



## INTEGRATING MACHINE LEARNING, DEEP LEARNING, AND IOT IN RECENT HEALTHCARE

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### ABSTRACT

The combination of Machine Learning (ML), Deep Learning (DL), and the Internet of Things (IoT) in biomedical engineering is transforming healthcare by providing innovative solutions for diagnosis, treatment, and patient care. Recent high-tech medical devices capture real-time patient data, including vital signs and environmental conditions, which ML algorithms and DL algorithms evaluate to detect trends, forecast outcomes, and support clinical decision-making. This integration of algorithms, biomedical sensors, and processing platforms enhances the accuracy of patient diagnoses and doctors' decisions while reducing morbidity and mortality. However, this integration enables accurate prediction of results, early disease detection, proactive management of chronic conditions, and improved treatment procedures. The combination of these technologies into medical instruments, such as wearable health trackers, implantable sensors, and smart diagnostic implements, proposes encouraging opportunities for developing patient outcomes, decreasing healthcare costs, and addressing the cumulative request for healthcare facilities.

**KEYWORDS:** Machine Learning, Deep Learning, Internet of Things, Biomedical Engineering, Healthcare Solutions.

### 1. INTRODUCTION

The integration of Machine Learning (ML), Deep Learning (DL), and the Internet of Things (IoT) in biomedical engineering has the potential to transform healthcare by increasing efficiency, tailored care, and accessibility. Biomedical engineering has always been at the forefront of improving medical devices and technologies that help with diagnosis and treatment. This significant cooperation between these fields leads to rapid improvement and makes the data used in the healthcare field more useful. Healthcare providers can use this continuous data stream to make informed decisions and remotely monitor patients (Rai, Gupta et al. 2025).

ML, DL, and IoT have the power to transform the data of patients to an advanced level of technology. ML is an area of artificial intelligence (AI) that allows computers to learn from data without requiring explicit

programming. It entails algorithms that can increase performance over time as they are exposed to more data. In essence, it allows systems to automatically learn and adapt to new knowledge, boosting their capacity to make predictions, judgments, or execute other activities. However, DL is a subset of machine learning that uses multilayered neural networks, or deep neural networks, to imitate the complex decision-making power of the human brain. Most AI applications used today are powered by this new technology (Channa, Asmatullah et al. 2024).

The primary distinction between deep and machine learning is the structure of the underlying neural network architecture. Traditional ML models, known as "nondeep," employ simple neural networks with one or two processing layers. DL models normally train with three or more layers, but they might have hundreds or thousands of layers. DL algorithms are incredibly

complex, and there are different types of neural networks to address specific problems or datasets. Some problems might get great results using ML models, while others require more hidden layers in the implementation of the structure in the model to obtain better results (i.e., more accurate). One probable weakness across them all is that DL algorithms are frequently “black boxes,” making it challenging to recognize their inner workings and posing interpretability challenges. But this can be offset against the overall advantages of high accuracy and scalability (McCall 2025).

Moreover, IoT is a network of physical objects, automobiles, home appliances, and other items equipped with sensors, software, and network connectivity to gather, exchange, and analyze data. Essentially, it is the interconnected universe of “things” that can communicate and interact with one another and with the digital world. IoT devices, also known as “smart objects”, can vary from simple “smart home” gadgets like smart thermostats to large industrial machinery, transportation systems, and medical imaging devices like MRIs and CTs. Technologists even imagine entire “smart cities” based on IoT technologies (Ghazal, Hasan *et al.* 2021, Sharma, Haque *et al.* 2021).

IoT allows these smart devices to communicate with one another and with other internet-connected devices. Like smartphones and gateways, they comprise a huge network of interconnected devices capable of exchanging data and performing various functions autonomously. This may include wearable Glucose check instruments, monitoring environmental conditions on farms, managing traffic patterns with smart automobiles and other smart automotive technologies, controlling machinery and processes in factories, and monitoring inventories and shipments in warehouses.

