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Review Article

Next-Generation of Smart Healthcare: A Review of Emerging AI Technologies and Their Clinical Applications

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Abstract

The integration of Deep Learning (DL) techniques with the Internet of Things (IoT) has emerged as a transformative paradigm in the advancement of smart healthcare systems. Numerous recent studies have investigated the convergence of these technologies, demonstrating their potential in improving healthcare delivery, patient monitoring, and clinical decision-making. The ongoing evolution of Industry 5.0 in parallel with the deployment of 5G communication networks has further facilitated the development of intelligent, cost-effective, and highly responsive sensors. These innovations enable continuous and real-time monitoring of patients' health conditions, a capability that was not feasible within the constraints of traditional healthcare models. Smart health monitoring systems have thus introduced significant improvements in terms of speed, affordability, reliability, and accessibility of medical services, particularly in remote or underserved regions. Moreover, the application of Deep Learning and Machine Learning algorithms in health data analysis has played a pivotal role in achieving preventive healthcare, reducing mortality risks, and enabling personalized treatment strategies. Such methods have also enhanced the early detection of chronic diseases, which previously posed considerable diagnostic challenges. To further optimize scalability and cost-efficiency, cloud computing and distributed storage solutions have been incorporated, ensuring secure and real-time data availability. This review therefore provides a comprehensive perspective on smart healthcare innovations, emphasizing the role of intelligent systems, recent advancements, and persisting challenges in the domain of digital health monitoring.

Keywords

Deep learning (DL), Internet of Things (IoT), Internet of Medical Things (IoMT), Industry 5.0, Real-time health monitoring, Smart healthcare.

I. INTRODUCTION

Healthcare delivery systems are currently undergoing a fundamental transformation driven by the integration of data engineering, predictive analytics, and artificial intelligence (AI) models. These advanced technologies have enabled a paradigm shift from traditional reactive approaches, where medical intervention was primarily provided after the onset of illness, toward more proactive and preventive healthcare models. By enabling healthcare providers to anticipate potential health issues, optimize the allocation of medical resources, and tailor interventions to patient-specific needs, these technologies have significantly improved clinical decision-making processes, enhanced operational efficiency, and raised the overall quality of patient care [1]. This shift has been particularly critical in an era marked by growing population demands, rising healthcare costs, and the need for systems capable of delivering scalable and reliable medical services. The emergence of the Internet of Things (IoT) has further accelerated innovation in the healthcare domain. IoT devices are now widely deployed in hospitals, clinics, and even at the patient's home, where they are used to monitor vital signs, track recovery progress, and support treatment adherence. The continuous flow of real-time data collected from these devices allows physicians and healthcare teams to detect anomalies at an early stage, intervene promptly, and reduce risks associated with late diagnoses. This technological integration has created the foundation for the Internet of Medical Things (IoMT), which constitutes a revolutionary healthcare ecosystem connecting medical devices, software

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applications, and health IT systems [2]. The IoMT does not only streamline communication between devices but also enables interoperability across various platforms, ensuring that patient information is available whenever and wherever it is needed. Such interoperability enhances the continuity of care and reduces the likelihood of medical errors that often arise from fragmented systems. Recent progress in data engineering and data science has played a crucial role in strengthening IoMT-based healthcare systems. Through advanced data pipelines, large-scale patient datasets can be seamlessly combined, rapidly processed, and transformed into actionable insights. For example, heterogeneous data sources such as electronic health records, imaging data, genomic information, and wearable sensor outputs can now be integrated and analyzed within a unified framework. Through this integration, healthcare institutions can monitor patient conditions in real time while also predicting disease progression and treatment outcomes with greater accuracy [3]. This progression leads to the concept of a smart health system, as illustrated in Fig. 1, which highlights its key benefits. Predictive models, supported by machine learning and deep learning algorithms, are increasingly capable of identifying subtle patterns in complex datasets, enabling earlier interventions and improving patient prognoses.

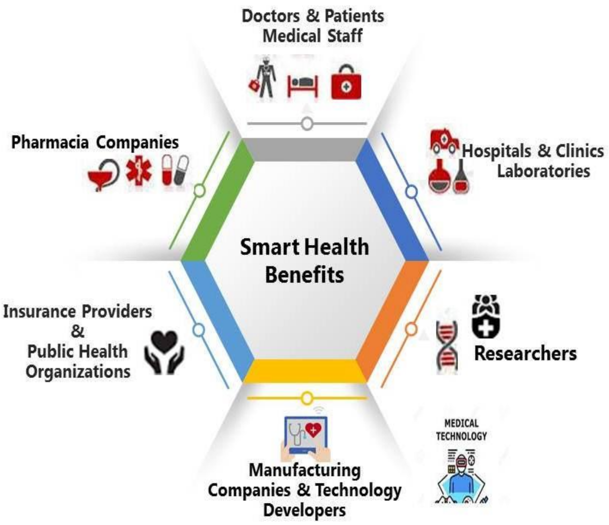

Fig. 1. Smart Healthcare Benefits

The incorporation of AI into patient care systems represents another milestone in this digital transformation. AI-driven solutions are being used to design and recommend personalized treatment plans based on individual patient characteristics, genetic profiles, and lifestyle factors. Moreover, AI significantly enhances the accuracy of disease detection and diagnosis, with applications ranging from medical imaging analysis to the identification of rare diseases. Automation of routine clinical decision-making processes has also become feasible, reducing the cognitive burden on healthcare professionals and allowing them to focus on more complex tasks that require human expertise [4]. In addition, AI contributes to the optimization of hospital operations, including resource scheduling, supply chain management, and patient flow optimization, thereby reducing costs and improving service delivery. The applications of Smart Healthcare Monitoring (SHM) are illustrated in Fig. 2, which highlights how data acquisition, connectivity, and analysis converge to deliver intelligent health monitoring services.

To ensure the scientific rigor of this study, a systematic methodology is adopted in selecting relevant literature. Clear criteria are established, which included publication date, topical relevance, study design, and geographic scope. A comprehensive search is carried out across multiple reputable databases such as Research Gate, Google Scholar, and Web of Science, using carefully selected keywords to capture the breadth of studies available. Each article undergone a screening process that involved the review of titles, abstracts, and full texts to determine eligibility based on the predefined inclusion criteria. Irrelevant or low-quality studies were excluded to maintain the robustness of the review. Additionally, the reference lists of the selected studies are thoroughly examined to identify further sources that might not have been captured during the initial search. To guarantee reliability, the quality assessment of the included studies is performed by the authors using parameters such as study design rigor, methodological soundness, adequacy of sample size, and the academic credibility of the researchers. Following this assessment, key information, including findings, methodologies, and conclusions, is extracted and systematically organized to facilitate meaningful analysis. This structured approach ensured that the review provided a comprehensive, evidence-based overview of recent advancements in smart healthcare systems, while also highlighting the existing challenges and research gaps that need to be addressed in future studies.

