METHODICAL EVALUATION OF HEALTHCARE INTELLIGENCE FOR HUMAN LIFE DISEASE DETECTION

ABSTRACT

Event intelligence for early disease detection is highly demanded in the current era and it requires reliable technology-oriented applications. Trusted emerging technologies play a vital role in modern healthcare systems for early diagnoses of different medical conditions because it helps to speed up the treatment process. Despite the enhancement of current healthcare systems, robust diagnosis of different types of diseases for intra-patients (outside of hospital settings) is still considered a difficult task. However, the continuous evolution of trusted technologies in health sectors narrates the reboot process which could upgrade the healthcare service provision as the trusted next-generation health unit. In order to assist healthcare providers to carry out early diseases detection for intra-patient clients, we designed this systematic review. We extracted 40 studies from the databases i.e. IEEE Xplore, Springer, Science direct and Scopus, from March 2016 and February 2023, and we formulated our research questions based on these studies. Subsequently, we rectified these studies using two filtration schemes namely, inclusion-omission policy and quality assessment, and as a result, we obtained 19 studies that successfully mapped our defined research questions.We found that these 19 studies highlighted the different trusted architectures of the internet of things, mobile cloud computing, and machine learning, which are significantly beneficial to diagnose medical conditions for intra-patient clients such as neurological diseases, cardiac malfunctions, and other common diseases.

Keywords: Internet of Things (IoT); Cloud Computing; Mobile Edge Computing; Brain Tumor; Cardiac Diseases; Healthcare systems

1.0 INTRODUCTION

Ages of technology enhance the comfort of daily life activities. However, the exploration of technology paradigms in routine life activities is affecting the human life dependency factor. In the context of technology dependency, healthcare systems are the emerging area in this era, where technology plays a vital role in generating better health monitoring units. Additionally, these technology-oriented healthcare systems are quite handy for the recognition of different kinds of human diseases. Healthcare intelligence is the emergent area that belongs to the combination of the formation of digital healthcare systems and artificial intelligence approaches. Nowadays, numerous intelligent clinical decision systems are used to recognize different human diseases in both inside and outside of the hospital settings [1]. In clinical decision systems, pattern recognition is a game changer in time series data. The differentiation between regular and irregular patterns is highly desirable in such cases that involved urgency and high risks [2], [3]. Early diagnosis of different kind of diseases is useful in both patients within the hospital (intra-patient) and outside of the hospital (inter-patient). In the context of intra-patient hospital, data from magnetic resonance imaging (MRI) scan can monitor the unusual behavior of the brain (brain tumor), data from computed tomography (CT SCAN) relates to the broader picture of the human body, and data of electrocardiography (ECG) highlights the heart activities. Currently, the uncertainty factor still exists in these diagnostic tools in both cases intra-patient and interpatient. Such uncertainty factors are related in terms of robustness, efficient and reliable flow of electronic health records in both inter-patient and intra-patient hospital[4], [5]l Figure 1 is taken from a study [6] which shows the collage of CT brain scan for the detection of hemorrhagic stroke (brain stroke) and chest X-ray and CT scan for lungs diseases detection.

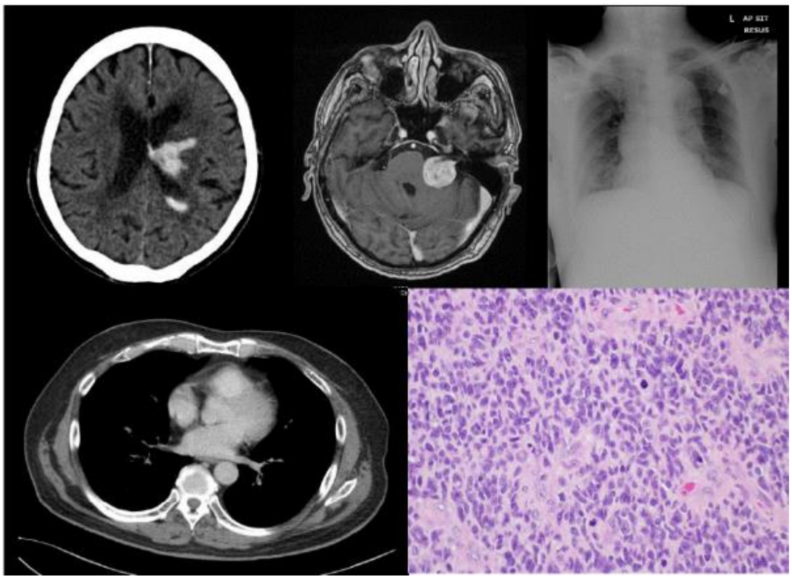

Fig. 1: Collage of CT brain images, CT chest, and chest X-ray [6]. (CT Brain: Top left to right, CT Chest: Bottom left, Chest X-ray: Top right)

