An Intelligent Healthcare System: Leveraging AI and IoT for Efficient Diagnosis and Treatment

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Abstract
Healthcare has not been exempt from the rapid changes brought about by artificial intelligence (AI) and the Internet of Things (IoT). In order to improve the effectiveness of diagnosis and treatment, this paper introduces an intelligent healthcare system that makes use of AI and IoT technologies. This system aims to enhance patient care, lower medical errors, and maximise resource utilisation in healthcare settings by integrating AI algorithms and IoT devices. AI algorithms are used in the proposed intelligent healthcare system to provide effective diagnosis and treatment. Large amounts of medical data, including electronic health records, medical images, and clinical notes, are analysed using machine learning techniques. These algorithms can spot patterns, forecast how a disease will progress, and help medical professionals make precise diagnoses. Additionally, to enable thorough patient understanding, natural language processing algorithms can extract useful information from clinical data that is unstructured.

Keywords*:* Artificial Intelligence, Internet of Things, Intelligent, electronic health records and Machine learning.

1. INTRODUCTION

With the rapid development of Internet of Things (IoT) and artificial intelligence (AI) technologies, the healthcare sector is undergoing a profound transformation. By improving diagnosis, treatment, and patient care, these cutting-edge technologies have the potential to revolutionise healthcare delivery[1]. The intelligent healthcare system described in this paper uses IoT and AI to effectively diagnose and treat medical conditions. This system aims to optimise resource utilisation, lower medical errors, and ultimately enhance patient outcomes by integrating AI algorithms and IoT devices. The need for accurate and prompt diagnosis, efficient allocation of resources, and effective treatment plans are just a few of the difficulties that healthcare systems around the world must overcome[2]. Traditional medical procedures have a heavy reliance on manual labour and are constrained by human capacity and knowledge. However, the development of AI and IoT technologies offers fresh ways to deal with these difficulties[3]. AI algorithms can process enormous amounts of medical data, spot patterns, and offer insightful information that helps medical professionals make precise diagnoses[4]. Real-time monitoring capabilities are provided by IoT devices like wearable sensors and medical equipment, allowing for remote patient management and preventative interventions. Various methods used in structural health monitoring are intended to identify the presence, location, and extent of damage as well as to predict the useful life left in a structure after damage[5]. The civil, aeronautical, and mechanical infrastructure industries frequently use this concept. It entails the continuous measurement of the loading conditions and dynamic response of a structure, both for the system as a whole and for each of its component parts[6]. Health monitoring measures performance, identifies operational incidents and anomalies brought on by wear and tear or damage, and assesses the structure's resilience to extreme events. Identification of damage, which is typically divided into four tiers, is the primary goal of SHM.

A system is continuously monitored as part of SHM by having a variety of sensors record its dynamic response[7]. Damage-sensitive features are derived from these measurements and statistical analysis is performed on them to determine the system's current state of health. Long-term monitoring ensures up-to-date information on the structure's performance and functionality, even taking into account natural ageing and degradation brought on by operational conditions. Regular updates are provided[8]. In addition, SHM is used as a quick screening tool in the aftermath of severe occurrences like earthquakes or blast loading, with the goal of delivering accurate and nearly real-time information about the structural integrity.

2. LITERATURE SURVEY

The literature examines the currently used techniques for classifying and identifying cancer in histopathological images. It then looks at the various important research methods that have been used, including feature extraction, feature selection, detection, classification, and optimal performance enhancement. The majority of research works have used features like morphological features, global features, texture features, colours, sizes, and shapes. Deep learning techniques based on multifractal analysis, wavelet transform, neural network, k-Nearest Neighbour (k-NN), k-means, fuzzy c-means, PCA, ICA, LDA, QDA, SVM, and convolution neural network (CNN) have been used for detection and classification[9]. However, the majority of studies have asserted that using CNN and SVM methods, detection and classification performance can be improved. The receiver operating characteristic curve, Mann Whitney U test, higher order statistics, and spectra values have all been examined and evaluated for cross-validation.

