International Journal of Computer Applications (0975 – 8887)
Volume 187 – No.39, September 2025

AI-Driven Smart Healthcare: A Comprehensive Survey of Data Collection, IoT-Enabled Sensing, 5G/6G Communications and Deep Learning for Early Diagnosis

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ABSTRACT
The healthcare sector continues to face significant challenges in disease prediction, with late diagnoses exposing limitations in existing systems. Artificial Intelligence (AI) has emerged as a transformative force, reshaping patient data management, diagnostic processes, and treatment strategies. AI-enabled healthcare systems optimize diagnostic processes leveraging machine learning (ML) and deep learning (DL) techniques to optimize diagnostics and decision-making. Data collection—often driven by wireless sensors and IoT-enabled healthcare devices—serves as a critical foundation for training these models.

In this paper, we first present an overview of AI applications in healthcare, focusing on data acquisition, IoT-based sensing, and the role of 5G and 6G communications in enabling real-time healthcare services. We then explore system recommendation frameworks and CNN-based image captioning models for medical imaging analysis. The role of deep neural networks (DNNs) in powering smart healthcare systems is discussed in detail, alongside the potential of Software Defined Radio (SDR) technology for monitoring respiratory diseases. We also examine the use of Intelligent Reflecting Surfaces (IRS) to enhance wireless communication reliability in medical environments. Finally, we highlight key challenges and ethical considerations in the design and deployment of AI-driven smart healthcare systems.

General Terms
Convolutional neural network (CNN), deep neural network (DNN), SDR technology and Intelligent Reflecting Surfaces (IRS)

Keywords
Smart Healthcare; Artificial Intelligence; Early Diagnosis

1. INTRODUCTION
The healthcare sector tackles countless challenges during patient management [1]. These challenges include disease diagnosis [2], decision-making of treatments [3], hefty treatment costs [1] and the workload of healthcare professionals [4]. To overcome these challenges in the past few years, healthcare systems all around the world have implemented AI-based healthcare solutions [5]. The COVID-19 pandemic highlighted the global healthcare systems' fragility in patient management and resource allocation. 75% of the people died due to the failure of healthcare systems to manage the unexpected increase in incoming patients [6]. In developed countries e.g., China, Japan, the UK and Europe rise in the elderly population is also causing a burden [7]. Healthcare solutions based on AI can potentially impact the overall performance of the healthcare sector through diagnostic cost reduction, improvement in patient administration, prompt decision and workload management of healthcare partitioners [8].

The chances of wrong diagnosis lessened due to advanced ML and DL techniques [9]. Precious human lives saved can be lost because of late or inaccurate diagnoses of lethal diseases [2]. Every year almost 10,000 cancer patients lose their lives because of late diagnosis, flawed judgment and inadequacy of data [3]. In 2019, 1.4 million Tuberculosis patients died because of late diagnosis and poor healthcare management [10]. Similarly, lung cancer cannot be predicted or diagnosed at an early stage which caused 1.6 million deaths in 2012 across the world [8]. Approximately 250,000 lives [6] could be saved annually by applying machine learning and deep learning in healthcare. Wireless sensing technologies have opened new possibilities for novel diagnostic and data collection techniques in healthcare [11]. This will help to improve the overall performance of the healthcare management systems when it comes to late diagnosis [5]. IoT-based sensors promote AI solutions in the healthcare system to monitor and diagnose [3], such devices facilitate healthcare providers to collect and process patients' data [12]. IoT in healthcare systems based on ML/DL [13] enables healthcare professionals to perform medical treatment without any delay due to early diagnosis [14]. AI-based technology in the healthcare system facilitates medical professionals [15] to monitor patients by IoT sensors and devices [16] such as wireless apparatuses and sensors to detect abnormality through body movement [17]. AI solutions are designed to enhance medical services' efficacy [18]and effectiveness [19]. IoT-based sensors provide AI solutions for diagnosing diseases at an early stage [18], this altered various methods of medical diagnosis and treatments for different diseases. AI-driven systems aim to enhance diagnosis accuracy [20], optimize treatment plans [21], streamline administrative tasks [22] and ultimately improve service quality in the healthcare sector [14]. Exploiting ML and DL for AI solutions develops a cost-effective healthcare system [1] and reduces the workload of medical professionals [17]. AI-driven healthcare systems improve the performance of delivery [23] in many countries which has proven to be the best solution for fulfilling future needs in the healthcare industry [2].

