Advancements in IoT and Machine Learning: A Comprehensive Review of Current Methods and Implications for Patient-Centric Healthcare Management

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Abstract: ***This paper explores the revolutionary possibilities arising from the integration of the Internet of Things (IoT) with artificial intelligence (AI) and cloud technologies in healthcare. The paper investigated the machine learning approach with integration of Internet of Healthcare (IoHT) to facilitate real-time disease prediction, patient monitoring, and personalized medical guidance. The core of this paper is to review different approaches for developing a patient-centric, intelligent decision-making framework using IoT devices and machine learning models. To provide a comprehensive overview, the paper also assess the current challenges and future scope of IoH.***

Keywords: Internet of Healthcare (IoHT), Artificial Intelligence, Real-Time Patient Monitoring, Disease Prediction, Machine Learning

1. Introduction

In today's world, even individuals in excellent health face a multitude of challenges due to shifting dietary habits and environmental factors. To thrive in this changing landscape, it is imperative to raise awareness about our well-being. The healthcare sector grapples with various issues, including a lack of access to accurate medical information, preventable errors, data security risks, misdiagnoses, and delayed information transmission [1]. From a technical standpoint, the Internet of Things (IoT) refers to the transformation of physical devices, objects, or "things" into digital entities, imbuing them with enhanced intelligence. This involves equipping these objects with computing capabilities, whether they are connected to cloud servers or not, and integrating backend applications to facilitate data visualization, analysis, and device control [3]. IoT envisions a world where everyday objects communicate by utilizing various sensors like Radio-Frequency Identification (RFID) and actuators, working in unison to detect, capture, and transmit crucial data to the Internet from their surroundings [4]. IoT represents a concept that bridges the gap between the physical and digital realms, relying on cutting-edge technology. However, the rapid proliferation of digital contexts, the sheer number of users, and the widespread use of smartphones have led to alarming levels of energy consumption in the past decade. It is projected that by 2030, the number of connected devices could reach a staggering 100 billion [1].

The Internet of Things (IoT) has evolved from merely connecting embedded computing devices to connecting smart sensor devices. When implemented in smart cities, challenges like low storage and limited processing power arise. Cloud computing can help overcome these by offering better processing and storage capabilities, hence the push for IoT-cloud integration, especially for crucial services like smart healthcare. Smart healthcare revolves around real-time patient monitoring and communication [4]-[6]. With the merger of IoT and cloud technologies, the urgency for a healthcare system that is both patient-centric and cost-effective has grown. Such a framework should integrate artificial intelligence (AI) and deep learning to introduce human-like intelligence for better decision-making, especially in dynamic environments like smart cities. In smart cities, the need for quick and accurate medical responses is paramount. For instance, critical patient data like EEG signals from IoT devices are complex and demand sophisticated processing techniques. Achieving high-quality, low-cost smart healthcare in such an environment is challenging, even with technological advancements. Thus, there's a move towards integrating cognitive behavior into IoT frameworks to provide intelligent decision-making. In a smart city, a smart healthcare system gathers data from various IoT sensors attached to patients, analyzing health indicators to determine if there's a need for emergency care [7]. Keeping all stakeholders updated in real-time is crucial, emphasizing the importance of cognitive capabilities. Over the years, machine learning has played a pivotal role in disease identification and has given medical practitioners a reliable second opinion during diagnostics. Cyber-physical-social systems, combining AI, big data analytics, and cloud computing, are essential for the future of healthcare systems aiming for personalized and patient-centered services. Efforts are ongoing to develop smart medical systems based on these principles for enhanced diagnosis and treatment [8]-[10].