The use of Whole Slide Imaging (WSI) in various pathological imaging scenarios has shown promising results in recent studies[10]. Digital pathology developments have made it easier to identify various cancerous cells, such as those that are present in the brain, breast, cervix, liver, lung, prostate, and colon (Sirinukunwattana et al., 2016). In the past, Medical Image Processing (MIP) techniques helped with the development of remote disease diagnostic systems as well as the analysis of cancer cells with greater consistency and accuracy. However, due to the wide range of cell positions and sizes, it can be difficult to extract Sub-Cellular Components (SSCs) from pathological images (Mandal et al., 2013). Additionally, the image contrast between SSC boundaries and the background varies as a result of uneven illumination during image capture (Deschler et al., 2006). An approach based on wavelet transform (WT) for analysing nuclei textures was introduced by Niwas et al. in 2010. Algorithms like thresholding combined with morphological operations, region growing, level sets, k-means, fuzzy c-means, and graph cuts are frequently used in current cancer cell detection techniques[11]. Numerous studies use supervised or unsupervised pixel-wise classification of small rectangular image regions based on colour and texture to categorise cancers (Roa et al., 2011). Similar decisions are made when classifying data using a set of features. These features are used in automated classification systems, just as pathologists frequently use structural or pattern recognition tasks (Chowdhury et al., 2019). It is important to remember, though, that pathologists do not always have to rely solely on computer features[12]. Pathologists have determined that some difficult features can be easily extracted and used in automated systems.

It is currently the goal of intensive research to establish a perfect correlation between immunohistochemistry (IHC)-based molecular classifications of cancer and prognostic studies that concentrate on cell morphology[13]. Clinical researchers need a comprehensive strategy to accurately assess cell morphological features due to the wide variety of cancers and the limited prognostic capabilities of histopathological image classification, according to Gurcan et al. (2009). Pathologists must examine biopsy-stained tissue slides and assess a variety of factors, including cell size, surface area, mitotic counts, and more sophisticated IHC molecular markers, in order to improve cancer diagnosis and understanding[14]. Especially when looking at low-magnification images, this process takes time and can be subject to statistical variations, distribution discrepancies, and human errors[15]. These issues erode the validity of various classifications used in standard cancer diagnosis. Therefore, overcoming these challenges and producing more trustworthy results can be accomplished by creating an automated and dynamic predictive system[16]. The programmes for diagnosing and categorising synovial sarcoma in limb tumour cancer are presented and discussed in this section. It examines various methods for feature extraction, feature selection, and classification that are currently in use[17]. Despite the fact that the literature only contains a small amount of concentrated work, the existence of a large number of features calls for efficient feature selection to handle the analysis of multiple features.

3. PROPOSED METHOD

In the modern world, objects can sense, transmit, and receive data, and they frequently connect to the Internet via distinctive IP addresses, much like personal computers do. This idea is covered by the Internet of Things (IoT), wherein objects use their specific IP addresses to communicate data within the network and gather environmental data whenever and wherever they are. The Wireless Sensor Network (WSN) is the key component of the Internet of Things (IoT) and has applications in a number of fields, including air quality monitoring (AQM), healthcare systems (HS), vehicular area networks (VAN), and structural health monitoring (SHM). In order to speed up repairs and ensure safety, SHM involves gathering data from sensors placed on structures in order to extract damage-sensitive information[18]. Manual data collection has historically been used for structural health monitoring, but it is time-consuming, unreliable, and ineffective. Also used are wired monitoring systems, which need a lot of installation space and power. IoT integration in SHM has been comparatively underdeveloped, highlighting the importance of timely and accurate data collection for critical infrastructure[9]. This paper suggests an all-encompassing implementation of the SHM system that integrates WSN, AI, and IoT. The framework uses AI algorithms to locate and identify structural damage while sending sensor data and prediction results to a cloud server. Through interactive interfaces, users can access these results virtually instantly from any location. Several contributions are introduced in this paper[20]. First, it suggests a larger IoT-enabled network made up of 40 accelerometer sensors that would send information to a distant site about the structure's current health condition and damage-sensitive information. For experimental purposes, a three-story mild steel 3D building frame is created and realised to show off the IoT-enabled framework. Second, two Deep Neural Network (DNN) models are presented, outperforming SVM, Naive Bayes, and Decision Tree in terms of classification/identification and localization of damage[21]. Two datasets—one produced from the lab building frame and the other obtained from the Los Alamos Laboratory website—are used to evaluate the models. Extensive experiments show that the suggested techniques work. A mobile application for Android, a web application, and a standalone application are three additional user interfaces that are designed and created.