Moreover, the prerequisites of intelligent clinical systems are the target sources that highlighted the ideal health status of the human body [7]. Therefore, controlling these target sources is necessary when designing a high accurate responsive intelligent systems before deploying into the internet of things (IoT) or Cloud-based technology [8], [9]. However, robust recognition of different life diseases in intra-patient environments (patient outside the hospital) is still an open job for researchers. Therefore, the efficacy of machine learning-based IoT or cloud technologies needs to be justified, especially on how they can perform robust and accurate diagnoses for intra-patients[10][11]. Hence, this study helps to review the technologically oriented healthcare systems and delivers the outcome of different high-impact technological healthcare systems namely; convolutional neural network (CNN) based MRI and cloud-based CNN for ECG analysis.

The exploration of the trusted Technologies IoT and mobile cloud computing (MCC) that are commonly used in smart devices to monitor human health status[12], [13], as well as wearables devices, smart mobile applications, and smart recommender systems, are worth to be conducted[14]. Moreover, these technologies are also frequently used in monitoring activities that would affect the health status of an individual, like measuring heart rate during physical activities and monitoring sugar level and blood pressure readings [15], [16]. Hence, a trustworthy intelligent system should be able to showcase impressive findings that are related to health based on an individual's daily routine behavior [17], [18]. However, existing studies indicated that that need to be resolved for further improvements and these issues represent the loose holes that present in the analytics of life diseases through technology-oriented solutions [4], [5].

Thus, the scope of this study includes the exploration of different factors of common diseases that are dependent on trusted technologies and identifying the technologies that are commonly used in monitoring the impact of daily activities on health. The contributions of this study are summarized below

1. Critical investigation for early diagnosis of common human life diseases by using the trustworthy intelligent units
2. Knowledge-based learning for evaluation of human life diseases mining
3. Discussion on the reliable flow of electronic health records between online and offline mobile edge devices

2.0 MATERIAL AND METHOD

The next era of trusted healthcare systems has particular attention on defining paradigms that involve high level of efficiency in diagnostic results, the robustness of data stream processing, and secure encrypted data transfer. To follow up with these defined paradigms, there are a few prerequisite queries for the achievement of next-level trusted healthcare systems. These prerequisites are summarized in different research questions (RQ) that were used to search for literature that designs trusted next-generation health units.

RQ1: What are the impacts of trusted healthcare systems on early-life diseases?
RQ2: How to define the inter-dependency of life diseases through technology-oriented healthcare systems?
RQ3: What are the key parameters for early-life diseases detection?

2.1 Study Identification

Identifying studies for this survey study is a very crucial process. Thus, this process is done by assigning electronic health (e-health) identifiers for the collection of recent studies that addressed the issue of early disease detection based on technology use.

2.1.1 Keywords

The allocation of e-health identifiers was further enhanced into keywords strings based on different digital tools that are used for diagnostic purposes in modern healthcare systems. Below are the highlighted keyword strings.

1. 'MRI' OR 'X-Ray' OR 'ECG' OR 'CT-Scan'
2. 'Brian tumor' OR 'MRI' OR 'CT-Scan'
3. 'Heart diseases' OR 'Cardiac diseases' OR 'Cardiovascular Diseases' OR 'ECG'
4. 'Computerized tomography scan' OR 'CT-Scan'

Subsequently, we add a few technology-oriented diagnostic tools to the search strings: Deep learning models-based, and IoT Cloud-based. Below are the combined connection string used for the extraction of relevant studies.

[Deep learning models(MRI' OR 'X-Ray' OR 'ECG' OR 'CT-Scan') AND ('Brian tumor' OR 'MRI' OR 'CT-Scan') AND ('Heart diseases' OR ' Cardiac diseases' OR 'Cardiovascular Diseases' OR 'ECG') AND (' Computerized tomography scan' OR ' CT-Scan')] AND [IoT Cloud based (MRI' OR 'X-Ray' OR 'ECG' OR 'CT-Scan') AND ('Brian tumor' OR 'MRI' OR 'CT-Scan') AND ('Heart diseases' OR ' Cardiac diseases' OR 'Cardiovascular Diseases' OR 'ECG') AND ('Computerized tomography scan' OR ' CT-Scan')]

Based on the accuracy of current healthcare technologies and tools, the running of further analysis on these studies' identification seems logical. Table 1 presents the existing e-health identifier which is related to the key role of disease detection.

