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Smart Health Monitoring Using Deep Learning and Artificial Intelligence

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ABSTRACT

The genesis and spread of illnesses are a major concern in today's rapidly developing technological and evolutionary environment. The prevention and management of illnesses using technological means have emerged as one of the most pressing challenges facing the medical community. With today's hectic schedules, it's nearly impossible to stick to a healthy routine. The problems above can be fixed by using a smart health monitoring system. Two of the most rapidly emerging technologies are the Internet of Things (IoT) and artificial intelligence (AI). As more people relocate to urban areas, the idea of a "smart city" has become increasingly commonplace. Increased efficiency, decreased expenses, and a renewed emphasis on improving the quality of care provided to patients are central to the idea of a "smart city." There has to be a thorough familiarity with the various smart city frameworks before the Internet of Things (IoT) and artificial intelligence (AI) can be effectively used for remote healthcare monitoring (RHM) systems. Technologies, gadgets, systems, models, designs, use cases, and applications are all examples of frameworks. The RHM system, based on the Internet of Things, relies heavily on artificial intelligence (AI) and deep learning (DL) to analyse the data it collects. However, DL techniques are widely utilised for making analytical representations, and they are included in CDSS and other kinds of healthcare services. Patients are given personalised recommendations for therapy, lifestyle changes, and care plans by clinical decision support systems after each element is thoroughly analysed. Supporting healthcare applications, this technology may assess activities, etc. In light of this, this paper presents a survey that zeroes in on the best smart city applications for the Internet of Things in health. By analysing the most important monitoring applications across many models using appropriate IoT-based sensors, this research provides a comprehensive assessment of the technologies and systems involved in providing RHM services. Finally, this study makes a contribution to scientific understanding by identifying the primary constraints on this field of study and suggesting directions for further investigation.

1. INTRODUCTION

Physical and mental well-being are vital to every human being. Lack of disease and improvement in one's physical and mental well-being are two of the hallmarks of good health, which is a great benefit. The health and healthcare systems in every culture are becoming more modern and technologically advanced. There has been a worldwide economic impact from COVID-19 recently, leading to the implementation of cutting-edge healthcare technology [1]. Intelligent healthcare systems use remote nursing of patients to prevent the spread of disease and maximise the efficiency of healthcare spending. An excellent option in this setting is the combination of machine learning and IoT-enabled healthcare systems [2]. Efficiency in IoT) and machine learning-based solutions is a result of developments in sensing, processing, spectrum use, and artificial intelligence. The development of microelectronics has made feasible these solutions by creating tiny, low-cost medical sensing devices, which have fundamentally altered the delivery of healthcare [3]. Therefore, healthcare organisations divide these approaches into two categories: symptomatic therapy and preventative treatment. People today place a premium on illness prevention, early diagnosis, and the most effective treatment for a wide range of chronic conditions [4]. As a result, building comprehensive healthcare surveillance networks across the country is becoming the norm.

Healthcare has long benefited from technological advancements, and now those advancements are being made digitally information and smart devices, medical records, and portable devices create a vast infrastructure in healthcare systems [5]. The advancement of computational methods in healthcare, in tandem with the expansion of physical facilities, has given healthcare professionals and academics the ability to create creative solutions across a wide range of previously unexplored areas. The purpose of this study was to identify the critical elements influencing people's propensity to embrace wearable technologies in healthcare [6]. In order to better facilitate the Internet of Health Things in the industrial setting, recent studies have provided a comprehensive overview of the relevant literature. The research offered a literature assessment and reported on the current state of big data organization, analytics, and their technical software design in the healthcare sector [7]. Patients' records are organised in a standard way so that we can reliably file away and retrieve the data we need to care for them. Systems of traditional healthcare have been replaced by systems of digital healthcare thanks to smart IoT-based applications like gadgets, and smart mobile phone healthcare systems. In spite of a patient's geographical location, doctors are now able to easily diagnose and track their condition because to technological improvements [8].

Technologies have integrated detection and classification of activities through different sensor modalities, allowing for autonomous and real-time behaviour analysis, monitoring, activities of daily living, living, rehabilitation, elderly care, smart home surveillance, and entertainment. [9]. Smartphones, wearables, and ambient surrounds devices are equipped with a wide variety of smart sensors for detecting and monitoring activities, including magnetometers, heart rate monitors, accelerometers, pressure, and wearable cameras. [10]. After being collected by these sensors, several feature sets are extracted and transformed using machine learning algorithms so that human actions may be monitored and classified. These feature sets include frequency domain, temporal domain, and wavelet transform. Using deep learning for autonomous feature representation has been projected to simplify the need for manually produced features and improve performance accuracy [11].

Artificial intelligence (AI) techniques like data science underpin many of the innovations in today's healthcare system. Early identification, analysis, management, and presentation are all facilitated by these. IoT, edge devices, drones, robots, webcams, and intelligent medical equipment can all be helpful in a pandemic crisis [12]. In modern healthcare systems that make use of the Internet of Things, machine learning and deep learning algorithms are routinely deployed. There is a stronger connection and outliers in the data produced by these IoT devices, but there is also a lot of unstructured telemedicine data. Therefore, in order to lessen the likelihood of redundant data being collected from athletes, it is necessary to employ machine learning and deep learning methods to extract useful characteristics from raw telemedicine data [13]. Wasted resources and disastrous health outcomes [14] are the results of storing and processing redundant, lossy, and noisy data in off-site cloud data centres. When it comes to getting rid of anomalies and unnecessary information, machine learning and deep learning algorithms are invaluable. These algorithms ensure that the management information system only has highly processed telemedicine data available for making critical health choices. These algorithms guarantee the optimal choice is made for delay-sensitive and time-critical applications by extracting useful characteristics from massive volumes of raw data [15]. Deep learning, in contrast to machine learning, utilises several concealed nodes and layers to achieve comprehensive coverage and advanced feature extraction from raw telemedicine data. Massive amounts of diverse data are produced in sports informatics, which calls for standardised methods of analysis and information extraction. Without the need for manual engineering or intervention, a deep neural network may produce useful features from an existing unstructured dataset using typical learning processes.

This study proposes a real-time, smart healthcare system that makes use of deep learning algorithms and the Internet of Things. The suggested system employs mobile medical devices to collect data from the human body, where it is then processed by a variety of deep learning algorithms. There have been several advances in the development of health monitoring systems in recent years. Here, we take a look back at some of the more report on the state of the art in the sector with regards to deep learning and transfer learning. Therefore, the purpose of the proposed work is to provide a comprehensive overview of the current techniques, approaches, and methodologies linked with deep learning and transfer learning for health monitoring in order to address these shortcomings. Based on the facts presented here, academics will be better able to articulate new ideas for streamlining healthcare thanks to this review.

