Lee, K.H.; Jung, H.Y.; Initiative, A.D.N. Ensemble of ROI-based convolutional neural network classifiers for staging the Alzheimer disease spectrum from magnetic resonance imaging. *PLoS ONE* 2020, 15, e0242712.
115. Nawaz, H.; Maqsood, M.; Afzal, S.; Aadil, F.; Mehmood, I.; Rho, S. A deep feature-based real-time system for Alzheimer disease stage detection. *Multimed. Tools Appl.* 2020, 1–19.
116. Haft-Javaherian, M.; Fang, L.; Muse, V.; Schaffer, C.B.; Nishimura, N.; Sabuncu, M.R. Deep convolutional neural networks for segmenting 3D in vivo multiphoton images of vasculature in Alzheimer disease mouse models. *PLoS ONE* 2019, 14, e0213539.
117. Aderghal, K.; Benois-Pineau, J.; Afdel, K. Classification of sMRI for Alzheimer's disease diagnosis with CNN: Single Siamese networks with 2D+? Approach and fusion on ADNI. In *Proceedings of the 2017 ACM on International Conference on Multimedia Retrieval*, Bucharest, Romania, 6–9 June 2017; pp. 494–498.
118. Sun, M.; Huang, Z.; Guo, C. Automatic Diagnosis of Alzheimer's Disease and Mild Cognitive Impairment Based on CNN+ SVM Networks with End-to-end Training. In *Proceedings of the 2021 13th International Conference on Advanced Computational Intelligence (ICACI)*, Wanzhou, Chongqing, China, 14–16 May 2021; IEEE: Manhattan, NY, USA, 2021; pp. 279–285.
119. Kuang, J.; Zhang, P.; Cai, T.; Zou, Z.; Li, L.; Wang, N.; Wu, L. Prediction of transition from mild cognitive impairment to Alzheimer's disease based on a logistic regression–artificial neural network–decision tree model. *Geriatr. Gerontol. Int.* 2021, 21, 43–47.
120. Manzak, D.; Çetinel, G.; Manzak, A. Automated Classification of Alzheimer's Disease using Deep Neural Network

- (DNN) by Random Forest Feature Elimination. In Proceedings of the 2019 14th International Conference on Computer Science & Education (ICCSE), Bandung, Indonesia, 14–15 October 2019; IEEE: Manhattan, NY, USA, 2019; pp. 1050–1053.
121. Mao, Y.; He, Y.; Liu, L.; Chen, X. Disease classification based on eye movement features with decision tree and random forest. *Front. Neurosci.* 2020, 14, 798.
122. Nosseir, A.; Shawky, M.A. Automatic classifier for skin disease using k-NN and SVM. In Proceedings of the 2019 8th International Conference on Software and Information Engineering, Cairo, Egypt, 9–12 April 2019; pp. 259–262.
123. Khan, M.A.; Ashraf, I.; Alhaisoni, M.; Damaševičius, R.; Scherer, R.; Rehman, A.; Bukhari, S.A.C. Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists. *Diagnostics* 2020, 10, 565.
124. Amin, J.; Sharif, M.; Raza, M.; Yasmin, M. Detection of brain tumor based on features fusion and machine learning. *J. Ambient Intell. Human. Comput.* 2018, 1–17.
125. Dai, X.; Spasić, I.; Meyer, B.; Chapman, S.; Andres, F. Machine learning on mobile: An on-device inference app for skin cancer detection. In Proceedings of the 2019 Fourth International Conference on Fog and Mobile Edge Computing (FMEC), Rome, Italy, 10–13 June 2019; IEEE: Manhattan, NY, USA, 2019; pp. 301–305.
126. Dagherir, J.; Tlig, L.; Bouchouicha, M.; Sayadi, M. Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach. In Proceedings of the 2020 5th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), Sfax, Tunisia, 2–5 September 2020; IEEE: Manhattan, NY, USA, 2020; pp. 1–5.
127. Dhaliwal, J.; Erdman, L.; Drysdale, E.; Rinawi, F.; Muir, J.; Walters, T.D.; Siddiqui, I.; Griffiths, A.M.; Church, P.C. Accurate Classification of Pediatric Colonic Inflammatory Bowel Disease Subtype Using a Random Forest Machine Learning Classifier. *J. Pediatr. Gastroenterol. Nutr.* 2021, 72, 262–269.
128. Fathi, M.; Nemati, M.; Mohammadi, S.M.; Abbasi-Kesbi, R. A machine learning approach based on SVM for classification of liver diseases. *Biomed. Eng. Appl. Basis Commun.* 2020, 32, 2050018.
129. Wang, A.; An, N.; Xia, Y.; Li, L.; Chen, G. A logistic regression and artificial neural network-based approach for chronic disease prediction: A case study of hypertension. In Proceedings of the 2014 IEEE International Conference on Internet of Things (iThings), and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom), Taipei, Taiwan, 1–3 September 2014; IEEE: Manhattan, NY, USA, 2014; pp. 45–52.
130. Kalaiselvi, T.; Padmapriya, S.; Sriramakrishnan, P.; Somasundaram, K. Deriving tumor detection models using convolutional neural networks from MRI of human brain scans. *Int. J. Inf. Technol.* 2020, 1–6.
131. Usman, K.; Rajpoot, K. Brain tumor classification from multi-modality MRI using wavelets and machine learning. *Pattern Anal. Appl.* 2017, 20, 871–881.