According to the discussion, the fundamental purpose of this paper is to discuss and analyse the literature on AI solutions for the intelligent healthcare system supported by ML/DL techniques to diagnose diseases at an early stage and predict them through constant monitoring. The information gap is identified to suggest future work in AI solutions for healthcare by adopting advanced techniques of ML/DL. In this survey paper, AI-based healthcare applications and solutions will be discussed. This would be a valuable addition to the field and will guide researchers in AI-based healthcare solutions. The review has the following sections: section II presents the literature review of AI solutions in health by deploying ML/DL and section III includes the overview of the methodology. The section IV presents the ethical considerations for using AI solutions and the challenges in the process of implementation of them. The final discussion, prospects and conclusions are deduced based on previous literature.

2. LITERATURE REVIEW

The fundamental purpose of research is to find AI solutions for the healthcare system through the literature review of previous papers to design exceptional ML/DL integrated healthcare systems. The literature is reviewed after reading research material from relevant papers on AI-enabled smart healthcare systems. In this study, papers related to designing AI algorithms for early diagnosis of diseases, treatment recommendation, and patient monitoring, also added Electronic Health Records (EHR), existing healthcare infrastructure, IoT-based sensors, medical imaging systems, advance SDR and IRS based techniques.

2.1 Application of AI in Healthcare Systems

AI solutions have huge significance due to the incredible applications of sensors, medical devices and advance technologies [4]. Healthcare sector has encountered different challenges with the increase in medical treatment expenses with an increase in the elderly population and the decrease in healthcare providers' efficiency in the past few years. In addition, the COVID-19 pandemic has drastically increased the amount of sick people and health issues which has outnumbered the ratio of paramedics and healthcare professionals across the world [24]. This situation has increased the importance of AI-driven smart healthcare system applications to bring ease to doctors and patients. In [25] integration of AI solutions in healthcare systems transforms the processes of diagnosis and monitoring [26], and it helps doctors in accurate analysis of medical reports [27] e.g., MRI, CT scan [22] and X-rays [5]. AI algorithms especially DL models facilitate healthcare providers [28] in making accurate treatment decisions without losing precious time [29]. It evaluates the symptoms of patients to extract a conclusion and diagnose without human intelligence [30]. Such a system is designed to recognise abnormalities [31], risk factors [26] and future results associated with patient healthcare by using AI-based sensor data [32] and medical reports [5]. Different AI algorithms e.g., logistic regression [9], Naive Byes [30], Random Forest [14] and Support Vector Machine [18] considered suitable to analyse electronic health reports [4]. Wearable devices, sensors and WiFi-based sensing systems perform persistent monitoring for data acquisition [33]. For instance, Apple Watch [14], Dexcom's Glucose Monitor [18] and identifyHer [34] are AI-enabled wearable devices to monitor patients constantly, similarly, software-defined radio (SRD) technology has proven to be effective [12] for respiratory health monitoring and data collection process [2].

2.1.1 Data Collection for AI enable Smart Healthcare Solutions

All the data collected through the sensor network and other devices required to be arranged before secure storage [35]. In addition, the essential data will be collected through ML agents to keep a record of data type and rate of recurrence of activities [36], a record of battery life [37] and devices performance [25]. In addition, the agents are obligated to collect data to make the process secure from any ambiguity [38]. The fundamental goal can be achieved by developing models based on the sections from supervised, unsupervised, and reinforcement learning for AI [13]. Research shows that AI-driven cybersecurity solutions are used to arrange and gather data to eliminate the chances of expected threats to the system [20]. In this regard, such threats could be from malware to ransomware in the cybersecurity system [39]. Furthermore, such data is considered helpful in making the right decisions in less time [40]. However, the integration of AI in cybersecurity can enhance the performance of different activities in man-made systems [41] e.g., monitoring [42], evaluation [43]and fast response [9] in case of violation [19]. Machines now perform all those tasks which humans perform. Models used for disease diagnosis enhance the performance of smart healthcare systems by integrating AI-driven sensors in all components [24]. It releases data points of great significance from a communication gateway which is fully protected to pro-vide data through a central repository for further monitoring [21], alerting [4], predictive/reactive analysis [36] and reporting purpose [44]. In this case, the data belongs to different areas e.g., consultation data, wearable sensor devices automobiles etc [16]. The data processing is performed by data mining and analysis to take action against impending or current issues. The proposed model for IoT-based healthcare architecture has the following three sections as illustrated in Figure. 1 [13]

2.1.1.1 Data Source

The data source is based on IoT devices to gather the data related to employees of the hospital, patients, transport and equipment etc [16].