2. BASIC KNOWLEDGE OF SMART HEALTHCARE IN CITIES

2.1 Smart city and healthcare facilities

Many non-smart cities want to implement conventional healthcare infrastructure in an effort to mimic the notion of smart city healthcare. To ensure the success of smart cities in providing residents with quality healthcare services, objectives of the smart city include ensuring residents have access to high-quality housing and healthcare and fostering an environment that is more agreeable to healthy living. There has to be a system in place to produce new, effective healthcare solutions.

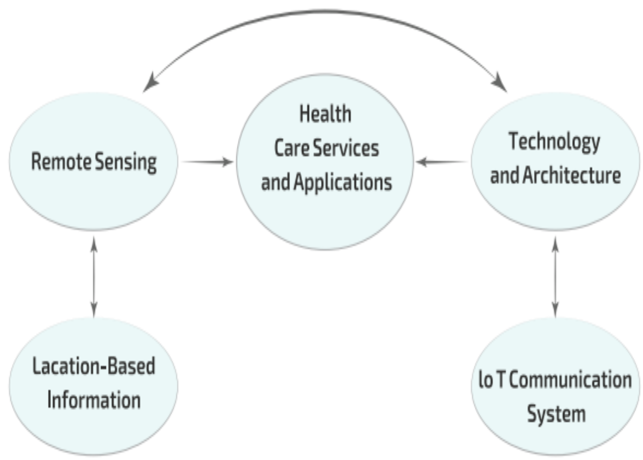

Figure 1. Rudimentary elements of an IoT-enabled keen city healthcare scheme

As can be seen in Figure 1, the fundamental components of an IoT healthcare system are realised through the cooperation of various systems, architectures, and frameworks. There are six primary parts to what we call "smart services," and they are as follows: I smart economics; (ii) smart environments; (iii) smart governments; (iv) smart people; (v) smart mobility; and (vi) smart living. The many forms services can take have been outlined in detail. Life in a smart city is superior in almost every way. Moreover, it enables people to participate in societal activities that directly serve their needs. Citizens employ an array of smart gadgets to interact with and make advantage of these offerings. When individuals use the Internet to provide a large quantity of personal data, the result is a smart service, which is an explicit, complex network design. Virtual visits increased from around 1000 in February 2020 (before the COVID-19 epidemic) to between 3000 and 3500 on an outbreak day in April 2020. By providing care while the patient engages in social isolation, telemedicine centres may help decrease the spread of illness during an epidemic. Case study of machine learning's application to smart cities is shown in Table 1.

Table 1. Machine learning procedures and use in smart city health care

Machine Learning Algorithm	Application and Use Cases for Smart City Health care	Function
K-means	Health care in the comfort of your own home and in the bustle of a metropolitan area	Identifies patterns in data that have not been identified Utilizes a Clustering Algorithm to handle Massive Datasets
Dbscan	As a result of the M-IoT network's ability to process data gathered from human sensors (such core body temperature), we will be able to gauge the efficacy of our communication efforts.	Using dbscan, you may see how your unstructured data is arranged. Provides compatibility with a wide range of file types Clustering HR databases using conceptual schemas
Support Vector Machines	Forecasting Healthcare Solutions Human health pattern, such as real-time detection of blood sugar near	Controls massive amounts of information by sorting it into useful categories. Processes massive amounts of data of varying types Powerful enough for use in sophisticated algorithms for processing data High-speed data processing and transmission
Clinical Correlation Analysis	Use in creating medical answers by bringing together and combining a wide range of devices, instruments, and cases	Both of these techniques are commonly used to extract features from data. CCA draws attention to the connection between the two sets of data through comparison and visualisation. A data source for use in a multi-source anomaly detection system.
Neural Networks	Medical hardware, software, and instruments are all enhanced by machine learning techniques. Application examples can be found in the field of rehabilitation administration	It offers a useful learning approach for addressing problems with approximate function evaluation.
Anomaly Detection Algorithms	Uses unique to monitoring tasks, such as those involving blood pressure or electrocardiogram (ECG) readings. Robotic aid for discovering data outliers	Statistics on a range of normal and pathological data Using esoteric data sets for comparison Construction deductions and a binary classifier

2.2 Healthcare services, requests, and remote sensing

In a smart city, residents may use services that address common problems in their neighbourhood. In terms of functionality, the hospital are the most relevant. Numerous studies and applications have shown that remote sensing can be useful in the healthcare monitoring sector. Patients' electronic internals, such as an (ECG), blood pressure, and pulse, are detected and collected, and a patient record management centre (PRMC) helps handle and store this data. Using the patient's linked medical sensor, doctors may monitor environmental factors like humidity and temperature and send that data to a central database for analysis and perhaps remote therapy.

2.3 Technology and construction of RHM

The data for the health nursing facility comes from the patient's smart device and the caretaker's as well. The (HMS) is the brains of the operation, analysing current conditions and past data to provide an IHP that may be implemented immediately. During times of crisis, it can also send out alerts, warnings, and special cases. The core components of the intelligent service are the health monitoring service used for assessment and supervision, the hospital service used to acquire diagnosis of health issues, and the rapid response to these issues. The PRMC is also concerned with data storage and analysis. The IHP receives real-time data from the health monitoring system. The hospital system allows doctors to infer a patient's health state based on the HMS report and the patient's medical history accessed through the PRMC.

The PRMC is a repository for all patient medical information and data, including current health problems as recorded in electronic medical records. Headers of limitations and protocols are also sent to other linked systems. Local storage is available inside the health monitoring service. The patient's medical data and history are kept here, making it a crucial part of any reduced technological architecture for smart healthcare service. The PC-EHR is a flexible repository for a patient's medical history and other identifying information (name, address, phone amount, etc.).

2.4 Sensing, monitoring, and regulatory

Intelligent healthcare communities will require sensors, monitoring, and control. Feedback values from these sensors provide automated monitoring and control for healthcare facilities. The data reported by these sensors allow healthcare practitioners to automate a variety of monitoring and control procedures. These objectives may be effectively achieved through the use of the Internet of Things, wireless sensor networks, deep learning, and other technologies. Because of their access to real-time data, smart cities can respond rapidly to the healthcare requirements of large populations. Doctors and other medical professionals can make effective choices quickly. The Internet of Things, AI, and computers have revolutionised the healthcare industry. Various types of sensors, such as those used in smartwatches, can be either implanted or worn externally on the human body.