2. Literature Review

Zhihan lv et al. [5] proposed convolutional neural network (CNN) models to build an interactive smart healthcare prediction and evaluation model (SHPE model). The model is optimized and standardized for data processing. The results show that accuracy of the constructed system reaches 82.4%. Nancy et al. [6] proposed a smart healthcare system for monitoring and accurately predicting heart disease risk built around Bi-LSTM (bidirectional long short-term memory) and achieved an accuracy of 98.86%. Chakraborty and Kishor [7] proposed a machine learning (ML) classification algorithms to predict heart disease. The IoMT-based cloud-fog diagnostics for heart disease have been proposed. Fog layer is used to quickly analyze patient data using ML classification techniques. The performance of the healthcare model is evaluated with different simulations and achieves 97.32% accuracy. Ferdousi et al. [8] propose a novel machine learning based health CPS framework that addresses the challenge of effectively processing the wearable IoT sensor data for early risk prediction of diabetes as an example of NCDs. In the experiment, a verified diabetic dataset has been used for training, while the testing has been performed on an artificially generated data collection from sensors. The experiment with several machine learning algorithms shows the effectiveness of the proposed approach in achieving the maximum precision from the Random Tree algorithm, which requires a minimum time of 0.01s to construct a model and obtains 94% accuracy to predict the probability of diabetes at an early point. Muthu et al. [9] designed Generalize approximate Reasoning base Intelligence Control (GARIC) with regression rules to gather the information about the patient from the IoT. Finally, Train the data to the Artificial intelligence (AI) with the use of deep learning mechanism Boltzmann belief network. Sarmah et al. [10] executed via `3' steps: I) Authentication, ii) Encryption, and iii) Classification. First, by utilizing the substitution cipher (SC) together with the SHA-512, the heart patient of the specific hospital is authenticated. Subsequently, the wearable IoT sensor device, which is fixed to the patient's body, concurrently transmits the sensor data to the cloud. This sensor data is encrypted and securely transmitted to the cloud utilizing the PDH-AES technique. After that, the encrypted data is finally decrypted, and by employing the DLMNN classifier, the classification is done. The classified outcomes comprise `2'types of data: i) normal and ii) abnormal. Mohan et al. [11] proposed a novel method that aims at finding significant features by applying machine learning techniques resulting in improving the accuracy in the prediction of cardiovascular disease. The prediction model is introduced with different combinations of features and several known classification techniques. Author produce an enhanced performance level with an accuracy level of 88.7% through the prediction model for heart disease with the hybrid random forest with a linear model (HRFLM). Umar et al [12] deep learning model accomplish better accuracy than the high-tech systems. The cognitive healthcare model it combines IoT–cloud technologies for detection and classification. We used two convolution neural network (CNN) models that were pre trained on a normal EEG dataset. Author adopted raw time-domain EEG signals as input to the CNN model for classification, which proved that end-to-end learning is suitable for EEG data. The cognitive module then decides based on the services and medical support that the patients need. Syed, Liyakathunisa, et al [13] proposed a new technique to observe the healthcare situation of an individual, support from sensor and IoT devices is essential. The health protection benefit to the unhealthy as well as healthy population during remote monitoring utilize intelligent algorithms, equipment, and method with faster analysis and expert intervention for better treatment recommendations. The data collected by the IoT devices, via biomedical sensors connected to the human body, is analyzed, and by the application of machine learning. Gunasekaran Manogaran et al [14] propose a replacement technique a scalable machine learning technique to spot the DNA range change across the ordination. Bayesian hidden markov model (HMM) and gaussian Mixture (GM) clustering approach are employed in this paper to model the DNA range amendment across the ordination. Arun das et al [15] has been planned by proposed AMD-Res web convolution neural network with one hundred and fifty two layers will then analyze the pictures to identify and verify AMD diseases severity. Pham et al. [16] introduced an RNN architecture (called DeepCare) to predict the future medical risks based on patients' health status and abnormalities. RNNs have a powerful ability in learning new representations from the collected HER. DeepCare model uses a modified short-term memory (LSTM) unit to handle irregular patient inter-visit periods. The performance of the model was tested for the prediction of unplanned re-admission within 12 months, where an Fscore of 0.791 was obtained, an improvement over traditional machine learning techniques such as SVM (F-score of 0.667) and random forests (Fscore of 0.714). Miatto et al [17] introduced deep stacked diagnosing auto encoder (SDA) for training a universal feature extractor for clinical risk-prediction tasks. SDA can predict chronic health diseases such as diabetes mellitus, cancer of rectum and anus, cancer of liver and intrahepatic bile duct, congestive heart failure (non-hypertensive), among others. However, supervised learning model was needed to map the representation of each predicted risk.