2.1.1.2 Central Repository

A central repository is the stage in which the entire data is released [45] and gathered then saved to use in the future [46].

2.1.1.3 Monitoring and Analytics

A method to process the collected data of the healthcare system provides a great overview [47] and recommends the required initiative [35].

2.1.2 Internet of Things (IoT)

IoT is the terminology coined by Kevin Ashton during a presentation for Procter & Gamble in 1999. He used the term IoT to explain the integration of RFID in the supply chain of Procter and Gamble Company. During the presentation, Ashton analysed the usage of these systems by humans to gather data. Ashton was the first person who emphasized on the Internet of Things to bring accuracy in collecting data [48]. IoT is described as a virtual environment in which electronic devices are integrated into an internet network and facilitate processes of various sectors. Internet applications and services are provided on the Internet to take benefits from these smart devices [49].

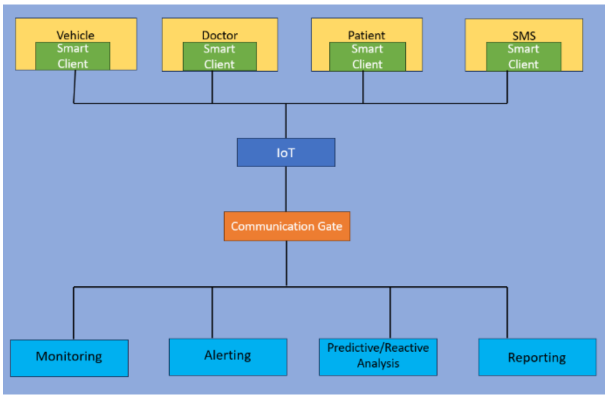

Fig 1. Flowchart of IoT based Smart Healthcare Model illustrating data collection from smart client to monitor, alert, predictive/reactive analysis and report.

2.1.2.1 Internet of Things (IoT) sections in healthcare

Such a system has various IoT sections for safely detecting, gathering and transferring the data in raw form to the central repository [35]. In addition, IoT sections are based on customized software to gather data through the integration of sensors and devices [50]. In addition, IoT-based devices of different types can be used in innumerable situations [19]. Examples of data sources and IoT devices are wearable equipment [9], software for healthcare facilities and AI-based modules [47]. Such devices are developed to monitor any change in the vitals of the human body e.g., temperature [51], blood pressure [45], saturation [42] and heartbeat [52]. In addition, software is used to understand the data occasionally collected through such devices [53]. In this given scenario, a bundle of software components is added to the management system of the hospital [54] to gather outdoor patient and operator data [41]. Furthermore, this also contains track records and data related to hospital transport developed by adding IoT-based devices [14]. These transport facilities can monitor every movement by vehicles and patient data [46]. Furthermore, the IoT-based devices designed to carry out smart clients [54], they will be responsible for collecting data and transferring it to a similar central repository [55]. After all this, the raw data to be analysed through the analytic process and then given a significant shape [13]. This research presents a separate system to read altered data [11] by subsequent to the decided rules and then give warnings. Such warnings will be given through messages, emails, and calls [56]. In addition, such systems are usually based on AI-based devices to collect data [1] that can transform the information in an intelligent way [10]. This will help improve the efficiency and effectiveness of medical staff [35]. These systems will develop the ability to audit and control [11] for data storage and accessibility. Research shows that these types of data enable the system to use previous data patterns to get personalised medical cure [45]. However, the suggested end-to-end system required breaking into various fields e.g., sensors [22], communication protocols [23], storage [50], security [46], management [57], operations [11] and application services [56].

2.1.3 Sensors

It is an electronic device that identifies signals from the surroundings of the physical environment to change into a quantifiable digital signal to collect information. That physical environment generates signals due to changes in pressure, temperature and motion or any other change in the physical environment [49]. The output response is typically an electrical stimulus e.g., electric current, electrical capacity, voltage and resistance [58]. This signal is then either displayed in a readable format or transmitted electronically over a network for further reading or processing [49].