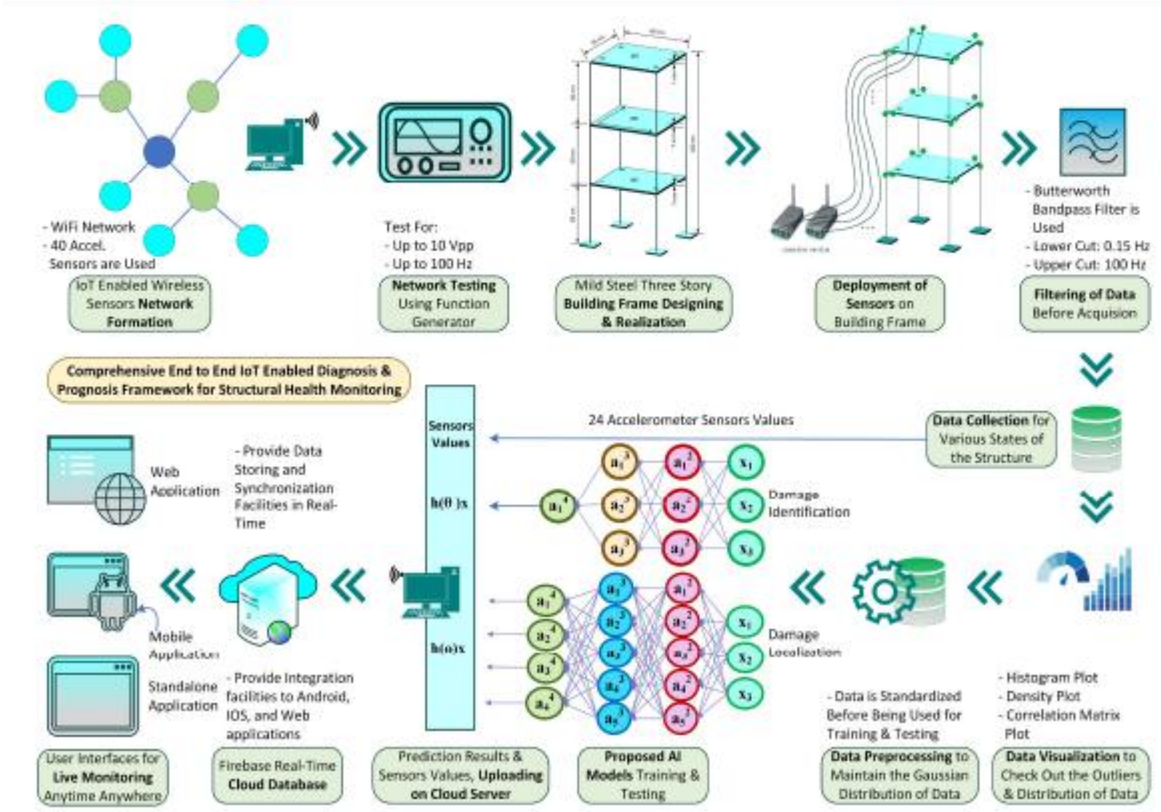

Figure.1: Proposed IoT Enabled Diagnosis system for Health Monitoring

These interfaces offer real-time sampled data from each sensor as well as the structure's current state of health. The proposed system can be used with other damage detection tools, with different algorithms being trained on particular datasets[22]. Figure 1 demonstrates how the proposed system can be combined with additional damage detection software that performs classification and localization tasks. In these applications, damage detection-related datasets can be used to train machine learning algorithms like Support Vector Machines (SVM), Naive Bayes, and Neural Networks[23]. The system improves its ability to precisely classify and localise structural damage by incorporating these algorithms. This makes it possible to monitor the structural health in a thorough and reliable manner and to take timely maintenance and safety measures.

4. CNN MODELS

Convolutional Neural Networks (CNN) have become effective image processing tools, especially for tasks like crack classification. However, one issue with CNNs is that extensive amounts of labelled data are required for efficient training. Transfer learning has been used to get around this restriction, which involves using pre-trained models. Inception-v3, ResNet-50, Xception, and InceptionResNet-v2 are six well-known deep CNN models that were retrained in this study to classify concrete surface cracks. These pre-trained models are adjusted using transfer learning on a dataset of crack and non-crack images collected from two different sources. To choose the best model, the performance of the re-trained models is assessed using a variety of metrics, such as Accuracy, Precision, Recall, F1-Score, Cohen Kappa, and Error Rate. The outcomes of the experiment show that the retrained CNN classifiers consistently produce high performance. On the first dataset, the accuracy ranges from 0.95 to 1.0, and on the new dataset, it ranges from 0.85 to 0.99. These results demonstrate the capability of

CNN variants to detect and classify cracks in real-world scenarios. The models also have strong generalisation abilities, which makes them trustworthy for real-world uses.