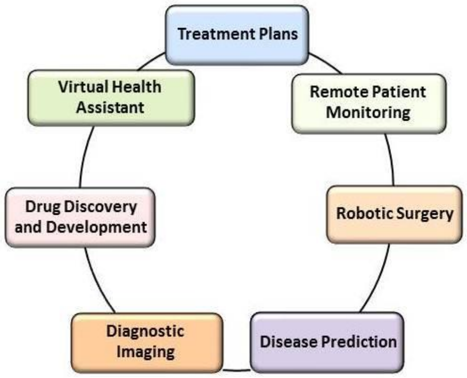

Fig. 2. Smart Healthcare Monitoring System

Smart health monitoring devices positions many important features such as: prevention of unnecessary visit of hospitals, doctors can remotely check the real time state of the patients. The data produced from these devices is safe from hacking. Healthcare services are costly today and the devices supports to solve this problem which is a great growth in medical field [5]-[8]. By growing the strains and belief of peoples on the smartness of devices and digitalization, the roles of the IoMT and SHM will have continuous role in the general evolution and development. SHM as an advanced technology in medical stream can be used to remotely controlled medical services to save the life of dangerous patient cases of heart attack, asthma attack, diabetic patients etc. [9]-[13].

II. ROLES OF DL, ML, AND AI IN HEALTH MONITORING

Deep Learning (DL) and Machine Learning (ML) are integral components of Artificial Intelligence (AI) as illustrated in Fig. 3. While both methodologies contribute significantly to modern healthcare, they operate at different levels of complexity and capability. ML primarily relies on algorithms that learn from structured datasets, identifying patterns and making predictions based on statistical models. In contrast, DL, which is a specialized subset of ML, employs multilayered neural networks capable of processing vast amounts of unstructured and heterogeneous data, thereby extracting progressively higher-level abstractions from raw inputs [14]– [17]. The strength of ML in SHM networks lies in its ability to perform predictive analytics using relatively smaller datasets with lower computational requirements. ML algorithms are widely applied in disease classification, risk prediction, and anomaly detection, offering reliable results in scenarios where data is structured and labeled. For example, ML models are effective in predicting patient readmissions, optimizing hospital resource allocation, and supporting decision-making in routine diagnostics. However, the performance of ML models often depends heavily on feature engineering and data preprocessing, which may limit their adaptability in highly dynamic healthcare environments. By contrast, DL provides several advantages that surpass traditional ML techniques, particularly in complex healthcare scenarios. Owing to its hierarchical feature extraction, DL models can handle large-scale and multimodal data sources, including medical images, bio signals, sensor outputs, and even textual clinical notes. In SHM networks, DL enables real-time data fusion and deep pattern recognition, which minimizes delays in reporting critical cases and enhances the accuracy of diagnoses. This makes DL particularly valuable in high-stakes contexts such as intensive care units, where rapid and precise decision-making can save lives. Moreover, DL-based approaches are instrumental in monitoring coma patients and other critical cases by integrating information from multiple sources, such as IoT-enabled medical devices, General Smart Monitoring (GSM) systems, and SHM modules [18]– [20]. In summary, while ML provides efficiency and interpretability in structured data environments, DL expands the scope of AI in healthcare by uncovering hidden relationships in massive and complex datasets. The combination of both approaches within SHM frameworks ensures a balanced solution: ML contributes to scalable and resource-efficient applications, whereas DL enhances diagnostic depth, predictive power, and adaptability in dynamic clinical settings. Together, they form the backbone of intelligent health monitoring systems, ultimately advancing preventive care, patient safety, and overall healthcare quality. Table I outlines a comparison of ML and DL in smart healthcare monitoring systems.

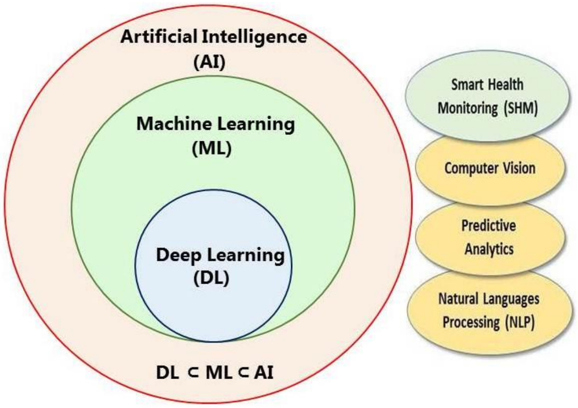

Fig. 3. Relation of DL and ML and AI in SHM

TABLE I.
COMPARISON OF ML VS DL IN SHM

Aspect	Machine Learning (ML)	Deep Learning (DL)
Data Requirements	Smaller, Structured Datasets	Large-Scale, Heterogeneous, And Unstructured Datasets
Feature Engineering	Manual Feature Engineering	Automatic Hierarchical Feature Extraction
Computational Needs	Lower Computational Cost	High Computational Demand (Gpus/Tpus Required)
Application In SHM	Disease Classification, Anomaly Detection, Risk Prediction	Real-Time Multimodal Data Fusion, Image/Signal Analysis, Coma Monitoring
Strengths	Efficient, Interpretable, Scalable for Structured Data	High Accuracy, Strong Predictive Power, Uncovers Hidden Patterns
Limitations	Limited Adaptability In Unstructured Data Environment	Resource-Intensive, Less Interpretable (Black-Box Models)

III. COMPONENTS OF SMART HEALTHCARE SYSTEM

The smart healthcare system is composed of several interrelated components as in Fig. 4, each playing a critical role in ensuring effective, reliable, and patient-centered medical services and summarized as follows [21][22]:

1. **Data Acquisition:** Smart biosensors and IoT-enabled medical devices form the foundation of data collection in modern healthcare systems. These include wearable sensors, implantable devices, and electronic health records (EHR), which together enable the continuous monitoring of vital parameters. By capturing real-time physiological signals and clinical data, these

technologies provide the basis for precision medicine and individualized treatment strategies tailored to each patient's condition.