ML and DL excel at processing massive amounts of data and identifying patterns that physicians may overlook. These algorithms can detect early indicators of disease, anticipate the start of medical disorders, and recommend individualized treatment plans based on a person's specific health profile. ML, DL, and IoT can create intelligent healthcare systems that accurately diagnose and anticipate medical disorders, provide tailored interventions, and improve patient outcomes.

## 2. Literature Review

ML, DL, and IoT are disruptive technologies in various areas. In the area of healthcare analytics, the ML and DL algorithms show promising results in disease prediction, medical imaging analysis, and personalized treatment recommendations. In finance, these technologies have been prevalent in credit scoring, fraud detection, and algorithmic trading. In smart cities, ML is widely used to predict traffic flows (Abadi, Rajabioun *et al.* 2014, Medina-Salgado, Sánchez-DelaCruz *et al.* 2022), optimize energy (Alabi, Aghimien *et al.* 2022, Samrose 2024), and analyze crime patterns (Sardana, Marwaha *et*

*al.* 2021, Alsoori 2024, Ganesan and Ravichandran 2024). ML can be used in agriculture for crop yield prediction, pest detection, and smart irrigation systems (Liakos, Busato *et al.* 2018, Benos, Tagarakis *et al.* 2021, Meshram, Patil *et al.* 2021)

Recent technological advancements have resulted in the successful integration of ML, DL, and IoT in a variety of sectors. While IoT is involved in data aggregation and resource management, ML and DL handle data analysis, data expansion, learning, and decision-making based on input data. The combination of these technologies can be of considerable benefit in the clinical sector in creating a receptive and interconnected environment, consequently delivering numerous services to healthcare staff and patients. The foundation of IoT devices is the creation of intelligent applications for medical usability, such as wearable modules, smart capsules, and sensory-based units that help medical professionals collect data. ML and DL-based models are used to assess and identify several changes in a patient's health state, recommend alternative diagnosis techniques, and enhance the patient's overall health.

Research is an important and exciting field for intelligent computerized systems and medical applications. A general practitioner usually gains insight from a patient's history and confirms the diagnosis based on the symptoms. As a result, a doctor's experience is essential for accurate diagnosis and for determining the significance of symptoms to certain diseases. Given the quick advancements in medicine and treatment for that specific cause, such as the emergence of new diseases. With medication availability, it has become both exciting and challenging for a physician to remain current with all of the latest advancements in clinical practice (Meesad and Yen 2003). Furthermore, as computer technologies advance, it is now simple to collect and store vast amounts of data in digital format, such as an exclusive database of patient records in electronic format.

Despite these advantages, ML, DL, and IoT have some limitations. Another challenge is the necessity of good quality and varied data. Models trained on biased or incomplete data may exhibit unreliable or biased behaviors. Furthermore, model interpretability still poses a big challenge, particularly in safety-critical scenarios such as healthcare and finance. Overfitting, underfitting, and challenges in generalizing models to new but related domains are also major concerns. In addition, there are remaining ethical concerns about bias, fairness, and accountability in deploying ML, DL, and IoT systems (Lu 2025).

DL, a subset of ML, emerges as a prominent technique to learn the underlying intricate patterns from a massive volume of data. Computer vision tasks, such as object detection (Zou 2019), facial recognition (Chen and Jenkins 2017), and autonomous driving (Bachute and Subhedar 2021), have been completely redesigned using

DL. And in natural language processing (NLP), thanks to DL models like transformers, we have today real-time translation, sentiment analysis, and intelligent virtual assistants. DL also finds important applications in predictive maintenance, anomaly detection, and medical diagnostics.

DL systems do, however, have some intrinsic drawbacks. They need significant hardware resources for both training and inference, making them computationally demanding. Another issue is data reliance; DL models frequently rely on enormous volumes of labeled data, which aren't always accessible. Furthermore, confidence and adoption in regulated industries are hampered by the fact that DL models are sometimes seen as "black boxes," meaning they are challenging to understand or interpret. Large DL model training's effects on the environment and energy consumption are also receiving more attention in recent research (McCoy, Brenna et al. 2022).