2.1.3.1 Internet of Things (IoT) sections in healthcare

All the healthcare systems based on machine learning and deep learning are integrated with wireless sensors [11]. This has employed Wireless Body Area Networks (WBANs) to develop an authentic system to collect real-time data [28], make the whole system capable of intensive care and diagnostics purpose [59]. In an e-healthcare system, innumerable sensors are used for monitoring and diagnosis of human body temperature [52], blood pressure [43], oxygen saturation level [52] and blood sugar level [43] etc. Sensors used for monitoring of vital signs of the human body are known as primary sensors required in every health facility[26], there are secondary sensors which are dependent on primary sensors to extract data for observations [60]. In addition, secondary sensors are integrated into different devices [9] e.g., wireless and wearable sensor devices [28], ambulances [61], testing machines [45] and apparatus and medical instruments [16]. Every device is recognised separately by using Radio Frequency Identification tags (RFID) technology [59]. Furthermore, these sensors are used to collect medical data of the patients [22] by electronic methods and then presented by doctors in the form of telemetry [59]. Such systems gather data not from one source [11], various sources utilize to facilitate medical professional [31]. The standard library is available to all the clients and agents in which all the tools [35], software and smart healthcare devices are integrated through different computer programming languages for better results [59]. In addition, such a system implemented to gather data e.g., medical facility [31], medical staff [26], transport and medical devices [31]. In addition, the healthcare-related data is moved towards the central repository to perform the pro-cessing and data analysis [62]. The collected data is transmitted to a central repository for further processing and analysis [60]. In this system, the designed architecture is capable of warning [63] after analysing the data and providing the final information [64]. In this research, the suggested system has developed a process to enhance the security of the smart healthcare system [57]. This system can be used to make the system more secure by integrating the Advanced Based Encryption model for deduplication [40]. In addition, the smart healthcare system based on IoT [11] has the ability to store data in great quantity for using deduplication in the system [65]. However, the duplication can be used to eliminate deduplicate data from the database [40]. Furthermore, the data relevant to patient health is required to be encrypted safely while storage in the system [25]. According to research by the National Institute of Standards and Technology (NIST) in 2000 developed AES (Advanced Encryption Standard) [41] algorithm to develop a secure system to fight against attacks based on DES (Data Encryption Standard). [40] research shows that the AES algorithm performed better than the DES [56], the reason behind this balanced main key cypher while similar encryption and decryption keys [46]. The key size for unprotected AES is 56 bits of AES which is the fundamental rea-son for shifting to AES from DES. In such a situation, the AES algorithm can manage the 256 bits of lengthy data keys [66] and the size of each key is 128 bits for 10 rounds [5] for 12 rounds this will be 192 bits and for 14 rounds it will be 256 bits [40]. This data storage process has an encryption technique based on integrating a round key for each plain text by exploiting sub-bytes, then shifting towards rows and columns to mix and shift them. After all this, it exploits the byte.

2.1.3.2 Advanced Sensors in Healthcare

2.1.3.2.1.1 Stress Monitoring Sensors

Three sensors, e.g., temperature, conductance, and pulsewave, are incorporated in a human stress monitoring patch. It covers a stamp-sized area $(25\,mm \times 15\,mm \times 72\,\mu m)$. The sensor design is compact and comfortable to wear due to less physical contact with skin, also guarantee malleability. Skin contact has been reduced by incorporating the formation of an integrated multilayer, and also by adding an innovative process of microfabrication process. This has decreased the contact with skin to 1/125 as compared to an ordinary sensor of a single-layer structure. [67]. A flexible pulsewave sensor has predominantly improved the malleability of the patch. In this research, the stress monitoring sensor is created by a flexible piezoelectric membrane to enhance the flexibility of sensors. This advanced stress monitoring sensor patch is built with a perforated polyimide membrane to sustain flexibility. Human body temperature can be detected within the susceptivity of $0.31\,\Omega/°C$ and measures skin conductance by the susceptivity of $0.28\,\mu V/0.02\,\mu S$. Stress patch can detect pulsewave within 70 milliseconds [67]. The sensor of stress monitoring is wearable on human skin to monitor bio-signals from the human body by wearing on the skin can monitor changes in emotions [68].