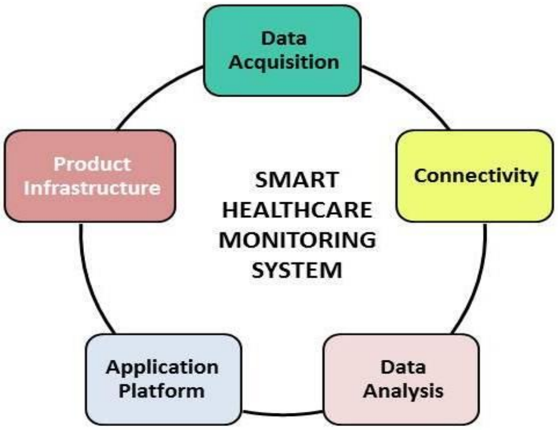

Fig. 4. Components of Smart Healthcare Systems

2. **Connectivity**: Reliable connectivity is essential for enabling seamless communication between medical devices and healthcare platforms. This involves the use of Wi-Fi, Bluetooth, ZigBee, and advanced 4G/5G networks, in addition to cloud-based platforms. Such connectivity ensures that data collected from patients can be securely transmitted, stored, and accessed by healthcare providers without delays, thereby facilitating remote monitoring and timely interventions.
3. **Data Analysis**: The massive volume of health-related data generated through biosensors and wearable technologies requires advanced analytics for meaningful interpretation. Data analysis leverages machine learning and artificial intelligence models to identify trends, detect anomalies, and support evidence-based medical decisions. In addition to physical health monitoring, these analytical approaches are increasingly applied in mental health management, offering insights into behavioral patterns and enabling early intervention for psychological disorders.
4. **Application Platform**: Application platforms serve as the user-facing interface of smart healthcare systems. Examples include telemedicine integrations, mobile health applications, and automated alert systems that notify patients and providers of abnormal readings. These platforms translate complex datasets into accessible and actionable information, enhancing the patient experience while supporting clinicians in delivering more informed and timely care.
5. **Product Infrastructure**: At the backbone of smart healthcare lies a robust product infrastructure powered by cloud computing technologies. This infrastructure provides scalable resources for data storage, processing, and secure sharing across distributed environments. By integrating servers, databases, networking tools, and intelligent software, cloud-based infrastructures enable flexible, cost-effective, and innovative solutions that accelerate healthcare delivery and support the continuous evolution of medical services.

IV. CHALLENGES AND SOLUTIONS

The integration of smart healthcare systems with the IoT and DL presents a transformative opportunity to revolutionize patient care, medical monitoring, and healthcare service delivery. Despite these promising prospects, several challenges hinder the effective implementation of such systems. Addressing these challenges requires both technological and organizational strategies that ensure security, scalability, and reliability of healthcare applications. All these challenges and their solutions are discussed herein [23]– [28].

One of the most critical concerns is **data privacy and security**. IoT-enabled healthcare devices continuously generate vast volumes of sensitive patient information, raising the risk of cyberattacks, data breaches, and unauthorized access. To mitigate these risks, multiple solutions have been proposed. These include **end-to-end encryption** to safeguard data transmission between IoT devices and cloud servers, **multi-factor authentication** mechanisms to strengthen user verification, and the use of **blockchain technology** to establish decentralized and tamper-proof data storage systems. Furthermore, **data anonymization** techniques play a crucial role in protecting patient identities in case of potential breaches.

Another major challenge lies in **system interoperability**. The healthcare ecosystem often includes diverse devices, applications, and platforms that may not seamlessly integrate with one another. To address this, the adoption of **standardized communication protocols** such as HL7 and FHIR has been emphasized. Additionally, the deployment of **middleware solutions and APIs** can bridge compatibility gaps between devices and healthcare applications, while **cloud-based platforms** enable scalable integration and facilitate secure data sharing across heterogeneous systems.

The issue of **data quality and quantity** also significantly impacts the performance of deep learning models. While IoT devices produce massive datasets, these are often noisy, incomplete, or inconsistent. To ensure reliable outcomes, healthcare systems must adopt **data preprocessing** techniques such as cleaning, normalization, and imputation. Moreover, **data fusion** methods that integrate information from multiple devices and sensors can enhance the comprehensiveness of datasets, while **outlier detection** algorithms filter out anomalies and reduce noise in the data pipeline.

A further limitation arises from **scalability and resource constraints**. Many IoT devices have restricted processing power, limited memory, and short battery life, making the deployment of complex DL models impractical. To overcome this, researchers and developers have explored **edge computing**, where data is processed locally on devices or nearby servers to reduce latency and server load. Additionally, **lightweight DL models** optimized through pruning and quantization can function effectively on constrained hardware. The development of **energy-efficient IoT devices** further ensures sustainable, continuous patient monitoring.

Real-time decision-making presents yet another challenge, as healthcare often demands immediate responses to anomalies in patient data. DL models, however, require significant computational resources, which may introduce delays. Solutions include the implementation of **real-time data processing** frameworks such as Apache Kafka and Apache Flink, coupled with **low-latency neural network models** designed for speed, such as lightweight CNNs and LSTMs. **Hybrid architectures** that combine local edge computing with cloud-based analytics are also emerging as effective solutions to balance speed with computational capacity.

In addition, the use of AI and DL in healthcare raises significant **ethical and regulatory concerns**. Ensuring **transparency in model decision-making**, **compliance with legal frameworks** such as HIPAA and GDPR, and incorporating **human-in-the-loop systems** where healthcare professionals validate AI-generated recommendations are crucial steps to maintain trust, safety, and accountability in AI-assisted healthcare.

Finally, **cost and infrastructure** constraints remain a barrier, particularly for smaller healthcare providers and resource-limited regions. Establishing IoT networks, integrating DL models, and maintaining cloud infrastructure can be financially demanding. To mitigate costs, the adoption of **cloud-based solutions** (AWS, Azure, Google Cloud), the use of **open-source software** platforms like TensorFlow and PyTorch, and the promotion of **public-private partnerships** are recommended. Such approaches can lower financial burdens while fostering innovation and wider accessibility.

In summary, while IoT and DL hold immense promise for smart healthcare, overcoming the challenges of security, interoperability, data quality, scalability, real-time processing, ethics, and cost is imperative. With strategic solutions, these technologies can pave the way for more effective, efficient, and patient-centered healthcare systems.

V. DATA SECURITY IN HEALTHCARE MONITORING SYSTEM

The integration of Smart Health Monitoring (SHM) networks and the Internet of Medical Things (IoMT) has ushered in a new era of connected and intelligent healthcare systems. These systems generate vast quantities of heterogeneous data, including physiological signals, diagnostic records, imaging outputs, and behavioral indicators. Such information is often classified as big health data, owing to its volume, variety, and velocity. Managing these complex datasets requires substantial computational resources, scalable architectures, and efficient storage mechanisms. To meet these demands, cloud computing and cloud storage solutions have become indispensable, offering healthcare providers on-demand processing capabilities, virtually unlimited storage, and high availability for mission-critical applications [7]. By leveraging these platforms, healthcare organizations can effectively analyze and store patient records while ensuring accessibility across distributed environments. However, while cloud-based infrastructures provide scalability and efficiency, they also introduce significant challenges regarding data security and patient privacy. Health data is highly personal and directly tied to patient identity, meaning that even a minor breach can have devastating consequences for individuals and institutions alike. Unauthorized access, intentional misuse, or exploitation of sensitive health information for financial or personal gain pose substantial threats. As a result, safeguarding patient data is considered a central challenge in SHM and IoMT-driven healthcare environments [29]– [32]. In Fig. 5, for example during COVID-19 pandemic, fog-based healthcare IoT proved vital and is expected to grow, but patient data analysis at fog servers still poses privacy and security risk. An overview of fog-based IoHT framework is demonstrated in Fig. 6.