Data is delivered via gateways and wireless networks to reach healthcare providers. Electrochemical glucose sensors are only one type of implanted sensor that can aid in the monitoring and management of diabetes. Artificial intelligence (AI) gadgets are also used by patients to self-manage and tailor their diabetic care. Patients with diabetes can use these devices to track their glucose levels via sensor data sent to their cellphones. Sleep apnea, rheumatoid arthritis, intracranial hypertension, and cardiac arrhythmias are all monitored and managed with the use of cutting-edge sensors. The primary barriers of these tools are in their administration and functioning. It's possible that those in charge lack the appropriate training or just neglect to keep the equipment charged. To alleviate the burden of managing and operating the sensors, it is crucial to implement zero-effects technologies (ZETs). A wide range of illnesses, including cardiovascular disease and dementia, may be tracked with the aid of remote sensing. To effectively treat these types of diseases, behavioural monitoring must be implemented. One estimate puts the number of persons living with dementia at 47 million in 2017. According to estimates, that figure will rise to 132 million by the year 2050. Improved remote sensing technologies supported by the (AI) might streamline the monitoring and control essential for treating chronic illnesses.

3. TAXONOMY ON HEALTHCARE NURSING SYSTEM

In this analysis, we have categorised all of the systems according to how frequently they have utilised certain hardware components. So, we've broken down every system into the following three classes.:

One, systems based on sensors; two, systems based on smartphones; three, systems based on microcontrollers for monitoring health.

In Figure 2 we see the classification scheme used by the reviewed intelligent health monitoring system.

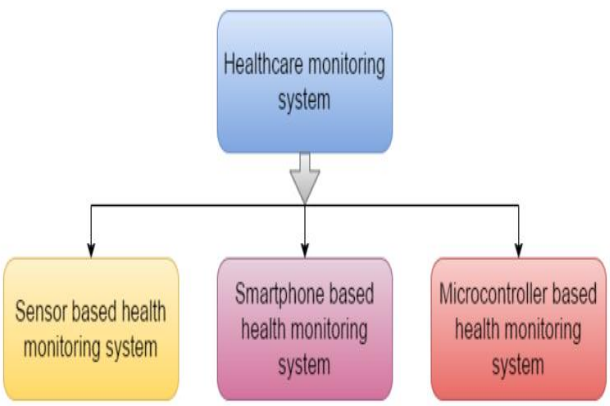

Figure 2. Taxonomy of the reviewed smart health monitoring schemes

3.1 Sensor-based health monitoring system

The electronic data stream from the sensors is translated into an audible alarm that alerts the patient to his or her current health status. Heart rate, temperature, and electrocardiogram (ECG) sensors are among the most popular [16]. Sensors for measuring temperature, heart rate, and body temperature (Max 30205) were often used in health trackers (BME 680). CO2 sensors are just one type of sensor used in health monitoring systems; others include temperature sensors, RFID readers, biochemical detectors like glucometers, and sensors that track things like body posture and breathing.

3.2 Smartphone-based health monitoring scheme

Smartphones are among the world's most valuable tools. There are now around 14 different types of sensors on a smartphone, and many more are expected to be introduced in the near future [17]. A smartphone's speech monitoring function is a powerful tool. Many different kinds of hardware systems have been created to take use of this adaptability. Wireless sensors, Bluetooth modules, accelerometers, fingerprint scanners, gyros, magnetometers, barometers, proximity sensors, GPS trackers, cameras, and NFC-near field sensors are all part of modern smartphones and are frequently employed in the creation of health monitoring systems [18]. Among the many benefits of smartphones is the large amount of space they provide for storing data. Primary storage on a modern smartphone is more than adequate for archiving the patient's information. Smartphones running the Android operating system make it simple to access and share information, manage multiple devices, and communicate in real time.

3.3 Microcontroller-based health monitoring system

All throughout the world, microcontrollers are the most popular and widely utilised components of health monitoring systems. Microcontrollers (MCUs) are great for quick processing of raw sensor data. The field of field-programmable gate arrays (FPGA) has seen widespread application for the concurrent processing of massive data sets. To facilitate communication between the sensors, an MCU was employed [19].

4. APPLICATIONS OF IOT AND REMOTE MONITORING IN HEALTHCARE

4.1 Remote intensive care in home healthcare

The IoT refers to a category of computing devices that includes devices like transceivers, microcontrollers, and remote sensors. Health care is prioritised because it is necessary for humans to oversee, control, detect, and react to data collected by the system, and costs are reduced as much as possible without compromising quality. In the last five years, advanced nations like the United States have been the primary adopters of telehealth remote monitoring. One reason for this shift is the rising faith in the efficacy of remote healthcare in enhancing patient wellness. The results showed that patients' expectations of success had minimal bearing on their decisions to utilise IoT for eHealth, which should encourage product designers, healthcare providers, and marketers to refine their approaches to these areas in order to increase adoption. Over 100 remote monitors were carefully placed in the homes of individuals with severe cognitive deficits for the investigations. Additional data was gathered to better comprehend patient demographics, treatment regimens, social networks, and clinical standing. This study set out to determine if the positive effects of remote healthcare monitoring on patients differed from those seen in a hospital setting by utilising a control group that was otherwise identical to the active group except that it did not get remote monitoring. The study showed a significant drop in the number of patients requiring hospitalisation (a testament to remote monitoring efficacy). Hospitalization rates were higher for the control group (45.5%) than for the remote healthcare monitoring group (35.6%) across all diagnoses. When comparing the remote monitor group to the control group, the study indicated that the number of weekly nursing visits decreased significantly.

Care for the elderly and the terminally sick might be provided in the comfort of their own homes with the help of RPM. As a result, this disproves the hypothesis that severe clinical conditions are difficult to handle via remote healthcare monitoring. Different indicators of detections and comprehensive monitoring by an applied totally automated AD monitoring report have been offered in recent studies. Also, the framework labels people as healthy or ill. The incorporation of remote healthcare monitoring into existing healthcare system infrastructure is essential. A recent analysis found that RPM had been implemented across 13 distinct healthcare programmes and services in the UK. One chronic obstructive pulmonary disease (COPD) patient on oxygen, one patient with chronic heart failure (CHF), one patient with diabetes, one patient in unstable condition (such as heart problems, high blood pressure, or irregular heartbeat), and four COPD-related projects were highlighted in the report. A link to primary care was included into the models and operational architecture, but the systems were not yet ready for implementation. meeting their shared health services goals prior to the initiative. After examining the problems, they developed a clinically-based, integrated monitoring system centred on primary care.