Due to its strength, durability, and long lifespan, concrete is frequently used today to build various structures in smart cities. However, over time, ageing, climatic conditions, human activity, and heavy loads can all cause concrete structures to degrade. If left unchecked and unattended, concrete damages like cracks and spalling can cause significant losses in terms of property damage and risks to human lives. Concrete damage has traditionally been found through manual inspections by civil engineers who visually inspect buildings for any indications of damage. However, this strategy has drawbacks, such as the possibility of oversight and human error. For automatic damage detection in concrete structures, there has been an increase in interest in using Artificial Intelligence (AI) techniques, particularly Machine Learning and Deep Learning algorithms. These AI-based methods benefit from increased accuracy, decreased error rates, and minimal time and resource consumption. Several vision-based techniques for detecting concrete cracks have been put forth in recent years. These approaches make use of the Grey-Scale Histogram, Fuzzy C-Means Clustering, Cascade Features, V-Shaped Features, Spatial Tuned-Robust Multi-Feature (STRUM), and Spectral Analysis techniques. These methods seek to analyse photographs of concrete surfaces in order to spot cracks or other types of damage. The use of Deep Convolutional Neural Networks (CNN) for object detection and classification in Computer Vision is a noteworthy development in the field. The ability of CNNs to detect concrete cracks among other image processing tasks has shown great promise. CNN models can be taught to automatically recognise and classify cracks in concrete surfaces with high accuracy by training them on large datasets of labelled images. A more effective and reliable method of keeping track of the health of concrete structures is provided by the incorporation of AI-based techniques, such as CNNs, in concrete crack detection systems. Automating the detection process enables the early detection of potential damages, enabling prompt maintenance and repairs to stop further deterioration and guarantee the security and durability of the infrastructure.

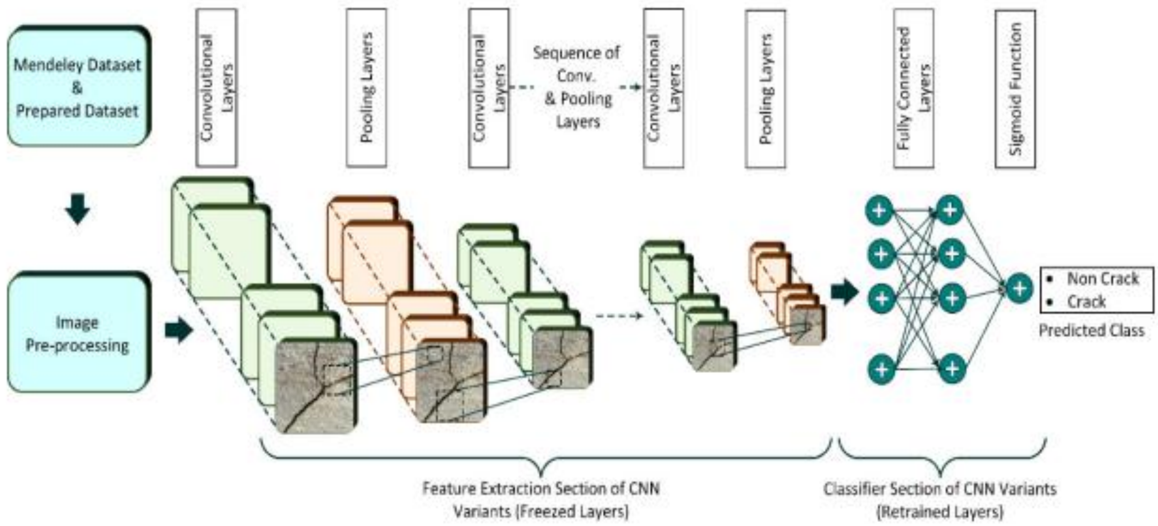

Figure.2: Convolution Neural Network Architecture with Transfer Learning Technique