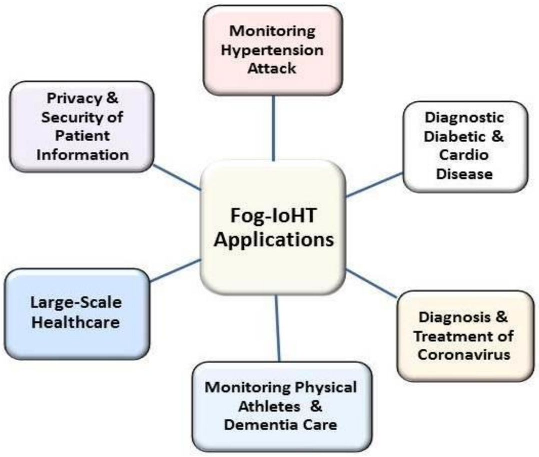

Fig. 5 The Main Applications of Fog-IoHT

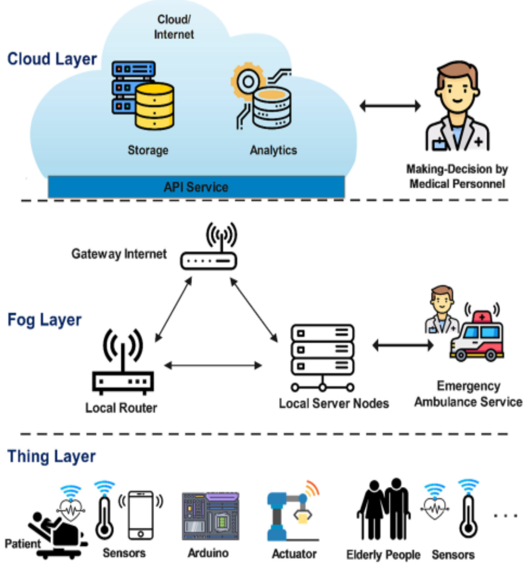

Fig. 6 An Overview of Fog-IoHT Framework [32]

Data security in healthcare is a multidimensional concept, encompassing technical, organizational, and regulatory layers. On the technical side, it includes measures such as physical system security, user authentication, network-level protection, computer system defense, and secure data storage. Several methods are already in practice, including cryptography, data encryption, genetic algorithms, and encoding/decoding techniques that aim to ensure data confidentiality, integrity, and availability. For example, end-to-end encryption protects data as it travels from IoT devices to cloud servers, while multi-factor authentication prevents unauthorized logins by adding additional layers of verification. Similarly, data anonymization techniques can mask sensitive attributes, thereby reducing the risk associated with data leaks. Despite these advancements, many existing privacy frameworks still rely heavily on third-party service providers, which introduces concerns around trust and accountability. Healthcare institutions must ensure that service providers comply with strict regulations and do not misuse or mishandle sensitive patient data. This reliance highlights the ongoing need for more decentralized, transparent, and verifiable solutions. In response, recent years have witnessed the emergence of blockchain technology and the Interplanetary File System (IPFS) as disruptive tools for secure data exchange. Blockchain operates as a distributed ledger system, where health records are stored in sequential blocks that are cryptographically linked to one another. Each block contains a validated set of transactions, and any new block integrates the full transaction history, ensuring immutability and transparency. Because of its decentralized nature, blockchain significantly reduces the risk of single points of failure, tampering, and unauthorized modification. Meanwhile, IPFS offers a peer-to-peer network for distributed data storage and sharing, reducing reliance on centralized servers and providing enhanced resilience. These technologies, initially deployed in finance and banking, are increasingly recognized for their potential in healthcare to secure sensitive medical data, improve patient trust, and enable secure interoperability across institutions [33]– [36]. In short, while SHM and IoMT devices offer unprecedented opportunities for precision medicine, real-time monitoring, and predictive healthcare, these advancements are only viable if matched with equally advanced security frameworks. By addressing the challenges of privacy, interoperability, and trust, healthcare providers can ensure that smart healthcare systems remain both innovative and ethically sound, ultimately safeguarding patient rights while unlocking the full potential of digital health.

VI. LITERATURE REVIEW

A. Disease Risk Prediction and Early Diagnostics

Recent advancements in AI and IoMT have significantly contributed to disease risk prediction. For example, the authors in [37] employed a Bi-LSTM model for predicting heart disease risks, benchmarking its performance against generic LSTM and fuzzy–LSTM hybrid approaches. A complementary study [38] proposed a MapReduce framework for elderly healthcare monitoring, where the Hybrid Dingo Coyote Optimization (HDCO) classifier was used to improve predictive accuracy. Additional diagnostic applications include [39], which developed a solution for Activities of Daily Living (ADL) monitoring through multimodal sensor data analysis for self-care planning in adult day centers. Similarly, [40] applied CNNs within an IoT framework for breast cancer diagnosis, and [41] advanced cardiovascular care by integrating wearable and home-monitoring data into AI-based analytical systems. Broader investigations were reported in [42], which covered AI-driven disease prediction across oncology, cardiology, endocrinology, and neurology, while [43] explored AI's utility for prognosis, precision treatments, and automated diagnostics.

B. AI in Healthcare Delivery, Patient Engagement, and Preventive Care

Beyond diagnostics, AI research has expanded into healthcare delivery and patient-centered applications. For example, [44] provided a systematic review of AI's transformative role and ethical implications, and [45] discussed its applications in personalized medicine, drug discovery, and surgical interventions. Remote patient monitoring (RPM) and virtual healthcare assistants (VHA) were examined in [46] through qualitative assessments of real-world implementations. Radiology has also seen rapid adoption: [47] highlighted deep learning breakthroughs for medical imaging, while [48] applied AI for analyzing health plan satisfaction and utilization. Nursing applications were investigated in [49], which performed a concept analysis of deep learning using Walker and Avant's framework. In preventive care, [50] discussed opportunities and risks of AI adoption, whereas [51] introduced a precision health service combining wearables with ML and DL for chronic disease prevention. More specialized applications include facemask detection systems using VGGx [52], forecasting tools for healthcare resource planning [53], and conceptual frameworks for Cloud-IoT adoption in healthcare [54].