4.2 IoT healthcare applications

Close monitoring of IoT applications is another feature of IoT services. New methods have been developed to create a healthcare system framework that can manage and analyse data from electronic health records (EHRs) and medical images. It's evident that app development is focused on the services required, and it's not a big surprise that sick people and other users rely on apps. It follows that whereas apps are tailored to the needs of end users, services focus on what the developer can provide. Emotion detection in functional technologies, accident intensity prediction in severe injuries, and effectively evaluating alcoholics are only few of the latest applications that have employed different ML algorithms in similar ways.

Research and development efforts have focused extensively on IoT-driven healthcare systems and technology, including how the IoT may aid with paediatric and geriatric care, chronic illness tracking, individual wellbeing and activity management, and more. The numerous pieces of technology, wearables, and healthcare instruments now available on the market were also explored in the research. These novel healthcare products and tools might be viewed as an example of the inventiveness and originality of the Internet of Things in delivering various forms of medical assistance. The many single- and multi-condition IoT-based healthcare applications are discussed in the following sections. Table 2 provides a synopsis of IoT-based sensors in healthcare applications and other use cases and deployments.

Table 2. IoT healthcare applications and specific use cases

Applications	Descriptions	Specific Use Cases	Technology Applied
Blood Pressure		Blood Pressure	
Glucose Level Sensing	A device that detects glucose levels in the blood without requiring a needle or other intrusive procedure. The system consists of a glucose monitor, some form of background processing, and either a phone call or a computer.	Maintaining a constant eye on the patient's blood sugar levels. Connect the patient's body to the doctor's in real time	IoT, IPv6
Electrocardiogram Monitoring	IoT-related ECG checking network comprising a wireless acquisition and transmission device	Electrocardiogram (ECG) monitoring with a signal-detection algorithm	Electrocardiogram, IoT frameworks, anomaly detection.
Imminent Healthcare	Possible deployment of Internet of Things-based services, systems, and apps improves access to healthcare throughout the world and strengthens data security.	Paediatric and elderly care, chronic disease supervision, private health, and fitness management	IoThNet framework, Intelligent Security Model
Body Temperature Monitor	It includes integrating a thermometer with an IoT channel. The Internet of Things' RFID node acts as themeasurement of body temperature and also aid in the transmission of data	Used to measure temperature and transmit data in real-time	Thermometer Sensors, IoT System

Rehabilitation System	As part of the rehabilitation process, patients' mental health may be monitored in real time thanks to a proposed IoT-based smart rehabilitation network.	Used in shortening the duration of the rehabilitation process in hemiplegic patients through integrated applications that can serve as self-care	IoT Frameworks, Machine Learning
Medication Management	An approach to managing medications that uses I2Pack and iMedBox to ensure that pills are genuine	Ambient Assistant Living Interventions to control medication prescription systems	RFID, IoT frameworks,
Wheelchair Management	Potential wheelchair design with a WBAN integration beaming in sensors pivoted by the IoT app	Create a smart wheelchair capable of monitoring a patient's health Processing prompts and relays location data	IoT Frameworks, Machine Learning
Oxygen Saturation Monitoring	The oximeter is connected to an IoT channel such as Bluetooth or the Internet to ensure the real-time transmission of data between the patient (who may be in a different location) and the health practitioner	Wearables that monitor oxygen levels in critically ill patients and instantly alert medical staff to any in development.	Oximeter, IoT system
Smart Devices	Capture data, process, and relay them in realtime	Temperature and BP measurement. Train patients and relay treatment information based on data gathered	IoT framework, Cloud Computing, Big Data
Essential Healthcare Services	Cardiovascular Diseases, Ambient Assisted Living, Fitness, and Neurological	Diseases involving the heart and blood arteries are known as cardiovascular diseases. Facilitating the performance of bodily actions such as walking, running, jogging	Machine learning, cloud computing, big data

4.3 Healthcare implementations using smart device requests

There has been a recent uptick in the production of electrical gadgets that are controlled by sensors sent from smart smartphones. Because of this shift, smart gadgets are becoming the primary forces behind the Internet of Things. Implementing quality service standards like flawlessness, dependability, and cross-device portability necessitates integrating IoT with specialised disciplines [20]. Smart devices have become a helpful instrument in the delivery of medical care as a result of the development of a variety of software applications and hardware items that are compatible with smart devices. In-depth research was conducted, and the characteristics of health apps and how they interact with those of smart devices were laid out in methodical detail [21]. The article covered topics including patient-focused apps and health apps in general. Apps that can aid in patient education, training, and information were also explored; these and other similar apps are referred to as auxiliary requests.

The following medical issues might be conveniently checked and diagnosed using the tools already available on smart devices. In addition, technological progress aids medical professionals in making correct diagnoses and providing effective treatment. It might be used to tell the difference between emergencies requiring immediate care (such as trips to the emergency department) and chronic conditions requiring complex management. Patients with severe cases of diabetes can have a wide range of complications. Asthma attacks, severe respiratory tract obstructions, allergic rhinitis, and other nasal-related symptoms might influence the lungs, heart rate, blood pressure, oxygen saturation in the blood, skin, and immune system [21].

5. RELATED STUDIES

The novel wearables-assisted smart health monitoring with optimum deep learning (WSHMSQP-ODL) model is the work of Hamza et al. [22]. For starters, the disclosed WSHMSQP-ODL method makes it possible for wearables to collect data on sleep-related activities. The next step is data pre-processing, which involves standardising the data in some way. The WSHMSQP-ODL model makes use of network (DBN) model to predict sleep quality. To improve the DBN model's ability to predict sleep quality, we employ the extended seagull optimization (ESGO) technique to fine-tune several of the model's hyper-parameters. A variety of metrics are used to analyse the WSHMSQP-ODL method's experimental outcomes. Extensive research reveals that the WSHMSQP-ODL model significantly outperforms competing models.

To build HI using SHM data fusion, Moradi et al. [23] presented a semi-supervised deep neural network. Instead than simply being utilised as a quality indicator for HI, prognostic criteria are really being employed as goals for the network itself. Here, composite panel fatigue stress was tracked using the acoustic emission technique, and the resulting feature extractions were put to use in the development of a smart HI. The generalised model achieves at least an 81.77 percent score on the prognostic criteria when tested using the leave-one-out cross-validation approach, while the holdout method demonstrates a 77.3 percent improvement in the quality of the HI. This research shows that a model can still be constructed to give HIs that coincide with the expected deterioration behaviour even when the real HI labels are unknown but the qualifying HI pattern (according to the prognostic criteria) can be detected.