2.1.3.2.1.2 Liquid Sensors and Off-Body Detection

All the fluids in the human body contain biochemical markers including small molecules. The health condition of human beings can be identified by assessing biomarkers through liquid sensors [69]. However, contemporary medical sensors encounter difficulties such as interference from unrelated compounds, limited sample sizes, and biomarker dilution. Medical liquid sensors, utilizing advanced algorithms, can effectively circumvent these issues. In human plasma, exosomes were detected to diagnose lung cancer at an early phase by surface-enhanced Raman spectroscopy and deep learning methods [70]. In this research, exosomes were taken out from human plasma, and the signals from Raman spectroscopy were obtained by using a gold nanoparticle-coated plate. To investigate the characteristics of plasma exosomes deep learning has been employed without any dependency on human data, also to identify their similarities. SERS signals-based supervised model can efficiently classify exosome data. The collected data is divided into two different clusters to predict lung cancer with accuracies of 95% and 90.7% [70]. This shows that deep learning techniques can act as diagnostic tools to predict lung cancer. However, examining biomarkers from blood extracts involves invasive procedures and requires multifaceted data-cleaning phases. Due to their extensive advantages in contraction, high output and automation, microfluidic dielectronic devices become popular in the clinical diagnostics process [69]. These devices offer extensive health information while requiring minimal sample volumes, increasing their effectiveness in medical applications [70]. The data from saliva samples is collected through a single-response microfluidic e-tongue to detect oral cavity cancer. The analysis is performed by integrating multidimensional prognosis methods, and unsupervised and supervised machine learning techniques.

2.1.3.2.1.3 Intra-body Wireless Nano Sensor Networks (iWNSNs)

The nanotechnology combined with sensor networks represents a unique kind of Wireless NanoSensor Networks (WNSNs). Intrabody health monitoring through intra-body Wireless NanoSensor Networks (iWNSNs) showed huge significance in the research area of the healthcare monitoring system [71]. In the intra-body nanosensor nodes, an Energy Balance Clustering Routing (EBCR) protocol is introduced which is categorised by partial computing power, short communication ranges and controlled energy reservoir [72]. The communication issue on nano-nodes was resolved by proto-col while applying a completely novel strategy of hierarchical clustering [71]. The nano-nodes transmit data as groups to the node head of the cluster as a single hop. However, cluster head nodes transmit data in the form of multi-hop to the nano-control node [72]. In addition, the selection of the next hop node is essential for distance balance and the capacity of the channel also facilitates reducing energy usage and ensures the safe transfer of data packets [71]. Results of the simulations indicate protocol usage in creating balanced energy usage, encompassing network life expectancy and guaranteeing the successful transfer of data packets [73].

2.1.4 Smart Healthcare 5G and Communication Module

In IoT-based smart healthcare systems, 5G can transform healthcare by increasing the speed of data transfer [74], this can increase the efficiency and performance of healthcare providers [19]. Integrating 5G in data management is the best option in healthcare systems to improve their performance due to the high speed of data transfer [47].

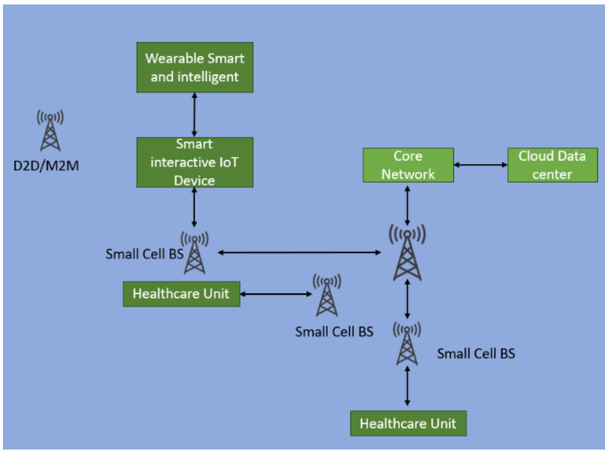

Fig 2. Architecture of 5G Cellular Network for fast-speed mobile links in smart healthcare to carry out the processes outside the hospital.

5G wireless sensing technology is capable of covering a large area [75], ability to handle network traffic [43], the high response rate [76], inexpensive and able to connect with various devices at the same time [23]. In addition, 5G is considered as the main feature in the area of sensors [32] and AI-driven smart healthcare systems because they can facilitate patients during their need for healthcare facility [75]. The integration of fast-speed 5G mobile links through smart healthcare [76] support in trustworthy and fast data transfer [65] e.g., photos equal to 1 gigabyte [35] for each patient. This can improve the healthcare processes outside the hospital and Figure 2 illustrates basic 5G network architecture [23].