C. Algorithms and Technical Innovations

Various machine learning and deep learning algorithms have been deployed to address healthcare challenges. For example, [55] utilized deep neural networks for diagnosing shoulder diseases with IMU sensor data, while [56] applied LSTMs and CNNs for arrhythmia detection, achieving rapid diagnostics despite dataset limitations. Meanwhile, [57] explored ML methods applied to electronic health records (EHRs) for cyber-threat detection, which demonstrated promise but required high-quality datasets and significant computational power. Such innovations reflect the algorithmic diversity underpinning modern healthcare applications and underscore the balance between technical effectiveness and practical feasibility.

D. Practical Case Studies and Emerging Applications

Case studies demonstrate how AI is being integrated into practical healthcare solutions. For instance, [58] applied SVM for real-time sensor-based patient monitoring.

Innovative models include the Tomatoes Health Check System using YOLOv8 and MobileNetV3 [59], and a DNN-based heart disease prediction model implemented with NI myRIO hardware [60]. Cancer detection has been advanced by CNNs trained on the PatchCamelyon dataset [61], while hybrid LSTM–CNN models have been applied in HIoT environments [62]. Other emerging uses include real-time mask detection [63], lung cancer classification using transfer learning CNNs on CT scans [64], Optimized CNN for Skin Cancer Classification [65], Alzheimer’s diagnosis from MRI via CNNs [66], Smart Monitoring System for Brain Tumors using IoT [67], AI-Powered Breast Cancer Diagnosis [68], diabetes diagnosis using K-Nearest-Neighbor-Based-OneR (KNNB1R) [69], AI-ECG Risk Estimation (Aire) for Heart Disease Prediction [70], ECG monitoring through wireless module and LabVIEW modules [71], and IoT-based Remote Cardiovascular Patient Monitoring [72], monitoring the cognitive changes for Alzheimer Disease (AD) and Dementia [73][74]. Collectively, these case studies highlight the growing role of AI, ML, and DL in enabling smarter, faster, and more reliable healthcare solutions.

In summary, taken together, these contributions demonstrate the wide-ranging applications of AI, ML, and DL in healthcare, spanning disease prediction, diagnostics, patient engagement, monitoring, and cybersecurity. However, persistent challenges—such as data privacy, interoperability, dataset quality, and ethical considerations—remain critical, calling for sustained innovation, robust evaluation, and regulatory oversight in the development of future smart healthcare systems.

VII. CONCLUSION

This review has highlighted the Smart Health Monitoring (SHM) systems as a transformative advancement in healthcare, highlighting their ability to overcome the limitations of traditional monitoring approaches. Conventional systems often suffer from delayed responses, medication latency, and insufficient preventive measures, which can adversely affect patient outcomes, particularly in critical cases. SHM addresses these challenges by leveraging intelligent sensing, real-time data acquisition, and advanced analytics, enabling continuous, proactive monitoring and early detection of anomalies for timely interventions and optimized treatment planning.

A key strength of SHM lies in its integration with **cloud computing**, which provides the computational power and scalable storage necessary to manage large volumes of heterogeneous health data from wearable devices, IoMT sensors, and electronic health records. This facilitates real-time analytics, remote accessibility, and seamless interoperability among healthcare stakeholders, enhancing collaboration and reducing the burden on local systems. Additionally, the incorporation of **blockchain technology** ensures data security, transparency, and immutability, fostering trust among both healthcare providers and patients.

SHM systems have demonstrated substantial benefits in critical care, supporting intensive monitoring and rapid clinical decision-making through predictive models and smart alert systems. Beyond acute care, SHM enables **personalized healthcare**, allowing individuals to track health metrics, set wellness goals, and adopt healthier lifestyles guided by real-time feedback and tailored recommendations. Despite these advances, the adoption of SHM outside clinical settings—such as in sports science, occupational health, and general wellness—remains limited. Despite these advances, the adoption of SHM outside clinical settings—such as in sports science, occupational health, and general wellness—remains limited. Future research should focus on expanding SHM into these domains, leveraging emerging technologies such as **5G, AI-driven predictive analytics, and energy-efficient IoT devices**. Such expansion could democratize access to personalized healthcare, reduce costs, and improve population-level health outcomes. In conclusion, SHM stands at the forefront of healthcare innovation, bridging preventive care, acute intervention, and personalized wellness. Its integration with cloud and blockchain technologies not only enhances technical performance but also reinforces ethical responsibility, laying the groundwork for the next generation of smart, secure, and patient-centered healthcare systems.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

REFERENCES

[1] M. Dharavath, "Transforming Healthcare Through Data Engineering, Predictive Analytics, and AI Models", *International Journal of Research in Computer Applications and Information Technology (IJRCAIT)*, vol. 7, no. 2, p.p. 1710-1718 2024, doi:10.5281/zenodo.14265469

[2] R. Kumar and J. Manikandan, " Fortifying Medical IoT Systems: A Comprehensive Analysis of Advanced AI Techniques for Network Security", *9th Proceedings of the International Conference on Innovative Computing & Communication (ICICC 2024)*, 2024. http://dx.doi.org/10.2139/ssrn.4999651

[3] E. Zeydan, S. Arslan, and M. Liyanage, "Managing Distributed Machine Learning Lifecycle for Healthcare Data in the Cloud." *IEEE Access*, vol. 12, p.p. 115750-115774, 2024, doi:10.1109/ACCESS.2024.3443520

[4] S. Maleki Varnosfaderani and M. Forouzanfar, "The Role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st Century", *Bioengineering (Basel)*, vol. 11, no. 4, p. 337, Mar. 2024, doi: 10.3390/bioengineering11040337

[5] A. Singh, R. Saxena, S. Saxena and N. Maurya, "Artificial Intelligence Revolution in Healthcare: Transforming Diagnosis, Treatment, and Patient Care" *Asian Journal of Advances in Research,* vol. 7, no. 1, Page 241-263, 2024.

[6] N. S. Jozi and G. A. Al-Suhail, "Lung Cancer Detection in Radiological Imaging using Deep Learning: A

Review", *2024 5th International Conference on Communications, Information, Electronic and Energy Systems (CIEES)*, Veliko Tarnovo, Bulgaria, pp. 1-8, 2024. doi: 10.1109/CIEES62939.2024.10811230.

[7] M. Alsabah, M. A. Naser, A. S. Albahri *et al*., "A comprehensive review on key technologies toward smart healthcare systems based IoT: technical aspects, challenges and future directions", *Artificial Intelligence Review*, vol. 58, no. 343, 2025, doi: 10.1007/s10462-025-11342-3.