In order to forecast the system's true operational states, Keleko et al. [24] took a data-driven strategy, focusing on the Deep Neural Networks' (DNN) multi-class classification for unbalanced data. Although DNNs perform well, there are still some unanswered problems about how trustworthy they will be as "black box" models in more complicated applications, especially with regards to the decision-making processes and the potential ethical, economical, and transparent consequences on stakeholders. As for the explanation strategy, the Deep SHapley Additive exPlanations (DeepSHAP) techniques are used to both provide reliable findings and offer context for the decision-making process within the DNN. Accuracy, F1-Score, Recall, and Precision are all indicators of the DNN classifier model's robustness and efficiency, which are in turn shown by the resulting framework based on the two primary modules. Last but not least, the DeepSHAP method provides an explanation of the developed model's results, making it easier for humans to understand, interpret, and trust the model, thereby increasing the support or stimulation of AI model applications on large-scale problems, including those in the industrial sectors.

The problems, services, and uses of smart healthcare systems are presented by Gupta et al. [25]. In addition, using edge computing and IoT paradigms, offer a CNN-based prediction model. Local edge provide for fast resource availability and response time within the context of edge computing. Health data gathered by IoT devices is analysed using a CNN model. Also, edge devices are essential because they allow for fast health-prediction results to be delivered to doctors and patients through edge servers. Accuracy and error rate are two performance metrics that may be used to evaluate the suggested process. When compared to other methods, the suggested mechanism has an accuracy of 99.23%.

By merging several cutting-edge approaches including IoT, DT, FoT, CoT, and Blockchain, Manocha et al. [26] create a smart framework for context-aware monitoring of physical activity without compromising the confidentiality of the healthcare sector. In the suggested research, we use deep learning's capacity to process data sequentially to examine an elderly person's motions in search of signs of abnormality. Furthermore, the suggested framework can protect an individual's data using the advanced security features of blockchain. The proposed system performed a highly accurate analysis of an out-of-the-ordinary occurrence in a person in real time. The results of the calculations reveal that DT can assist establish successful medical services by connecting patients and medical care specialists via the use of smart healthcare solutions. In addition, the effectiveness of the suggested solution is evaluated in terms of its ability to identify anomalous events, the speed with which models can be trained and tested, the latency of the data processing, and the cost of doing so. In this way, the efficacy of the suggested technique in the field of smart healthcare is defined by way of a case study.

Battery life can be conserved during transmission by reducing the bitstream burden of the raw ECG signal, as suggested by Sarma and Biswas [27]. A power-aware ECG processing architecture is described, which extracts features in real time for continuous health monitoring, and which may then be encoded into the bitstream. The suggested architecture investigates the benefits of computationally simple procedures with a particular emphasis on a sensor node with limited resources. The design detects R-peak and P-peak using an adaptive thresholding approach and handles two forms of cardiac abnormalities: irregular heart rate variation (HRV) and first degree AV block. Validation on the MIT-BIH arrhythmia database demonstrates that the proposed method has a sensitivity and positive predictivity of up to 99%. With an estimated power usage of 2.11 W and an area overhead of 0.087 mm2, the suggested design is synthesised at TSMC's 90 nm technology node. The minimum operational voltage for this design is 1.2 V, and the maximum operating frequency is 10 KHz.

For WT status monitoring, Zhu et al. [28] offer a new method based on a convolutional neural network (CNN) that cascades to a long- and short-term memory network (LSTM) and combines kernel PCA (KPCA). To begin, SCADA data was filtered using the density-based spatial clustering of applications with noise (DBSCAN) approach. By carefully choosing input variables, the KPCA method was then used to monitor and anticipate faults in WT. This led to the development of the KPCA-CNN-LSTM model. In conclusion, the created prediction model was utilised to analyse various parts of the WT, with the wind farm serving as an example. Verifying the efficacy of the suggested technique, experimental results show that the proposed model can aid in not only monitoring the condition of the WT, but also in forecasting the abnormal operating state of the WT at an early phase.

The HAR system developed by Helmi et al. [29] makes use of data collected from wearable sensors in combination with results from DL and SI applications. Residual convolutional networks and recurrent neural networks are used to provide a lightweight feature extraction strategy (RCNN-BiGRU). Here, we provide a novel approach for selecting features using the marine predator algorithm (MPA). Three binary variations of the MPA, designated MPA s, MPA s10, and MPA v, are created towards this end. To guarantee the quality of their performance, we put the suggested MPA variations through extensive testing, including comparisons to multiple optimization algorithms using various evaluation indicators and statistical tests. Accordingly, it is determined that MPA v achieved the highest performance when compared to other MPA variations and other comparable approaches.

To evaluate the state of bridges in third-world nations, Inam et al. [30] suggested a two-stage, deep learning-based system for smart infrastructure organization. First, it uses the Pakistani dataset and the publicly available SDNET2018 dataset to find instances of cracking in bridges. The dataset photos with cracks were analysed using You Only Look Once version 5 (YOLOv5). The YOLOv5 s, m, and l models are applied to the dataset in a 7:2:1 split for training, validation, and testing to calculate the primary indicators (precision, recall, and mAP (0.5)). All of the models' mAP (Mean average precision) results were compared to see which one performed the best. The results reveal that the YOLOv5 m model outperforms the YOLOv5 s and l models on the test set, with mAP values of 97.8%, 99.3%, and 99.1%, respectively. The U-Net model is used for segmentation of the crack to obtain their precise pixels in the second part of the investigation. Pixel width, height, and area are measured and displayed on scatter plots and Boxplots to distinguish between cracks, using the segmentation mask provided to the attribute extractor. In addition, the results of the suggested YOLOv5 models were verified by the segmentation phase. In addition to locating and grading the cracks according to severity, this research split the crack pixels to evaluate their width, height, and area per pixel in varying lighting situations. It's one of the few research efforts to focus on inexpensive bridge health assessments and damage detection in poor nations, which often have trouble keeping up with routine maintenance and repair of such essential infrastructure. Bridge and similar infrastructure may be assessed for their state and health on a regular basis using the suggested model, which can be employed by local agencies on their way to a smarter and automated damage assessment scheme.

In the study, Naseri et al. [31] construct an IoT-based face mask detector utilising a "Single Shot Multi-box Detector (SSD)" and a hybrid deep learning approach. The proposed model is novel because of the improvements made in face detection and face classification using the developed ASMFO by optimising parameters like the threshold in SSD, the number of steps per execution in ResNet, and the learning rate in MobileNet, allowing it to be more efficient and to perform better than previous models. In this case, an adaptive sailfish moth flame optimization technique is used to optimise the parameters (ASMFO). Next, the ASMFO-tuned parameters of a hybrid technique called Hybrid ResMobileNet (HResMobileNet-based classification) are applied to the identified face pictures in an effort to produce reliable mask detection findings. Traditional meta-heuristic methods and current classifiers are contrasted with the proposed mask identification model with IoT based on three standard datasets. Thus, the proposed framework's efficacy is measured against that of other frameworks and preexisting classifiers by means of experimental analysis. When compared to SVM, CNN, VGG16-LSTM, ResNet 50, MobileNetv2, and ResNet 50-MobileNetv2, the accuracy provided by the implemented ASMFO-HResMobileNet is, respectively.