Physical devices can now gather, share, and act upon data with little assistance from humans thanks to the IoT. Wearable IoT devices enable real-time patient monitoring in the healthcare industry; sensor networks in agriculture track weather and soil conditions; IoT supports public safety, waste collection, and traffic management in smart cities; and IoT powers predictive maintenance and process automation in industrial settings (Zantalis, Koulouras et al. 2019, Hussain, Hussain et al. 2020, Ahmad and Alsmadi 2021).

However, there are several obstacles to the extensive use of IoT. Since many IoT devices are susceptible to cyberattacks, security and privacy rank among the most important issues. Seamless integration is hampered by manufacturers' lack of standardization and compatibility. Additionally, IoT creates enormous amounts of real-time data, which makes analytics, processing, and data storage difficult. The intricacy of on-device analytics is further hampered by the limited power and computational capabilities of many devices (Usman, Zhang et al. 2014, Dritsas and Trigka 2024).

Intelligent, adaptable systems that can analyze and make decisions in real time have been produced by integrating ML and DL into IoT ecosystems. Applications like edge intelligence-powered health diagnostics, energy-efficient homes, driverless cars, and smart surveillance are made possible by this combination. In dynamic contexts, the synergy improves automation, lowers latency, and enables proactive reactions.

But there are also particular difficulties when incorporating ML/DL into IoT. Complex model deployment is challenging on edge devices due to resource constraints. It takes careful balance to provide real-time performance without sacrificing accuracy. Model versioning, synchronization, and continuous learning present technological challenges when updating

models in the field, particularly in a distributed setting. Furthermore, maintaining security, resilience, and openness throughout these interconnected systems continues to be a top research priority.

### 3. Uses and Challenges in Healthcare

Much research has combined ML, DL, and IoT techniques for the healthcare field. This section provides a summary of some ML, DL, and IoT uses and challenges in the healthcare sector. One of the important applications of these high-tech fields is remote patient monitoring and disease prediction. In this application, the use of Support Vector Machine is the usual DL model used. In this model, a big advantage can be obtained, which is real-time communication between patients and doctors (Jeddi and Bohr 2020, Shaik, Tao et al. 2023). But the challenge of results reliability and relevance is directly linked to the sensors that have appeared. Remote heart rate monitoring, respiratory rate monitoring, cough analysis, oxygen saturation monitoring, and blood pressure monitoring are other applications that utilize one or more models of ML and/or DL, like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Artificial Neural Networks (ANNs) (Arya and Mishra 2023). There are several advantages of using these models in these specific fields, which are the reduction of the quantity of disease transmission and the prevention of cough particle release. On the other hand, there are some challenges associated with these models in the healthcare sector, like domain complexity and overfitting. However, these models suffer from some challenges, like the small volume of the dataset, the complexity of the domain, and the overfitting.

Breast cancer and diabetic retinopathy are other applications that use these models in their implementation. These applications normally use DL algorithms such as CNNs, RNNs, Deep Belief Networks (DBN), and Autoencoder (AEs) models. The advantages of using such models here are the power in disease detection, the contribution across preprocessing, the ability to extract features, feature selection, classification, and clustering stage. Using these models in such applications may face some challenges since these models are source-intensive in terms of memory and time (Gopal, Al-Turjman et al. 2021).

Other healthcare applications utilize DL models that are pulse rate measurement and mapping from video. These applications are considered very important for diagnosing critical medical problems in patients. These applications mainly use a 3D-CNN DL model. This model is a kind of DL model that covers the competencies of 2D CNNs to process volumetric data. Also, 3D CNNs handle data with three dimensions: height, width, and depth, making them appropriate for analyzing medical images (like CT scans or MRI scans), video sequences, and other 3D data. This DL model has some other advantages, like extracting pulse rate without

the need for image processing, as well as unnecessary special image pre-processing. But there are some shortcomings in this model, like the utilization of a single channel as input for the model and the disregard for color factors. Psychological stress level perception is another application that uses these high-tech models. Specifically, this application uses a CNN model where there is no contact thermography-based stress recognition system, exploration of the nuanced breathing patterns, and high accuracy under non-binding conditions. It is important to mention that regarding the variability of heat signatures, this model suffers from inaccurate stress recognition (Varalakshmi, Premnath et al. 2021, Li and He 2023).