[8] S. Wangpitipanit, J. Lininger and N. Anderson, "Exploring the deep learning of artificial intelligence in nursing: a concept analysis with Walker and Avant's approach", *Wangpitipanit et al. BMC Nursing*, vol. 23, no. 529, p.p.1-10, 2024. https://doi.org/10.1186/s12912-024-02170-x

[9] M. Ali, U. Ali, S. Ali and H. Tanveer, "Transforming cardiac care: AI and machine learning innovations", *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 5, no. 4, pp. 379-384, 2024.

[10] Sh. Fatima, "Transforming Healthcare with AI and Machine Learning: Revolutionizing Patient Care Through Advanced Analytics", *International Journal of Education and Science Research Review*, vol. 11, no. 6, 2024.

[11] J. Anderson, "Smart Healthcare Systems for Cancer Patients: Remote Monitoring and Management", Revista *De Inteligencia Artificial En Medicina*, vol. 1, no. 15, 2024.

[12] V. Oliveira, A. Reis and J. Filho, "Assessing the Evolution of Structural Health Monitoring through Smart Sensor Integration", *7th International Conference on Smart Monitoring Assessment and Rehabilitation Conference on Smart Monitoring*,2024.

[13] A. Sadoon, Gh. Naymat and O. Jerew, "An architectural framework of elderly healthcare monitoring and tracking through wearable sensor technologies", *Multimedia Tools and Applications*, vol.83, p.p. 67825-67870, 2024, https://doi.org/10.1007/s11042-024-18177-0

[14] X. Zhou, C. Leung, K. Wang and G. Fortino, "Deep Learning-Empowered Big Data Analytics in Biomedical Applications and Digital Healthcare", *IEEE/ACM transactions on computational biology and bioinformatics*, vol. 21, no. 4, 2024, doi: 10.1109/TCBB.2024.3371808

[15] T. Shukla, "Beyond Diagnosis: AI's Role in Preventive Healthcare and Early Detection", *ICONIC research and engineering journals*, vol. 8, no.5, 2024.

[16] P. Gupta, M. Pandey, "Role of AI for Smart Health Diagnosis and Treatment", *Smart Medical Imaging for Diagnosis and Treatment Planning*, p.p.23-45, 2024. doi: 10.1201/9781003464884-4

[17] M. Aljumaily and S. Abdullah, "An AI-Driven Framework for Adaptive eSystems in Harsh Environments: A Case Study from Oilfield IoT Applications", *in International Journal of Mechatronics, Robotics, and Artificial Intelligence (IJMRAI)*, vol. 1, issue 1, pp. 1-7, June 2025, https://doi.org/10.33971/ijmrai.1.1.1

[18] S. Thangam, M. Gurupriya, A. Adithya Vardhan, Maganti Akshita Uma Sai and Y. Kumar, "Smart health monitoring system using IoT and machine learning" *Challenges in Information, Communication and Computing Technology*, pp. 518-523, 2025, doi: 10.1201/9781003559085-90

[19] S. Algethami and S. Alshamrani, "A Deep Learning-Based Framework for Strengthening Cybersecurity in Internet of Health Things (IoHT) Environments", *Appl. Sci*., vol. 14, no. 11, 2024, https://doi.org/10.3390/app14114729

[20] J. Kongsen, D. Chantaradsuwan, P. Koad, M. Thu, and C. Jandaeng, "A Secure Blockchain-Enabled Remote Healthcare Monitoring System for Home Isolation", *Journal of Sensor and Actuator Networks*, vol. 13,2024, https://doi.org/10.3390/jsan13010013

[21] P. Dutta, B. Singh, S. Lal, M. Arora, A. Raghav, G. Mensah and H. Alkattan, "Encoding IoT for Patient Monitoring and Smart Healthcare: Connected Healthcare System Fostering Health 6.0", *Babylonian Journal of Internet of Things*, vol.2023, p.p. 48–58, 2024, https://doi.org/10.58496/BJIoT/2023/007

[22] S. Alowais, S. Alghamdi, N. Alsuhebany, T. Alqahtani, A. Alshaya, S. Almohareb, A. Aldairem, M. Alrashed, K. Saleh, H. Badreldin, M. Al Yami, S. Al Harbi, and A. Albekairy, "Revolutionizing healthcare: The role of artificial intelligence in clinical practice," *BMC Med. Educ.*, vol. 23, no. 689, 2023, [Online]. Available: https://doi.org/10.1186/s12909-023-04698-z

[23] M. Nasr, M. Islam, SH. Shehata, F. Karry and Y. Quintana, "Smart Healthcare in the Age of AI: Recent Advances, Challenges, and Future Prospects", *Digital Object Identifier*, *IEEE Access*, vol.9, p.p. 145248 -145270, 2021. doi: 0.1109/ACCESS.2021.3118960

[24] X. Gao, P. He, Y. Zhou and X. Qin, "Artificial Intelligence Applications in Smart Healthcare: A Survey", *Future Internet*, vol. 16, no.9, 2024. https://doi.org/10.3390/fi16090308

[25] S. Agnihotri, V. V. Bhujade, A. Saravanan, K. Shankar, and G. Manogaran, "A comprehensive review on key technologies toward smart healthcare systems based IoT: technical aspects, challenges and future directions", *Artificial Intelligence Review*, vol. 58, pp. 1–46, Jan. 2025, doi: 10.1007/s10462-025-11342-3

[26] H. Ziwei, Z. Dongni, Z. Man, D. Yixin, Z. huanghui, Y. Chao and C. Chunfeng, "The applications of internet of things in smart healthcare sectors: a bibliometric and deep study", *Heliyon*, vol. 10,no. 3 , 2024. https://doi.org/10.1016/j.heliyon.2024.e25392

[27] R. Almsie'deen "Smart and Sustainable Cities: The Case of Amman, Jordan", *International Journal of Mechatronics, Robotics, and Artificial Intelligence* vol.1, no.1, p.p.45-35, 2025. doi: 10.37917/ijmrai.00.0.0

[28] N. Hamza, "An IoT Healthcare System with Deep Learning Functionality for Patient Monitoring", *International Journal of Communication Systems*, vol. 38, no. 3,2025. https://doi.org/10.1002/dac.6020

[29] Y.Raghav, S. Choudhary, Sarita, P. Pandey, S. Singh and D.Varshney, "Smart Healthcare: Cloud-IoT

Solutions for Enhanced Patient Well-Being, " *African Journal of Biomedical Research*, vol. 28, no.1 ,2025. https://doi.org/10.53555/AJBR.v28i1.4960

[30] R. Zaheer, M. Arif and A. Bibi, "Data Security Challenges in Healthcare System", Qlantic Journal of Social Sciences, vol. 1, no. 1, 2020, doi: 10.55737/qjss.883465001