Specifically, Kumar et al. [32] suggested a Block chain-orchestrated Deep learning solution for Secure Data Transmission in an Internet of Things-enabled healthcare system (hereinafter referred to as "BDSDT"). To guarantee data integrity and safe data transfer, a new, scalable block chain architecture is first presented, one that makes use of the Zero Knowledge Proof (ZKP) technique. Then, to resolve concerns with data storage costs and data security, BDSDT incorporates an Ethereum smart contract and the off-chain storage Inter-Planetary File System (IPFS). Finally, the verified information is used to develop a deep learning architecture for HS network intrusion detection. The latter creates a powerful IDS by fusing Deep Sparse AutoEncoder (DSAE) with Bidirectional Long Short-Term Memory (BiLSTM). Experimental results on two publicly available datasets (CICIDS-2017 and ToN-IoT) show that the proposed BDSDT surpassed state-of-the-arts in both contexts, achieving accuracy close to 99%.

In the study, Di Luzio et al. [33] provide a novel deep neural architecture for emotion identification using randomised parameters in a sophisticated classification scheme. It turns out that randomised deep neural networks offer a novel approach to investigating the trade-offs between efficiency and accuracy in practical contexts. In addition, it presents a novel sampling approach that eschews padding and uses input frames made up of the coordinates of 468 face landmarks. To prove the robustness of the proposed technique, we compare the classification accuracy and training time of the proposed randomised classifier with those of a non-randomized version of the same model and with well-known benchmark models.

The high-dimensional statistical feature matrix is mined by an auto-encoder-based dimension reduction model, as described by Li et al. [34]. The next step is to determine the level of deterioration by determining the canonical correlation between the baseline's feature space and the monitoring data acquired afterward. In order to quantitatively define a deterioration process for condition monitoring, a new HI is developed from this information. Experimental validation results show the suggested HI is able to detect incipient defect and is more sensitive to the early stage deterioration process when compared to other standard state-of-the-art.

By standardising the structural health monitoring data from the Wuhan Yangtze River tunnel, Tan et al. [35] create a multi-learning model based on a deep learning algorithm and name it GC-GRU to predict the future mechanical behaviours of the tunnel structure. In order to predict segment strain and opening over the next 45 days, we used GC-ability GRUs to capture the temporal dependencies of past performance and the spatial correlations among different monitoring data. Other experiments were conducted to discuss the model's predictive ability, and results were compared to both a single-indicator prediction model and several well-known classical prediction models like GRU, LSTM, XGboost, LR, and RNN. The results of the study show that up to a horizon of 20 days, GC-GRU is the superior model. Using GC-GRU, the learning capacity of the model rises by 2.2%, and the predicted errors for joint opening and segment strain are at least 0.02 mm and 8.62 %, respectively. Consequently, the GC-GRU model may be used to foretell the mechanical behaviours of tunnel constructions.

It is possible to rapidly assess the level of damage to a concrete structure via Ai and Cheng [36] suggested a deep learning method based on two-dimensional convolutional neural networks (CNNs). The method involves first segmenting the EMA signatures into multiple sub-range responses, then selecting the sub-range responses that correspond to the maximum indices, in this case root mean square deviations (RMSDs), to build the input of CNNs for training, allowing for rapid prediction of damage severity degree. Crossover studies on a cube-shaped concrete building detecting numerous mass loss damages confirm the validity of the suggested method. By creating a variety of CNN models, we can additionally assess the impact of input size on the method's overall performance. The experimental findings show that the suggested method is effective and accurate even for small damages, which opens the door to real-world monitoring of concrete buildings.

According to Phan et al. [37], a low-level laser treatment (LLLT) system supported by a deep neural network and the medical IoT is proposed. This paper makes significant contributions in three areas: (1) it proposes a deep learning model for facial dermatological disorder segmentation using a Modified-U 2 Net; (2) it provides a comprehensive hardware and software design for an automatic phototherapy system; and (3) it develops a synthetic data generation process for the proposed models to address the issue of the limited and imbalanced dataset. In conclusion, we present an LLLT platform that makes use of MIoT to enable remote healthcare monitoring and administration. With an average Accuracy of 97.5%, Jaccard index of 74.7%, and Dice coefficient of 80.6% on the untrained dataset, the trained U 2 -Net model outperformed other recent models. Results from our experiments showed that our proposed LLLT system successfully identified facial skin diseases and automatically applied phototherapy. Integrating AI with MIoT-based healthcare platforms is a major step towards the creation of medical assistant tools in the near future.

The work of Soni et al. [38], which uses deep learning techniques to recognise human physical activity in wearable and mobile sensor situations, has also garnered a great deal of interest. In this paper, we propose a DNN that combines the strengths of the convolutional neural network (CNN) and the bidirectional long short-term memory (Bi-LSTM). The model's efficacy was measured using the WISDM and UCI-HAR datasets, both of which are available to the general public. The model has an accuracy of 97.96% in the WISDM and 97.150% in the UCI-HAR. The simulation results also demonstrate the superiority of the proposed work over competing approaches.

Using multimodal deep learning and the Tucker decomposition, Yu et al. [39] introduce a novel high-order multi-modal learning approach (F- HoFCM). To improve the efficiency of its embedding in edge resources, it also proposes a private scheme supported by edge clouds. Parameter updates using a high-order back propagation algorithm and clustering with a high-order fuzzy c-means are just two examples of the kinds of computationally intensive tasks that can be handled efficiently in the cloud. Other processes, like multi-modal data fusion and Tucker decomposition, are carried out by edge resources. For privacy, feature fusion and Tucker decomposition are employed since they are nonlinear processes that cannot be performed on the cloud. The created edge-cloud-assisted private healthcare system greatly improves the clustering efficiency, and experimental findings show that the given technique significantly outperforms the existing high-order fuzzy c-means (HOFCM) on multi-modal healthcare datasets.

Using Ensemble Deep Learning with Framingham Feature Extraction (FFE), Sivakumar [40] presents a smart healthcare system for the diagnosis of the COVID-19 pandemic sickness. The Maps of pollution hotspots are constructed using data and attributes acquired with the help of forecasting techniques. Based on the maps, immediate mitigation steps are implemented to lower air pollution levels, such as storing the extracted data or feature in a Cloud server. Once implemented into patient management systems, this strategy would free up cloud storage once pollution thresholds were reached, therefore reducing pollution from patients' sensors. The Gini Index factor information gain strategy is used to pick the most significant characteristics while discarding the least important ones in order to further minimise computational overhead and boost system performance. An ensemble classifier based on deep learning is developed to forecast the development of COVID-19. There will be experimental assessments of prediction accuracy, error, precision, and memory for a range of patient counts. Experimental results show an 8% boost in prediction accuracy, a 47% drop in error rate, and a 36% decrease in prediction time compared to the state-of-the-art method.