2.1.5 Smart Healthcare 6G Communication Module

6G communication in healthcare is a revolutionary concept of AI through edge computing based on e-healthcare [77]. In the cyber-physical system, people's electronic devices e.g., laptops, smart watches and cell phones are major helping equipment for the healthcare setting [78]. The availability and integrity of CPSs, blackhole and grey-hole assaults are amongst the most hazardous. Results of unreliable safety due to monitoring and mitigation methods, there is persistent incapability to discriminate be-tween destructive and approved activity [79]. In this research, the suggested model for a smart healthcare system is based on 6G wireless communication for optimization and analysis of cyber-physical systems [78]. Quantum dirichlet convolutional learning coyote foraging optimizer used for data analysis and optimization. Furthermore, CPS analysis is performed via federated honeypot transmission through a model known as decentralized authentication. Analysis of the experimental work is performed by finding out the mean average of precision, F-1 score, convergence rate, and end-to-end de-lay. The suggested method has 96% network security, a mean average precision (MAP) 97%, F-1 score 77% and convergence 88% [78]. The predictive model is recommended for a health system and the experimental results have positive results [79]. CPS integrates the recommended model and improves the security of data.

2.1.6 Recommendation Systems (RSs) in Smart Healthcare

In smart healthcare, RSs are also used to recommend different healthcare options to patients [80] after analysing their previous health data. RSs implementation in healthcare is effective [81] due to their provided recommender outline data for the patients [81]. [82] shows the usage of RS in the healthcare system and its improvement in the market, as well as its constraints and prospects. [83] has analysed the different ML techniques to implement RSs in Healthcare systems to find the most trustworthy [80]. According to research, the best results are available from the Random Forest method [84]. In addition, this research has presented an independent hybrid technique for future treatments of patients [85] as per their health condition [81].

2.1.6.1. Fundamental Ideas and Phases of RS (Recommendation System)

In the healthcare system, the information FS (filtering system) category is implemented to differentiate patient's choice of treatment [86]. RSs help the medical staff to drive a mechanism for patients to get customized care systems at home or hospital [82]. In addition, this can help medical staff review the main aspects [86], give preventive help to patients who are willing to get customized treatment [87] and inform doctors about their current condition [53].

Phases of RS (Recommender System)

RSs has three phases which are known as IC (information collection) [86], LP (learning phase), and prediction or recommender phases [89].

- Phase 1

Phase 1 is for the collection of significant data relevant medical history of the patient [89], this data is required to develop a personal medical profile of the patient [83]. In addition, the data is collected to develop a better quality of treatment and resources [89]. RE (Recommender Engine) only works perfectly [86] by developing an authentic profile [90]. This kind of RS has great significance due to its foundation on the inputs which are collected through diverse paths [87] e.g., implicit [91], explicit [88], and hybrid examination performed by the system. In this phase, the patient can give their re-view about the selection of treatment known as explicit review [91]. On the other hand, patient reviews aren't taken directly due to their nature known as implicit re-view [87].

- Phase 2

Phase 2 is the learning phase where valuation builds up as i/p [91] and the processes review by using the Latent Allocation technique [92]. This is all performed to activate patient characteristics as a result [90].

- Phase 3

This phase recommends better treatments and prescriptions for the patient [87] after understanding and analysing data which is gathered in Phase 1 [92]. In addition, the system will perform calculations to develop a system [88] and medical offers based on the patient's previous medical record [87]. Phase 2 learns from the previous healthcare record and predicts disease or recommends suitable treatment in Phase 3 [91]. The different phases of RS are shown in Figure 3 [82].

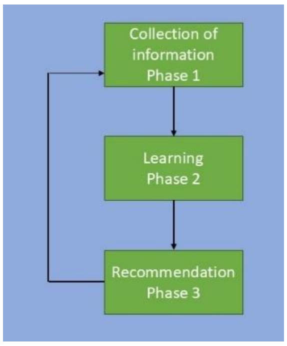

Fig 3. Flow Chart of three phases i) IC (information collection), ii) LP (learning phase), and iii) Prediction or Recommender phases of Recommendation System for Hospital