According to the literature presented, a critical summary is presented below in table 1.

Table 1: Critical Study of Recent Research Contributions

Ref	*Technique Used*	*Accuracy*	*Cloud*	*IoT*	*Fog*
ZhihanLv et al. [5]	CNN-based SHPE Model	82.40%	No	No	No
Nancy et al. [6]	Bi-LSTM for Heart Disease Prediction	98.86%	No	No	No
Chakraborty & Kishor [7]	IoMT-based Cloud-Fog Diagnostics with ML classification	97.32%	Yes	Yes	Yes
Ferdousi et al. [8]	Machine Learning with Random Tree Algorithm	94%	No	Yes	No
Mohan et al. [11]	Hybrid Random Forest with Linear Model (HRFLM)	88.70%	No	No	No

3. Disease Prediction and Healthcare Sector

The integration of Internet of Things (IoT), artificial intelligence (AI), and web-based technologies is revolutionizing healthcare by enabling real-time disease prediction, patient monitoring, and efficient treatment procedures. Point-of-care (POC) diagnostics offer immediate bedside testing, benefiting various patient groups including the elderly and those with chronic conditions. Innovations like portable ultrasound scanners facilitate remote healthcare and diagnostics. Companies like Comarch Healthcare offer comprehensive healthcare solutions that include hospital IT software, remote medical care, and specialized products such as wearable health monitors and diagnostic vests. These technologies collectively gather vital health data, which is stored in the cloud for healthcare professionals to access and manage, streamlining healthcare intervention and decision-making.

Matthew et al. [18] addressed the issue of limited medical data for detecting lung diseases. They used small datasets of fewer than a thousand samples and implemented deep convolutional neural networks (VGG16, ResNet-50, and InceptionV3) that were pre-trained on the ImageNet dataset. By employing a transfer learning approach and creating a pipeline that first segmented chest X-Ray images, they compared their framework's performance with existing solutions. Their findings show that even with simpler classifiers like shallow neural networks, they could compete with more complex systems. The performance of their approach was validated using the publicly available Shenzhen and Montgomery lung datasets. They achieved comparable accuracy to the best-performing models, but their method had the advantage of requiring fewer trainable parameters and being computationally less expensive. Hooda et al. [19] focused on the challenging task of automating the detection of Tuberculosis (TB) in chest X-rays, a critical part of initial screening recommended by the World Health Organization. The study presents a deep-learning-based system for TB detection that utilizes an ensemble of three standard neural network architectures: AlexNet, GoogleNet, and ResNet. Unlike other methods that use pre-trained models, this study trains these architectures from scratch to create a specialized ensemble for TB classification. The method is trained and evaluated on a combined dataset sourced from publicly available standard datasets. The ensemble achieves a high accuracy rate of 88.24% and an area under the curve (AUC) of 0.93, outperforming most existing methods in TB detection. Zabirul et al. [20] presented an automated system for the detection of COVID-19 using X-ray images, aiming to provide a fast and accurate diagnostic option. The system uses a combination of a convolutional neural network (CNN) and long short-term memory (LSTM) networks. CNN is used for deep feature extraction from X-ray images, while LSTM is employed for detection based on those extracted features. The authors suggest that the system could be even further improved as more COVID-19 images become available and emphasize its potential in aiding doctors in diagnosing and treating COVID-19 patients effectively. Khan et al. [21] focused on the use of deep learning techniques for the identification of brain tumors, a critical area in medical image processing. Brain tumors are common and can lead to high mortality rates if not treated in a timely manner. Early and accurate detection is therefore essential for effective treatment. The research leverages Magnetic Resonance Imaging (MRI) for brain tumor identification. The authors propose a methodology that integrates deep neural networks and Convolutional Neural Networks (CNN) for feature extraction, segmentation, and classification of MRI images. The system achieved a high accuracy rate of about 97.92%, demonstrating its potential for aiding in the early diagnosis and treatment planning for individuals affected by brain tumors. Deepak et al. [22] tackled the problem of brain tumor classification, focusing on differentiating among three major types: glioma, meningioma, and pituitary tumors. Utilizing the concept of deep transfer learning, the study employs a pre-trained GoogLeNet to extract features from brain MRI images. The extracted features are then classified using proven classifier models. A five-fold cross-validation process is used to test the system on an MRI dataset from figshare. The proposed methodology achieves a mean classification accuracy of 98%, exceeding the performance of existing state-of-the-art methods. The paper also evaluates other performance metrics like area under the curve (AUC), precision, recall, F-score, and specificity. Additionally, the study highlights the effectiveness of transfer learning in scenarios with limited medical image data and includes an analytical discussion on cases of misclassification. Fan Li et al. [23] presented a multiple cluster dense convolutional neural networks (DenseNets) to learn various local features from MR brain images. The process involves several steps. First, the whole brain image is partitioned into different local regions, and 3D patches are extracted from each. These patches are then clustered using the K-Means method. A DenseNet is used for each cluster to learn the features, which are then ensembled for classification. The results from different local regions are combined to enhance the final image classification. Zhu et al. [24] introduced a Dual Attention Multi-Instance Deep Learning Network (DA-MIDL) for early diagnosis of Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) using structural magnetic resonance imaging (sMRI). The DA-MIDL model consists of three main parts: Patch-Nets with spatial attention for focused feature extraction from sMRI patches, an attention multi-instance learning pooling operation for a weighted global brain representation, and an attention-aware global classifier for making final AD-related classification decisions. The model was evaluated on 1689 subjects from two independent datasets and demonstrated superior performance in identifying key pathological features and overall classification accuracy compared to existing methods.