In their study, Mahajan and Banerjee [41] use AE signals from PLB sources as training data to introduce and evaluate three models, including an artificial neural network and 1D and 2D convolutional neural networks (CNNs). The 2DCNN algorithm is stated to have a 94.79 percent success rate for classifying regions. As for location classification, it was found that 2DCNN was the most successful model, with accuracies of 73.12% and 79.37%, respectively, for determining where along the AE source's length the head, web, or foot was placed. After that, AE signals were generated from real-world rail damage by bending a segment of inverted rail under weights of 100 kN, 150 kN, and 200 kN. For all loads, the 2DCNN model accurately predicted the zone of the AE source, and for the loads of higher intensity, it accurately anticipated the position of the AE source along the length (150 kN, 200 kN). This study effort hopes that the deep learning technique given here will aid in the creation of an AE-based real-time monitoring system for rail inspection.

In order to facilitate healthcare data analytics and networking for personal health monitoring, Memon et al. [42] present AiDHealth, an intelligent personal health monitoring framework based on artificial intelligence. When it comes to healthcare data analytics, AiDHealth's prediction accuracy is based on a number of machine learning and deep learning models. Research has made use of the large Pima Indian Diabetes (PID) dataset. At which experiments show how well the proposed MLPD model works. When compared to other classifiers, AdaBoost's classifiers have the best prediction accuracy. The highest accuracy, 0.975%, was achieved with the AdaBoost classifier. The findings show that the suggested approach is superior to the current best practises. Next, we train the models to provide a 10-fold cross-validation sickness risk index for each sample. In light of these results, it is clear that more extensive trials are required to directly compare the aforementioned machine learning techniques. AdaBoost and Decision Tree, both with an AUC of 0.994%, were shown to work together to produce the best forecast. Therefore, the AdaBoost classifier can more accurately predict the risk of type 2 diabetes than the present algorithms and pave the way for smarter preventative measures and therapeutic approaches.

An EMI model of the embedded SA was initially created by Li et al. [43], and then the association between the SA's conductance resonant frequency (CRF) and conductance resonant peak (CRP) and the evolution of concrete strength was explored. Compressive strength was measured at various ages, and conductance profiles were tracked in real time. By examining the data, it was confirmed that as compressive strength of concrete increases, CRF falls while CRP increases, as predicted by the EMI model. Empirical equation, convolutional neural network (CNN), hybrid (LR-CNN), and linear regression model (LR) were the four models constructed. The created models use the SAs' conductance as inputs and provide the specimens' compressive strength as outputs. Four models were developed, and then compared against one another. At the same time, the LR-CNN model and other hybrids were compared across a variety of performance metrics. As can be seen from the findings, the LR-CNN model accomplishes quantitative prediction of concrete strength growth and shows good performance. Compressive strength of concrete may be evaluated and predicted using the suggested approach, which is straightforward, precise, quantitative, and dependable.

According to a proposal by Nancy et al. [44], deep learning has the potential to revolutionise our ability to quickly and effectively analyse massive amounts of data, gain insightful knowledge, and solve complex problems. Predicting the onset of illnesses with sufficient accuracy and in a timely manner is essential for providing early intervention and preventative treatment to those at risk. With the increased use of EHRs comes a greater need for accurate prediction models, which may be achieved by employing recurrent neural network versions of deep learning that are equipped to deal with sequential time-series data. The suggested system collects information from Internet of Things devices and applies predictive analytics to electronic clinical data stored in the cloud that is related to a patient's medical history. With an F-measure of 98.86%, sensitivity of 98.8%, specificity of 98.89%, and accuracy of 98.86%,

As part of their suggested method, Kondaka et al. [45] develop a novel algorithm they term iCloud Assisted Intensive Deep Learning (iCAIDL), which helps both healthcare providers and their patients by utilising an intelligent cloud infrastructure and machine learning tactics. Collecting preexisting medical information from the data repository is the first step in the training phase of an iCloud-assisted intensive deep learning algorithm. After the data training phase concludes, the suggested algorithm, named iCAIDL, begins collecting real-time data from the patient, which is treated as testing data and then processed using intense deep learning principles before being stored in the Cloud repository. This allows for sophisticated monitoring of health information and is clear to both physicians and patients. The purpose of a Smart Medical Gadget is to intensively gather data on a patient's vital signs, blood pressure, and blood flow in order to create a medical record for the testing phase. The data collected by the smart Medical Gadget must be transmitted to the Server end for processing; in this context, "processing" refers to machine learning-based processing, in which the received data is treated as the testing data and the results are mimicked appropriately. When the findings are replicated, they will also serve as training data for the subsequent round of tests. To that end, the information gleaned from the Medical Device will serve as testing data, and then, once processed, as training data for future medical summaries. Metrics such as the proportion of data sent from the Smart Medical Gadget to the server end, the precision of storage, and the efficiency of communication are used to measure the performance of the suggested solution. The simulation results show that the proposed approach, iCloud Assisted Intensive Deep Learning, may significantly enhance healthcare parameters.

In the system suggested by Rajan Jeyaraj and Nadar [46], an accurate signal prediction and estimate technique is based on a Deep Neural Network. With the help of a smart sensor for signal measurement and a National Instrument myRIO for savvy data capture, a prototype of the suggested system has been developed. The Smart-Monitor incorporates an intelligent sensor into a home monitoring system. We calculated the accuracy of the proposed Smart-Monitor system in predicting four physiological signals for two users. An average accuracy of 97.2% was achieved in prototype experimental setup. Because of this, it is clear that the suggested automated system can provide accurate monitoring as intended. The experimental outcomes prove that the suggested system is capable of providing trustworthy aid and precise signal prediction.

6. LIMITATIONS IN SMART HEALTH MONITORING

In Table 3, we depict for thorough comprehension the potential restrictions, repercussions, and enhancement procedures for IoT based smart healthcare systems.