2.1.7 Image Captioning Model

In AI-enabled healthcare systems, the Image Captioning model plays the significant role [93] because it is the standard model for encoding images in features by using CNN (Convolutional Neural Network) [94]. On the other hand, decoding is performed by RNN (Recurrent Neural Network) that decodes features [95] in meaningful words to understand the image results of X-rays, CT scan and MRI [96]. in this model, almost 21 million parameters are used in inception_v3 net [97] of CNN network [98]. Furthermore, the dimension of the image is 299x299x3 [93] in the pre-trained neural network [99] with the outputs of the probability vector of the 1000-dimension class [93]. In this model, the image feature is extracted by inception_v3 net [99] without de-fining the last layer. The image feature vector is developed by getting the 2048-dimension [98] vector which is completely attached to the last layer [97]. Furthermore, for the decoder RNN, the feature vector acts as input [100]. As input, token and image features are taken by decoder RNN that is an attention LSTM (Long Short-Term Memory) network [101]. This can predict the word next in the line of a caption, there is a constraint [99], inability to predict words in any caption more than 20 words [94]. The beam search of a beam size 3 is used as a method to prevent a greedy strategy to predict the captions [98]. The 3 most accurate predicted captions are again inserted in the model for image captioning which is rearranged [98]. This model predicts the most accurate caption from all three predictions and this process ends after reaching the caption with maximum length.

The detailed model architecture is illustrated below in Figure. 4 [94]:

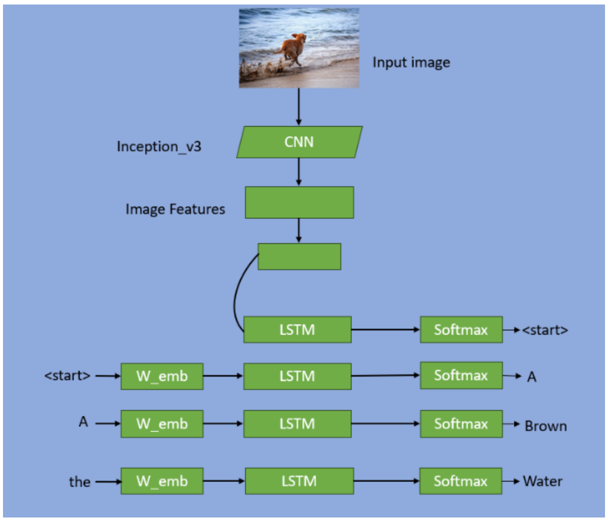

Fig 4. Image Captioning Model Architecture: A brown and white dog running through the water predicted accurately.

Image captioning model applied as medical image captioning in smart healthcare to bring efficiency to the work of healthcare providers [102], also help to predict and diagnose diseases at an early stage [2]. This AI-enabled model extracts the pictographic medical data of patients to understand the complicated data by converting it into voice and text [103]. Chest X-rays, CT-scan and MRI images are analysed through the attend-and-tell Model by using the encoder-decoder model [3]. Experimental work was completed after evaluating data sets [99] and the image captioning model based on AI algorithms [100].

2.1.8 Deep neural networks (DNNs) in AI-based Healthcare

Input data is organised in different kinds through DNNs [104], this helps in healthcare system to differentiate between chest X-rays of infected and healthy lungs [43]. In healthcare, DNNs are designed by using training datasets of huge quantity [105], capable of differentiating between kinds or groups [106]. This classification technique would work better than human intelligence [104], the level of precision is tremendous [108]. However, there is inadequate comprehensibility in DNNs which is a big disadvantage [106]. On the other hand, the presence of a large number of datasets for training is compulsory to achieve accurate results from DNNs [109], rightly categorization of data is also essential to differentiate and train datasets under the specified period [110]. In the healthcare system, there is the extensive usage of handwritten numerals which has given rise to the need for large datasets [111] to attain an accuracy of more than 90% [43]. Chest X-rays and CT scan images of pulmonary diseases help identify ailments by training DNNs. In the datasets tested, DNN reached up to the ac-curacy of 0.983 [55]. In addition, the DNN algorithm can improve the accuracy of dis-ease detection in the radiology department [112] without changing the results of the CT scan and X-ray images [110]. However, in the field of radiology, DNNs play a significant role in to timely diagnosis of diseases in the lungs [112], figure 5 [43] shows the future potential of machine learning integration in hospitals.

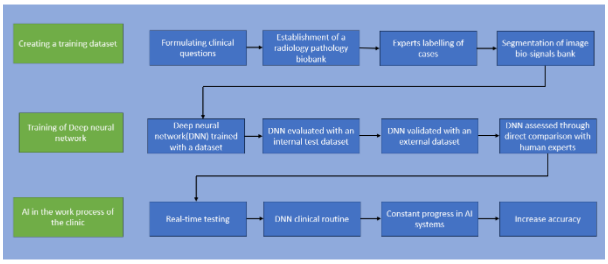

Fig 5. Basic techniques for Typical path for machine learning model development and its incorporation into clinical practice.