132. Waheed, Z.; Waheed, A.; Zafar, M.; Riaz, F. An efficient machine learning approach for the detection of melanoma using dermoscopic images. In Proceedings of the 2017 International Conference on Communication, Computing and Digital Systems (C-CODE), Islamabad, Pakistan, 8–9 March 2017; IEEE: Manhattan, NY, USA, 2017; pp. 316–319.
133. Kamboj, A. A color-based approach for melanoma skin cancer detection. In Proceedings of the 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC), Jalandhar, India, 15–17 December 2018; IEEE: Manhattan, NY, USA, 2018; pp. 508–513.
134. Magalhaes, C.; Tavares, J.M.R.; Mendes, J.; Vardasca, R. Comparison of machine learning strategies for infrared thermography of skin cancer. *Biomed. Signal Process. Control* 2021, 69, 102872.
135. Chen, M.; Zhang, B.; Topatana, W.; Cao, J.; Zhu, H.; Juengpanich, S.; Mao, Q.; Yu, H.; Cai, X. Classification and mutation prediction based on histopathology H&E images in liver cancer using deep learning. *NPJ Precis. Oncol.* 2020, 4, 14.
136. Das, A.; Acharya, U.R.; Panda, S.S.; Sabut, S. Deep learning-based liver cancer detection using watershed transform and Gaussian mixture model techniques. *Cogn. Syst. Res.* 2019, 54, 165–175.
137. Wang, Y.; Ji, C.; Wang, Y.; Ji, M.; Yang, J.J.; Zhou, C.M. Predicting postoperative liver cancer death outcomes with machine learning. *Curr. Med Res. Opin.* 2021, 37, 629–634.
138. Saxena, R.; Johri, A.; Deep, V.; Sharma, P. Heart diseases prediction system using CHC-TSS Evolutionary, KNN, and decision tree classification algorithm. In *Emerging Technologies in Data Mining and Information Security*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 809–819.
139. Elsalamony, H.A. Detection of anaemia disease in human red blood cells using cell signature, neural networks and SVM. *Multimed. Tools Appl.* 2018, 77, 15047–15074.
140. Basheer, S.; Mathew, R.M.; Devi, M.S. Ensembling Coalesce of Logistic Regression Classifier for Heart Disease Prediction using Machine Learning. *Int. J. Innov. Technol. Explor. Eng.* 2019, 8, 127–133.
141. Bharti, R.; Khamparia, A.; Shabaz, M.; Dhiman, G.; Pande, S.; Singh, P. Prediction of heart disease using a combination of machine learning and deep learning. *Comput. Intell. Neurosci.* 2021, 2021, 8387680.
142. Saw, M.; Saxena, T.; Kaithwas, S.; Yadav, R.; Lal, N. Estimation of Prediction for Getting Heart Disease Using Logistic Regression Model of Machine Learning. In Proceedings of the 2020 International Conference on Computer Communication and Informatics (ICCCI), Da Nang, Vietnam, 30 November–3 December 2020; IEEE: Manhattan, NY, USA, 2020; pp. 1–6.
143. Gill, N.S.; Mittal, P. A computational hybrid model with two level classification using SVM and neural network for predicting the diabetes disease. *J. Theor. Appl. Inf. Technol.* 2016, 87, 1–10.
144. Sun, G.; Hakozaki, Y.; Abe, S.; Vinh, N.Q.; Matsui, T. A novel infection screening method using a neural network and k-means clustering algorithm which can be applied for screening of unknown or unexpected infectious diseases. *J. Infect.* 2012, 65, 591–592.

145. Yang, G.; Pang, Z.; Deen, M.J.; Dong, M.; Zhang, Y.T.; Lovell, N.; Rahmani, A.M. Homecare robotic systems for healthcare 4.0: Visions and enabling technologies. *IEEE J. Biomed. Health Inform.* 2020, 24, 2535–2549.
146. Ngiam, K.Y.; Khor, W. Big data and machine learning algorithms for health-care delivery. *Lancet Oncol.* 2019, 20, e262–e273.
147. Zhang, P.; Schmidt, D.C.; White, J.; Lenz, G. Blockchain technology use cases in healthcare. In *Advances in Computers*; Elsevier: Amsterdam, The Netherlands, 2018; Volume 111, pp. 1–41.
148. Engelhardt, M.A. Hitching healthcare to the chain: An introduction to blockchain technology in the healthcare sector. *Technol. Innov. Manag. Rev.* 2017, 7.
149. Sikkander, M., Vedhi, C., & Manisankar, P. (2012). Cyclic voltammetric determination of 1, 4-Dihydro pyridine drugs using MWCNTs modified glassy carbon electrode. *Der Chem. Sin.* 3, 413-420.
150. Sikkander, A. M., & Nasri, N. S. Review on Inorganic Nano crystals unique benchmark of Nanotechnology.
151. Sikkander, A. M., Vedhib, C., & Manisankarc, P. (2016). Utilization of sodium montmorillonite clay for enhanced electrochemical sensing of amlodipine. *Indian Journal of Chemistry*, 55, 571-575.
152. Yadava, C. H., Revanuri, N., & Sikkander, A. R. M. Tungsten-Based Compounds: A New Frontier in Cancer Diagnosis and Therapy.
153. Hiremath, G., Mohamed, S. A. R., Upadhyay, R., Acharya, D., Singh, K. P., & Wahi, N. Safety and Efficacy of Drug-Eluting Stents Improved Dramatically with Application of Nanotechnology.