Inception-v3: Google created the CNN model known as Inception-v3. It is renowned for using inception modules and for having a complex architecture. To capture features at various scales within the same layer, these modules employ parallel convolution filters of various sizes (1x1, 3x3, and 5x5). Inception-v3 has received a lot of attention for its excellent performance in transfer learning tasks involving image classification. DenseNet-121: Another CNN model who has grown in popularity is

DenseNet-121. The idea of dense connections is introduced, in which every layer is connected to every other layer in a feed-forward manner. This high degree of connectivity promotes feature reuse across the network and improves gradient flow. DenseNet-121 has proven to perform well in a variety of image classification tasks. ResNet-50: A well-known CNN model that pioneered residual connections, ResNet-50. These connections allow the network to avoid some layers, which improves the efficiency of gradient propagation. In order to overcome the difficulties presented by vanishing gradients and enable the successful training of models with more than 100 layers, ResNet-50 has demonstrated to be incredibly effective in very deep neural network training. VGG-16 stands for Visual Geometry Group 16 and is a well-known CNN model. It has a 16-layer structure that is straightforward and uniform, with most of those layers being 3x3 convolutional filters followed by max-pooling layers. The VGG-16 has a reputation for being highly effective at image recognition tasks and has influenced the design of CNN architectures. Xception: The Inception architecture is modified in Xception to emphasise depthwise separable convolutions. By separating the spatial and channel-wise convolutions, Xception uses fewer parameters and computational resources than traditional convolutional filters. The effectiveness and performance of image classification tasks have been enhanced as a result of this design decision. The InceptionResNet-v2 architecture integrates concepts from the Inception and ResNet architectures. Inception modules and residual connections are included to efficiently capture multi-scale features. InceptionResNet-v2 is renowned for its powerful representation learning capabilities and has demonstrated state-of-the-art performance in a number of image classification challenges. These CNN models have learned detailed representations of visual features through pre-training on massive image datasets like ImageNet. It is possible to take advantage of the knowledge gained from these models and achieve high accuracy and generalisation capabilities in detecting and classifying cracks in concrete surfaces by utilising transfer learning, where the pre-trained models are tuned on specific tasks, such as concrete crack classification.

5. METHODOLOGY

Five main stages make up the research procedure you described in your statement: transfer learning, database creation, image pre-processing, evaluation metrics, training and testing, and result analysis. The process is shown in Figure 2, which begins with the CNN models being ready by freezing the Feature Extractor section and changing the Classifier section for crack classification. Seven evaluation metrics are measured before, during, and after training on the preprocessed datasets. The results of the training and testing are then analysed. In transfer learning, a pre-trained convolutional network is used as a starting point rather than completely training the convolutional network from scratch with random weights initialization. This pre-trained network was developed using ImageNet, a sizable dataset. The network's top fully connected layer (classifier), which generates 1000 class scores, is eliminated. For the newly discovered dataset, which consists of photographs of damages, the convolutional network that is still present but without the classifier is referred to as the Fixed Feature Extractor. To carry out the desired classification, a modified classifier is connected to the Fixed Feature Extractor. During training, only the classifier section is retrained. Transfer learning is the process used in this method, which combines a Fixed Feature Extractor and a pre-trained network. It enables the task of classification to benefit from the knowledge acquired from training on a large dataset. The network can be improved to work well on the specific crack detection task using the new dataset by modifying and re-training the classifier section. The idea of Fixed Feature Extractor-based Transfer Learning is illustrated in Figure 2. Overall, this methodology makes it possible to use CNN models that have already been trained, reduces the need for a large amount of labelled data, and makes use of the models' already-learned knowledge and representations to achieve accurate crack classification.

Figure.3: Image Pre-processing Steps

To evaluate the AI-based crack classification algorithms for concrete surface defects, two different datasets were used in this study. Selected images from the Mendeley Crack Dataset make up the first dataset. This dataset includes RGB images in JPG format with a 227x227 pixel resolution. There are 40,000 total images after the images are divided into Positive (cracked) and Negative (non-cracked) directories, each of which contains 20,000 images. The Middle East Technical University is home to a number of high-resolution images (4032x3024 pixels), generated using the method suggested by Zhang et al. (2016), of 458 different buildings. These pictures were taken at a distance of about one metre from the intended object. From this dataset, 5010 images of concrete surfaces were chosen for this study. Prior to further processing, these images were reduced to 227x227 pixels in size. For the purposes of training and validating the CNN models, 80% (3206 + 802 = 4008) of the randomly chosen images from both datasets were used. For testing, the remaining 80% (1002 images) were set aside. The images were pre-processed before being used for training, validation, and testing. The specifics of the image pre-processing methods used will probably be covered in a later section of the research. The first dataset (Mendeley Crack Dataset) is referred to as DB1 in this research context.