2.1.9 SDR Technology and AI to Mo[15][15][15][15][15]nitor Respiratory Illnesses

SDR technology-based healthcare system enabled contactless monitoring of hu-man vital signs e.g., breathing. [27] designed interlinked system by integrating SDR and AI [15]. Such system channel frequency response is implemented to dig out wireless channel state information [52]. This research uses channel frequency response [27] via multi-carrier orthogonal frequency division multiplexing technique [55]. The work is based on simulated channels to evaluate channel frequency response for white Gaussian noise which is additive and ideal for diminishing and diffusing networks [12]. The experiment based on this approach was able to reach an accuracy of up to 99.3% [27], this precision is achieved by using machine learning and deep learning algorithms [19] to classify four breathing of varying category [27]. SDR technology-based system enabled healthcare providers to monitor patients without any physical contact [113]. The system design is built on two universal software-defined radio peripherals and two computers in which one acts as a transmitter and the other one as a receiver [114]. Omni-directional antenna is used to examine breathing patterns for different diseases as illustrated in Figure 6.

2.1.10 Intelligent Reflecting Surfaces (IRS) Application in Healthcare

Human activity monitoring is an area of research with the purpose to develop system that develop physical independence for elders and disable people. Different types of human activities have been proposed in the last few years to detect different human activities by using cameras, sensors, wearable devices and wireless microwave sensing. Nowadays, microwave sensing technology has enabled researchers to solve the issue of privacy intrusion posed by cameras, wearable devices and sensors and uneasiness by wearable sensors [115]. The fundamental drawback of microwave sensing technology is functioning trouble in non-line-of-sight and multi-floor settings. The essential factors are precise and controlled surroundings for detecting human activity precisely for all these methods. [115] research shows RIS systems have the ability to give results with more precision as compared to microwave sensing in multi-floor and non-line-of-sight surroundings and employed support vector machines, Bagging, and Decision Tree algorithms to the data of the IRS [115]. To accomplish more accuracy in the results a data subset used based on human activities. Additionally, the research investigates the time of processing consumed by the classifier while training the IRS dataset and feature investigated for the first time [115].

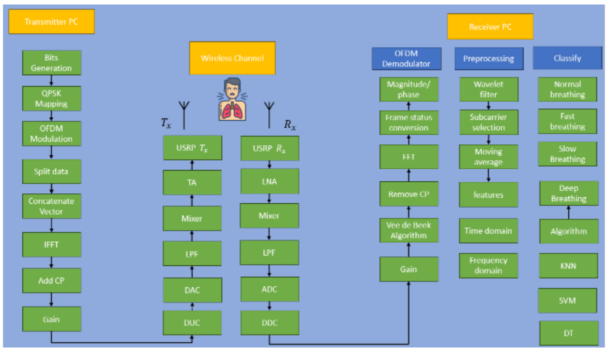

Fig. 6. Flow chart of SDR Integration in Interlinked Smart Healthcare

3. Ethical Consideration and Challenges

Data collection has a significant role in AI-based research for healthcare systems; this step needs to be performed by keeping in focus ethical considerations and challenges. Patients' data should be obtained by consent to avoid lawsuits or legal claims. In addition, the patient medical reports and data need to remain private while designing AI-based healthcare solutions. There is a significant role for those people who are re-sponsible for storing patient's data because in case of error and leakage of data should be considered accountable. AI-based algorithms are designed based on biases that can further increase socio-economic disparity and racism among patients. Such biases in algorithms can suggest the wrong treatment for the patients due to their specific race and group. On the other hand, the system design for the healthcare system needs to be based on ethical principles. However, there are different challenges and ethical issues in AI-enabled healthcare systems research which is why patients' electronic healthcare reports cannot easily be available. Researchers face difficulties in collecting healthcare data to proceed further to get desirable results.

4. CONCLUSION

AI-based Healthcare systems imperative to improve patients' well-being at an early stage. The advancement in AI has improved healthcare systems due to the integration of IoT-based sensors, wearable devices 5G communication modules etc. AI-based models from machine learning and deep learning are enabling doctors to predict disease through image processing and recommendation systems. SDR technology has also promising results due to the capability to detect any change in breathing patterns. Furthermore, IRS is a promising technology to monitor multiple-person activity with precision. In future, robotics can perform surgery without any assistance of humans which is auspicious in healthcare. Similarly, real-time image processing would help detect anomalies in MRI, x-rays and CT scan images. The technological progress in healthcare through machine learning and deep learning emerging as a great source of improvement in patients' well-being and decreases the workload of healthcare partitioners.

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