[31] A.Sujitha, G. SekharSajjab, V.Mahalakshmic, S. Nuhmanid, B.Prasanalakshmie, " Systematic review of smart health monitoring using deep learning and Artificial intelligence", *Neuroscience Informatics 2*, vol. 2, no. 3, 2022, https://doi.org/10.3390/engproc2024070054

[32] V. K. Quy, N. V. Hau, D. V. Anh, *et al.*, "Smart healthcare IoT applications based on fog computing: architecture, applications and challenges", *Complex Intell. Syst.*, vol. 8, pp. 3805–3815, 2022, doi: 10.1007/s40747-021-00582-9

[33] G. R. Pradyumna, R. Hegde, K. B. Bommegowda, T.Jan and G.Naik, "Empowering Healthcare With IoMT: Evolution, Machine Learning Integration, Security, and Interoperability Challenges", *IEEE Acsess*,2024. doi**:** 10.1109/ACCESS.2024.3362239

[34] S. Adibi, A. Rajabifard, D. Shojaei, N. Wickramasinghe, "Enhancing Healthcare through Sensor-Enabled Digital Twins in Smart Environments: A Comprehensive Analysis", *Sensors* vol. 24, 2024. https://doi.org/10.3390/s24092793

[35] A. Ahmad, A. Husnain, A. Shiwlani, A.Hussain , Mahnoor N. Gondal 4 and Ayesha Saeed, " Ethical and clinical implications of AI integration in cardiovascular healthcare", *World Journal of Advanced Research and Reviews*, vol. 23, no.3, p.p.2479-2501, 2024. doi: 10.30574/wjarr.2024.23.3.2907

[36] A. Almalawi, A.Khan, F.Alsolami , Y.Abushark and A.Alfakeeh, " Managing Security of Healthcare Data for a Modern Healthcare System", *Sensors (Basel)*, vol. 23, no. 7, 2023. https://doi.org/10.3390/s23073612

[37] A. Nancy, D. Ravindran, R. Vincent, P.Srinivasan, D, Reina, "IoT-Cloud-Based Smart Healthcare Monitoring System for Heart Disease Prediction via Deep Learning", *Electronics* vol. 11, 2022. https://doi.org/10.3390/electronics11152292

[38] U. U. Maida, S. Mian, and A. Hmari, "Big Data-Based Smart Health Monitoring System: Using Deep Ensemble Learning", *IEEE Access*, vol. 11, pp. 114880–114903, 2023. doi: 10.1109/ACCESS.2023.3325323

[39] D. Ma, M. Jin, Z. Zhou, J. Wu and Y. Liu, "Deep Learning-Based ADL Assessment and Personalized Care Planning Optimization in Adult Day Health Center", *Applied and Computational Engineering*, vol. 118, no. 1, p.p. 14-22, 2024. doi: 10.54254/2755-2721/2025.18474

[40] A. Khameesa, M. Altaay, "Evaluating the Efficiency of Finance Methods in Residential Complex Projects in Iraq. Engineering", *Technology & Applied Science Research*. vol.12, no. 1, p.p.8080–8084, (Feb. 2022). https://doi.org/10.48084/etasr.4663

[41] A. Khan, H. Zainab, R. Khan, and K. Hafiz, "Implications of AI on Cardiovascular Patients' Routine Monitoring and Telemedicine", *Jurnal Multidisiplin Ilmu*, vol. 3, no. 05, 2024, https://doi.org/10.47709/ijmdsa.v3i4.4956

[42] S. S. Dhanda, "Advancement in public health through machine learning", *Journal of Big Data*, 2025, doi:10.1186/s40537-025-01201-x.

[43] A. Daemi, S. Kalami, R.Tahiraga, O. Ghanbarpour, M. Barghani, M. Hooshiar, G. Özbolat and Z. Yönden, "Revolutionizing personalized medicine using artificial intelligence: a meta-analysis of predictive diagnostics and their impacts on drug development", *Clinical and Experimental Medicine*, vol. 25, no. 255, 2025, doi: 10.1007/s10238-025-01723-x.

[44] K. Brahmaji, "Integrating AI-Driven Healthcare Solutions: Bridging Technical Advancement and Ethical Governance in Modern Medicine", *International Journal of Research in Computer Applications and Information Technology*, vol. 7, no. 2,2024. https://doi.org/10.5281/zenodo.14050118

[45] S. Zeb, N. FNU, N. Abbasi, M. Fahad, "AI in Healthcare: Revolutionizing Diagnosis and Therapy", *International Journal of Multidisciplinary Sciences and Arts*, vol. 3, no. 3,2024. https://doi.org/10.47709/ijmdsa.v3i3.4546

[46] P. Mengkorn, B. Genesis and P. Jasmine, "AI-Powered Remote Patient Monitoring and Virtual Healthcare Assistants, "2024.

[47] H. Laçi, K. Sevrani, and S. Iqbal, "Deep learning approaches for classification tasks in medical X-ray, MRI, and ultrasound images: a scoping review", *BMC Medical Imaging*, vol. 25, no. 17, pp. 1–18, Jan. 2025. doi: 10.1186/s12880-025-01701-5

[48] R. Danda, A. Nishanth, Z. Yasmeen, K. Kumar, " AI and Deep Learning Techniques for Health Plan Satisfaction Analysis and Utilization Patterns in Group Policies", *International Journal of Medical Toxicology & Legal Medicine,* vol. 27, no. 2, 2024.

[49] S. Wangpitipanit, J. Lininger, and N. Anderson, " Exploring the deep learning of artificial intelligence in nursing: a concept analysis with Walker and Avant's approach", *BMC Nursing*,vol. 23, no. 1,2024. https://doi.org/10.1186/s12912-024-02170-x

[50] K. Zareinia, "Beyond The Diagnosis:The Transformative Role of AI in Proactive Healthcare",2024.

[51] A. Husnain, H.Khawar and Y. Hayat, " A Precision Health Initiative for Chronic Conditions: Design and Cohort Study Utilizing Wearable Technology, Machine Learning, and Deep Learning", *International Journal of Advanced Engineering Technologies and Innovations* vol. 1, no. 2, 2024.