Table 2: Critical Study of Recent Research Contributions

Models	Disease Type	Accuracy
VGG16 [18]	Lung	84%
ResNet-50 [18]	Lungs	86%
InceptionV3 [18]	Lungs	89%
AlexNet [19]	Lungs	83%
GoogleNet [19]	Lungs	80.5%
CNN+LSTM [20]	Lungs	92%
CNN[21]	Brain Tumor	97.92%
GoogleNet[22]	Brain Tumor	97.1%
DenseNet [23]	Alzheimer	89.54%
Attention CNN [24]	Alzheimer	92.4%

4. Current Challenges and Future Scope

- Data Quality and Availability: One of the biggest challenges is the availability of high-quality, diverse, and large-scale datasets for training deep learning models, particularly in the healthcare domain.
- Interoperability: Different healthcare systems often use different formats and standards for medical imaging and patient records, making it challenging to develop universally applicable models.
- Computational Requirements: Deep learning models, particularly those used for image recognition, require significant computational power, which may not be readily available in all healthcare settings.
- Explainability and Interpretability: Medical practitioners need to understand the reasoning behind a diagnosis made by a machine learning model. Currently, many deep learning models are seen as "black boxes," making it difficult to interpret their predictions.
- Regulatory and Ethical Concerns: The use of AI in healthcare comes with a range of regulatory challenges, including concerns around patient data privacy and the ethical considerations of AI decision-making in a medical context.
- Clinical Validation: Translating a model's high accuracy in experimental settings to real-world clinical utility is a significant challenge that involves rigorous validation.
- Model Generalization: Models trained on one dataset or in one particular setting may not necessarily generalize well to other datasets or settings, limiting their applicability.
- Human-Machine Collaboration: Integrating machine learning tools seamlessly into existing healthcare workflows without displacing or diminishing the role of human experts is a complex challenge.

5. Conclusion

The healthcare landscape is undergoing a transformation, triggered by rapid technological advancements in IoT, cloud computing, and artificial intelligence. By amalgamating IoT with machine learning, we manage to not only gather but also intelligently interpret health data, thus providing timely alerts and guidance from healthcare professionals. The paper also discussed multiple machine learning models and their respective accuracies in disease prediction based on existing literature, pointing out the critical challenges and opportunities that lie ahead. Despite hurdles such as data quality, computational requirements, and ethical concerns, the future scope is promising. Personalized medicine, real-time monitoring, and telemedicine are just a few avenues for further research and development. Therefore, the integration of IoT and AI in healthcare has the potential to profoundly impact not only disease prevention and treatment but also the broader healthcare ecosystem.

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