Moreover, IoT is a network of physical terminals or items that use sensors, software, and other technologies to communicate and exchange data with other terminals and systems on the internet. These terminals span from modest household items to more complicated industrial instruments. IoT has profoundly impacted a variety of areas, including e-Health. The researchers in (Stephen, Uzoewulu et al. 2023) developed a healthcare system to check patients' blood pressure. They designed a system that uses IoT to collect health-related data and incorporates cognitive algorithms. The goal was to predict systolic and diastolic blood pressure values by evaluating the postprandial plasma glucose (PPG) signal characteristics. According to the research published in (Anderson 2019). The future of health monitoring systems is dependent on the integration of ML and IoT. The authors of this paper offered a complete review, describing improvements in ML techniques, the ML pipeline, and the algorithms employed for this purpose. They offered standard algorithms suitable for context-sensitive applications, such as decision trees, Random Forest (RF), SVM, K-Nearest Neighbor (K-NN), Bayesian techniques, K-means, Gaussian mixture, blind source separation, and neural networks.

In<sup>[31]</sup>, the authors proposed a publication on IoT applications in smart healthcare, encompassing technologies, problems, and possibilities. According to the researchers, ML algorithms can spot new trends in medical data, build treatment plans and diagnoses, and provide individualized suggestions to healthcare practitioners based on each patient's specific needs (Al-Ali, Gupta et al. 2024). Remote patient monitoring (RPM) is a key technique for health monitoring. However, RPM allows patients to be observed outside of traditional clinical settings. It is a promising area that has the potential to enhance clinical outcomes while lowering chronic care expenses. This study (Zamanifar 2021) proposes an IoT-based solution for remote health monitoring. The system includes three sensors that measure blood oxygen levels, ECG signals, and body temperature. Heartbeats extracted from multiple sensors were classified using a convolutional neural network with attention layers.

RPM was also the goal of direct patient monitoring. This study conducted a thorough examination of remote patient monitoring architectures, which included video-based monitoring, IoT-enabled devices, cloud computing, blockchain, and fog and edge computing. Within each design, the review explained the algorithms used, the technologies used, and highlighted the advantages and limitations regarding patients' data, medical staff. The research conducted in (T Shaik, X Tao, N Higgins, 2023) was also fascinating. This paper describes a real-time healthcare system based on ML and DL techniques. The deployed system additionally utilizes IoT technologies for real-time remote monitoring. The authors outlined prospective applications and use cases for healthcare in smart cities, as well as the specific algorithms used. (I Ahmad, Z Asghar, T Kumar, G Li, A Manzoor, 2022) also highlights the benefits of the IoT and ML technology for heart attack prediction. Several algorithms have been developed for this purpose, including SVM, Simple Linear Regression, K-NN, and Gaussian Naive Bayes.

Additionally, the study published in (P Ratta, S Sharma, 2024) presents a novel IoT framework for providing ultra-reliable, low-latency communications for postoperative patient monitoring. It incorporates a regression analysis of patients' sensory data using ML, which results in very accurate forecasts of patients' vital signs. This method allows very accurate virtual observers to forecast data in the event of a communication loss. Gradient-boosting regression analysis also provides highly exact predictions for slowly or rapidly changing sensors while monitoring vital signs. IoT and machine learning are also implemented in (P Ratta, S Sharma, 2024). Decision tree techniques, random forest classifiers, and SVMs have been used to identify early-stage anterior heart disease.