6. RESULTS AND DISCUSSION

Using two prepared datasets—DB1, which contains chosen images from the Mendeley Crack Dataset, and DB2, which includes surface images of various buildings from CSIR-CEERI, Pilani—six CNN models with transfer learning were used in this study. There were two phases to the evaluation of the CNN models. The models were initially trained, tested, and the results were analysed on DB1. Second, DB2 was used to evaluate the models, and the resulting findings were discussed. The models' training and testing speeds were taken into account in addition to performance evaluation metrics like accuracy, precision, recall, and F1-score. Inception-v3, DenseNet-121, and ResNet-50 were the fastest models, while InceptionResNet-v2 was the slowest, according to Figure 4's comparison of the training times for the various CNN models. The classification probabilities obtained from the test data were compared to a threshold of 0.8 for the evaluation on DB1. The image was classified as a crack if the probability exceeded the threshold; otherwise, it was classified as non-crack. The performance indices for each class were displayed in the confusion matrix (Figure 5). Overall, all six CNN models' accuracy ratings fell between 0.95 and 1. ResNet-50 had the lowest accuracy score of 0.950099, while the Xception and Inception-v3 models had the highest accuracy scores of 0.992015 and 0.985029, respectively. The non-crack class had recall values ranging from 0.99 to 1, while the recall values for the crack class ranged from 0.90 to 0.99 across the trained models. The highest recall values for the non-crack class (1.0) were attained by DenseNet-121 and InceptionResnet-v2, while the highest recall values for the crack class were attained by the Xception and Inception-v3 models (0.985567 and 0.971134, respectively).

Figure.4: Time Consumed by CNN Models During Training on DB1

Figure.5: Time Consumed by CNN Models During Training on DB2

For both classes, ResNet-50 had the lowest recall values. The Xception model showed the best performance in categorising concrete cracks, with an estimated F1-score of 0.991701 for the crack class and 0.992306 for the non-crack class. ResNet-50, on the other hand, performed the worst. Based on the anticipated outcomes, two additional metrics, Cohen Kappa and ROC AUC, were computed. While Cohen Kappa was calculated using the ground truth test values and the predicted concrete class values (after converting the predicted probabilities using the threshold of 0.8), ROC AUC was determined by comparing the ground truth test values with the predicted probabilities. Inception-v3 and Xception obtained the highest ROC AUC scores (0.998500) and Cohen Kappa scores (0.984010), as shown in Figure. Inception-v3 and Xception showed overall good performance in classifying concrete cracks using the two datasets, according to evaluation metrics and performance analysis.

7. CONCLUSION

The research paper concludes by presenting an intelligent healthcare system that uses Internet of Things (IoT) and Artificial Intelligence (AI) to revolutionise the way that diagnoses and treatments are administered. In order to increase productivity, accuracy, and patient outcomes in healthcare, the paper emphasises the significant potential of integrating AI and IoT technologies.

Concrete surface crack classification and detection are essential components of structural health monitoring, but they also present significant challenges. In order to keep track of the strength and resilience of concrete structures, this paper compares deep convolutional neural network (CNN) models used in automated structural health monitoring. CNN models fall under a particular subset of deep neural networks that are frequently used for feature extraction, prediction, classification, and other functions. The intelligent healthcare system covered in this paper offers a number of significant advantages. By using AI algorithms to analyse medical data like patient records, medical images, and laboratory results, it first enables quicker and more accurate diagnosis. The AI algorithms can find patterns, spot anomalies, and give healthcare professionals insightful information to help them make decisions. The addition of IoT devices expands the system's potential by making it possible to track patients' vital signs, health metrics, and other pertinent data in real-time. Wearables and other Internet of Things (IoT) gadgets like sensors and wearables continuously gather data and send it to an AI system for analysis. Early detection of health issues, proactive intervention, and individualised treatment plans are made possible by this real-time monitoring.

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