[52] H. A. Alahmad and G. A. Al-Suhail, "Medical image classification using deep learning for brain tumors detection: An overview", *Intelligent Computing and Optimization (ICO 2023), Lecture Notes in Networks and Systems*, vol. 1169, P. Vasant et al., Eds. Cham, Switzerland: Springer, 2024, doi: 10.1007/978-3-031-73324-6_20

[53] P. Honey, S. Prabha, "Smart Health Monitoring System using IOT and Machine Learning Techniques", *6th International Conference on Bio Signals, Images, and Instrumentation (ICBSII)*, 2020, doi: 10.1109/ICBSII49132.2020.9167660

[54] Y. Raghav, S. Choudhary, Sarita, P. Pandey, S. Singh and D. Varshney, "Smart Healthcare: Cloud-IoT Solutions for Enhanced Patient Well-Being", *Afr. J. Biomed. Res*. vol. 28, 2025, https://doi.org/10.53555/AJBR.v28i1.4960

[55] K. Lee, J. Kim, H. Hong, Y. Jeong, H. Ryu, H. Kim, and S. Lee, " Deep learning model for classifying shoulder pain rehabilitation exercises using IMU sensor", Journal of Neuro Engineering and Rehabilitation, vol. 21, no. 1, 2024, https://doi.org/10.1186/s12984-024-01343-8

[56] A. Khan, H. Zainab, R. Khan, H. Hussain, "Deep Learning in the Diagnosis and Management of Arrhythmias ", *Journal of social Research*, vol. 4, no. 1, 2024. https://doi.org/10.55324/josr.v4i1.2362

[57] S. Arefin, "Strengthening Healthcare Data Security with Ai-Powered Threat Detection", *International Journal of Scientific Research and Management*, (IJSRM), vol. 12, no. 10, 2024, doi:10.18535/ijsrm/v12i10.ec02

[58] M. Khan, Z. Rahman, S. Chowdhury, Tanvirahmedshuvo, M. Ontor, M. Hossen, N. Khan, and H. Rahman, "Real-Time Health Monitoring with IoT", *International Journal for Multidisciplinary Research (IJFMR)*, vol. 6, no. 1,2024. doi: 10.36948/ijfmr. 2024.v06i01.22751

[59] L. Ouach K. Quoc, A. Quynh, H. Ngoc and N. Nghe, "Tomato Health Monitoring System: Tomato Classification, Detection, and Counting System Based on YOLOv8 Model with Explainable MobileNet Models Using Grad-CAM++", *IEEE Access*, vol. 12, 2024. doi: 10.1109/ACCESS.2024.3351805

[60] M. Hameurlaine, A.Moussaoui and M. Bensalah, " Real-Time Smart Healthcare System Based on Edge-Internet of Things and Deep Neural Networks for Heart Disease Prediction", *Informatica* vol. 49, no. 1, 2025. https://doi.org/10.31449/inf.v49i1.6875

[61] A. Naz, H. Khan, I. U. Din, A. Ali, and M. Husain, "An Efficient Optimization System for Early Breast Cancer Diagnosis Based on Internet of Medical Things and Deep Learning", *Eng. Technol. Appl. Sci. Res.*, vol. 14, no. 4, pp. 11728–11734, 2024, doi: 10.48084/etasr.8080.

[62] S. Sivalingam, S. Thisin, "A new framework to enhance healthcare monitoring using patient-centric predictive analysis", *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 14, no. 3, pp. 3295-3302, 2024. doi: 10.11591/ijece.v14i3.pp3295-3302

[63] H. Ahmed, A. Abood, A. Abed and A. Gallod, "Enhancing COVID-19 Safety: Automatic Mask Detection and Temperature Monitoring System using YOLOv5x and Mobile App Platform", *2024 IEEE 14th Symposium on Computer Applications & Industrial Electronics (ISCAIE), Penang, Malaysia*, pp. 466-471, 2024. doi: 10.1109/ISCAIE61308.2024.10576588

[64] N. S. Jozi and G. A. Al-Suhail, "Lung Cancer Detection: The Role of Transfer Learning in Medical Imaging," *2024 International Conference on Future Telecommunications and Artificial Intelligence (IC-FTAI)*, Alexandria, Egypt, 2024, pp. 1-6, doi: 10.1109/IC-FTAI62324.2024.10950018.

[65] P. Das, S. Roy, and A. Chakraborty, "Optimized CNN Models for Skin Cancer Classification with Explainable AI", *PLoS ONE*, 2025. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0317181

[66] H. Alahmed., G. Al-Suhail, " AlzONet: a deep learning optimized framework for multiclass Alzheimer's disease diagnosis using MRI brain imaging", *J Supercomput 81*, 423, 2025, https://doi.org/10.1007/s11227-025-06924-5.

[67] X. Zhang, Y. Liu, and L. Wang, "IoT-Based Real-Time Brain Tumor Detection and Classification Using Deep Learning", *Sci. Rep*., 2025. [Online]. Available: https://www.nature.com/articles/s41598-025-95803-3

[68] H. Zhao, L. Chen, and Y. Wang, "Multimodal Imaging-Based Breast Cancer Prediction Using Deep Learning," *Sci. Rep.*, 2025. [Online]. Available: https://www.nature.com/articles/s41598-025-99535-2

[69] A. Khaleel, G. Al-Suhail, and B. Hussan, "A weighted voting of k-nearest neighbor algorithm for diabetes mellitus", *International Journal of Computer Science and Mobile Computing*, vol. 6, no. 1, pp. 43–51, 2017.

[70] M. Malini, M. Kaur, P. Moniya, and M. Sudagar, "Real-Time Health Monitoring System Using Deep Learning and IoT Integrated Electronics", *J. Neonatal Surg.*, vol. 14, no. 29S, pp. 759–767, May 2025. https://www.jneonatalsurg.com/index.php/jns/article/view/6866

[71] H. Ahmed and A. Ali, "Smart intensive care unit design based on wireless sensor network and internet of things," *2016 Al-Sadeq International Conference on Multidisciplinary in IT and Communication Science and Applications (AIC-MITCSA)*, Baghdad, Iraq, 2016, pp. 1-6, doi: 10.1109/AIC-MITCSA.2016.7759905.

[72] S. Nayab, S. Chohan, A. Jameel, S. Shah, S. Zaidi, A. Jha, K. Siddique, "Advancing Remote and Continuous Cardiovascular Patient Monitoring through a Novel and Resource-Efficient IoT-Driven Framework", *arXiv preprint arXiv:2505.03409*, 2025. [Online]. Available: https://arxiv.org/abs/2505.03409

[73] M. Shaik, F. Anik, M. Hasan, S. Chakravarty, M. Ramos, M. Rahman, S. Ahamed, N. Sakib, "Advancing remote monitoring for patients with Alzheimer disease and related dementias: Systematic review", *JMIR Aging*, vol. 8, p. e69175, 2025. doi: 10.2196/69175

[74] S. Salvi, L. Garg, and V. Gurupur, "Stage-wise IoT solutions for Alzheimer's disease: A systematic review of detection, monitoring, and assistive technologies", *Sensors*, vol. 25, no. 17, p. 5252, 2025, doi: 10.3390/s25175252