#### 4. RESULTS AND DISCUSSION

Incorporating ML, DL, and the IoT into biomedical engineering has shown promise in improving healthcare technology, including real-time patient monitoring, predictive diagnosis, and individualized treatment. Combining ML, DL, and IoT in healthcare leads to improved diagnostic accuracy and early disease identification. Wearable and implantable sensors generate continuous patient data, which is then analyzed by algorithms implanted via ML and DL. Each of these high-tech models utilizes the proper number of hidden layers to obtain the optimal results. These data are used to detect patterns that indicate health concerns. ML and DL models trained on IoT data can better diagnose heart disease, diabetes, and cancer.

ML and DL algorithms surpassed human clinicians at detecting skin cancer from photographs, demonstrating the potential of AI-assisted diagnostics. Furthermore, IoT-enabled continuous monitoring devices, such as glucose sensors, have proven useful in forecasting swings in blood sugar levels, providing patients with

actionable insights for treating their diabetes. In cardiovascular healthcare, the combination of IoT and algorithms and models implemented via ML and DL has proven useful in predicting heart attack risk. ML and DL algorithms can detect minor changes in ECG data from IoT devices to forecast a heart attack and provide appropriate therapies. This early detection capability has the potential to save lives by giving patients the opportunity to get prompt treatment.

In biomedical engineering, ML, DL, and IoT address complicated problems and improve patient outcomes. These algorithms examine medical images to identify illness patterns, such as early signs of cancer. They also contribute to the development of breakthrough medical devices and technology, like surgical robots, and enable customized medicine by adapting therapies to genetic profiles. The influence associated with these models and algorithms on healthcare is varied. It improves medical devices and technology, increases patient outcomes, and lowers healthcare expenditure. One critical application is the detection and prediction of disease progression, allowing for early intervention and prevention. For example, ML, DL, and IoT automate processes such as medical record maintenance, appointment scheduling, health data analysis, and healthcare system management.

The implementation of models and algorithms faces a significant hurdle in terms of accessibility. High-tech-driven healthcare solutions must benefit all members of society, independent of socioeconomic (economic background, gender, culture) or biological (sex, race, ethnicity) factors. The affordability and economic viability of high-tech-powered technology in healthcare, as well as its bias, are key influences on this topic. The former must be considered to prevent high-tech-based healthcare from being limited to individuals with greater socioeconomic status. The former can result from human prejudice, as data used to train models frequently contains human bias. It has the potential to impact the quality of services delivered to various patients, which is a significant ethical concern.

Furthermore, while ML, DL, and IoT can analyze massive amounts of data, they still struggle to grasp the sophisticated medical knowledge required for successful diagnosis and therapy, particularly when it comes to comprehending the context of a patient's illness. The use of these models in healthcare raises significant ethical concerns, specifically with accountability and informed consent. Patients must be kept informed about how their data is being used, and their consent must be obtained regularly. There must also be an open conversation about how these models influence their care. One serious issue is determining who should be held accountable if these models make a mistake, whether it is the creators, healthcare personnel, or others.

ML, DL, and IoT can help with disease surveillance and epidemic prediction. Future research could focus on

developing tools that can be coupled with remote sensing technologies, such as satellite imaging, to monitor disease-friendly environments. Another potential area of research is high-tech telemedicine, in which these models may help triage patient cases, determine the urgency of conditions, and provide first diagnostic support. This can help to close the gap between rural patients and healthcare providers. Furthermore, it can be a useful tool for maximizing healthcare resource allocation by forecasting healthcare demands based on historical data and seasonal and present disease patterns.

## 5. CONCLUSION

ML, DL, and IoT models have the potential to significantly improve healthcare service delivery. To ensure the robust deployment of these models in clinical settings, many problems and issues must be addressed. This study discusses the uses and challenges of ML, DL, and IoT pipelines in healthcare and identifies potential pitfalls. Also, illustrates the different models and algorithms used in healthcare applications. This study highlights the importance of these high-tech models and algorithms. This paper addresses systems that rely on ML and DL approaches and algorithms, as well as IoT, for remote and real-time monitoring of medical services to better and faster patient consideration and decision-making.

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