Table 3. Limitations, insinuations, and improvement procedures in IoT smart healthcare applications

Limitations	Domain	Improvement Process	Implications
The transmission of data through machine learning software, devices, and bandwidth uses a lot of electricity.	Power, Energy	A small number of IoT gadgets have no rechargeable options while using a lot of electricity. As a result, implementations should prioritise using low-bandwidth connections. To allow data information transfer via the IoT, research power-aware and power-generation techniques. Implementation of software-defined networks (SDNs) and other virtualization technologies at a variety of points along the path to more efficient power generation techniques.	Batteries’ source limitation and capacity
Absence of clean and trained data for Artificial Intelligence algorithms. Tendentious dataset	Data	Decision-making using statistical analogies is often linked to Machine Learning. Data from the past is used to make forecasts about the future. The ML-based strategy should provide quick analysis of test data.	lead to network failure and service
Noisy data, dirty data, and incomplete data	Data	Data Learning must feed predictive analysis and referencing various labeled trained examples.	disruption
Poor QoS, reputation, Confidentiality, packet forwarding ratio, reputation,	Trust	Utilize domain expertise. At the level of individual transactions, trust management must be implemented. Service providers and software engineers need their roles defined.	It prevents incorporating all possible

varying social features, and reviews		Point out how certain parts cannavigate IoT-based systems with minimal technicality.	models
Machine learning tools are exposed to generate, collect, and process a vast amount of information, which includes unstructured and structured data.	Data	There is a need for centralization to enable it to run easily and simultaneously. An algorithm must be designed to designed not to expend extra time tracking unimportant data.	

6.1 Data security in RHM

Big data or health data refers to the information gathered by RHM networks and IoT devices. High-powered computing resources and ample data storage space are needed for managing this volume of healthcare data. The solution to the problem of managing health care data is found in cloud computing and cloud storages. Most of this information, however, is protected by patient confidentiality. The biggest problems in RHM are related to data privacy and security. Users, people, and organisations should refrain from misusing this information for their own ends. Physical, authentication, network, computer, and storage security all factor into data safety. Popularity of cryptography, data encryption, genetic algorithms, encipherment, and decipherment techniques Most privacy and security frameworks provide services through untrusted third parties. The banking and financial industries have recently seen a rise in the popularity of blockchain and the Interplanetary File System (IFS) as a means of safe data transmission. Blocks of data, each of which records a certain number of transactions, are linked together in a chain to form a blockchain. Each new block in the chain is a cryptographically certified addition to the public record of all prior transactions. Blockchain is a very safe method of transmitting data since each block includes a timestamp and the value of the hash of the block before it. There are now functioning blockchain applications in the fields of transportation, manufacturing, management, and healthcare. Some successful frameworks for medical health care services and SHM networks have been released into the public domain.

6.2 Limitations of RHM and IoT

However, these RHM and medical IoT devices do have their drawbacks, such as the fact that the data they collect is sometimes inconsistent and inaccurate due to the use of different types of sensors. Because of the annoyance that the wearable sensors, especially those aimed at youngsters, might cause, wireless sensors are preferred. Protecting patients' private information from hackers is an absolute priority. The issue of fraud in IoT-based healthcare systems is also discussed. Overall, smart medical systems benefit chronic patients more than the usual health care services. Remote areas do not have access to the electricity necessary to power Internet of Things devices. Real-time monitoring is made more challenging in low-powered devices and remote areas due to the need for a quick and dependable network connection. In other words, these restrictions are not tied to the development of new technologies and may be overcome.

7. FUTURE SCOPE AND ITS DEVELOPMENT

These studies show that DL-based MHMS can map raw equipment data to objectives without requiring a large amount of human effort or specialised knowledge. This means that deep learning models may be used to monitor the health of any system, rather than just a select few. Additionally, some current research tendencies and suggestions for future study areas are included:

- Performance of DL-based MHMS is highly dependent on the size and quality of datasets, which is why open-source large datasets are essential. DL approaches are backed by extremely sophisticated models. However, DL models can only go so deep until they hit a wall caused by the size of the datasets. Therefore, the big dataset ImageNet with over ten million annotated pictures can back up the 152-layer CNN model used as the standard for image recognition. When it comes to MHMS, however, the suggested DL models can include as much as five hidden layers. Additionally, models trained on such massive datasets can be used as model seed data for subsequent, more targeted tasks and datasets. Therefore, it makes sense to create and share massive databases of machines.
- Use of Domain Expertise: deep learning is not a silver bullet for all difficulties encountered in monitoring machine health. Applying DL models to MHM requires domain expertise for optimal performance. The size of the DL models being used may be decreased by removing discriminative features, and the final performance can be increased by using a regularisation term that is tailored to the specific job at hand.
- When it comes to modelling and data visualisation, deep learning methods—and particularly deep neural networks—have traditionally been seen as "black boxes," meaning that their underlying processing mechanisms are not understood. Understanding these DL models is made easier by visualisation of the learnt representation and the applied model, which in turn makes it easier to construct and tune DL models for complicated machine health monitoring challenges. It has been suggested that we may see the activations generated by each layer and the features at each layer of a DNN by means of regularised optimization, and an tSNE model has been presented for high dimensional data visualisation.
- Deep learning that has been transferred from one domain to another is called transfer learning. This line of inquiry is instructive in the field of machine health monitoring since certain issues in this area have adequate training data while others do not. It is possible

to move machine learning and deep learning models from one domain to another. It is true that there have been some prior research addressing transferred feature extraction/dimensionality reduction. The goal function of deep neural networks was modified to include a Maximum Mean Discrepancy (MMD) metric for assessing the difference between the source and target domains.

- ❖ Disparity of Class: Machine data follows a highly skewed class distribution in practise, with the majority of observations falling into a small number of categories. As an example, in fault diagnosis, the number of fault data is significantly lower than the number of health data. In order to rectify this inequity, many enhanced machine learning models (ELMs) and SVMs have been developed for machine health monitoring. CNN models with class resampling or cost-sensitive training, as well as the combination of boot strapping techniques with a CNN model, are two of the more recent and intriguing approaches that explore the use of deep learning in unbalanced class situations.

With the advent of large machinery data, it is expected that deep learning will have an increasingly significant future influence on machine health monitoring.

8. CONCLUSION

RHM has shown great success compared to traditional health monitoring system which is limited to delay, medication delay and pre-emption. RHM's integration of cloud computing and blockchain technologies has won the trust of healthcare professionals and patients in terms of data security and data privacy. RHM can meet the specific needs of critically ill patients and general health monitoring services to achieve individual health goals and healthy lifestyles. The wider application of SHM in sports and general maintenance is limited and can be further explored with constantly evolving technologies. RHM presents many future opportunities for medical services that were previously unattainable. The present work presents a review of smart health monitoring frameworks that have successfully implemented deep learning and machine learning approaches and algorithms to achieve high productivity. Similar review of works on SHM ML and DL do not report combined SHM-related works. Using IoT in RHM has led to fast and responsive remote and real-time monitoring of medical services.

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