Table 1: Key e-Health Identification

E-Health Identifier	Key role	References
Big Data Analytics	Analyzing, managing, and highlighting the correlation between different life diseases	[9], [19]–[22]
Intelligent Systems	Robust, accurate classification and prediction of different states of diseases through different machine-learning techniques	[2], [3], [23]–[25]
IoT Framework	Home-based health unit, which supports the doctor-free environment for the diagnosis of diseases.	[1], [8], [23], [26]–[29]
Cloud Computing	Process and storage of the huge number of electronic patients record with best accessibility for observation	[1], [19], [26], [30]–[32]

2.1.2 Collection Resource

We used five high-impact databanks to extract relevant studies based on the keyword strings on the impact of health and trustworthy technology from 1st March 2016 and 29th February 2021. Table 2 represents the summary of the electronic databanks. A few examples of technology that have an impact on health and disease detection such as ECG diagnostic tool on heart malfunctions, information on brain tumors through MRI scan, and different blood test and tool kits for diabetic status and these trusted technology narrates their roles in different diagnostic solutions [33]. In addition, trustworthy technology which is used to handle huge electronic health data records, smart wearables devices, and remote heart care units require continuous upgrading over some time [34] and resolving the health issues on early disease detection is in fact an ongoing task [35]–[37].

Table 2: Electronic Databanks

Identifier	Databases	URL
DB1	IEEE Xplore	http://ieeexplore.ieee.org
DB2	Springer Link	http://link.springer.com
DB3	Science Direct	http://www.sciencedirect.com
DB4	Scopus	https://www.scopus.com

2.2 Data Synthesis

After performing article extraction, the next step is cleansing the articles based on the defined policy. The inclusion and omission policy clearly define the extraction of those studies based on goal-oriented for the diagnosis of different life diseases. Therefore, the defined policy is constructed to highlight current challenges in the modern healthcare system, as well as, help to improve the loose holes seen in current healthcare units.

2.2.1 Inclusion and Omission policy

The extracted articles went through the first filtration process using the inclusion and omission policy. Formation of the policy was purely dependent on the technology-disease-oriented studies such as different cardiac status and neurological conditions that require a reliable platform for early disease diagnoses. Table 3 narrates the policy of inclusion and omission.

Table 3: Inclusion and Exclusion Policies

	Inclusion Scheme
ip1	Experimental studies for diagnosis of different diseases with real-time on non-real-time records
ip2	Articles highlighted life risky different cardiac and neurological states
ip3	Articles highlighted reliable and intelligent healthcare systems for the diagnosis of different diseases
ip4	Health protocol-oriented studies
	Omission Scheme
op1	Studies highlighted unclear results or finding
op2	Studies least discussed the technology parameters
op3	Articles without proper analysis of technology and diseases
op4	Experimental clinical studies without ethical approval

3.0 QUALITY APPRAISAL

The selected articles underwent another filtration stage which was based on the quality assessment to obtain relevant literature based on the quality assessment queries (Table 4). Additionally, all clinical studies[38], [39] were also assessed and focused on the ethical standards, as well as, medical recommended standards such as health protocol for diagnostic solutions, and more importantly, fulfilling the concept of intra-patients because the accurate diagnosis of different kinds of daily human life diseases for outside of clinic patients are deemed as a challenging task. Also, from the technical point of view, end-to-end reliable transmission of patients using electronic records either online system or offline system has been considered the second challenging task [30]. Therefore, all the selected articles from the above-mentioned policy need to undergo a thorough quality assessment process, and Table 4 highlights the assessment key statements. To stratify the quality statements of each article, we used the format of maximum followed (Max) average followed (Avg), and minimum followed (Min).

Table 4: Assessment Quality

Quality Assessment statements	**Check point**		
	Max	*Avg*	*Min*
Reliability measurement in e-heath records			
Follows the health protocol for diseases diagnosis			
Trusted Healthcare unit dependencies between online and offline states			
Diseases diagnostic solution for Intra-patients			

The manifesto of this study was to trace the factors of trusted high-impact technologies which still have some margin for further improvement. Figure 2 represents the summary of studies' selection processes with the inclusion of the two rectification stages. At the initial process, the identification of the studies was done based on keywords of common human life diseases and technology used in the diagnosis of these diseases. 40 different studies of technology-oriented life disease detection were extracted from different databases namely, IEEE Xplore, Springer, Science Direct, and Scopus. Next, we employed the inclusion and omission policy to the selected articles and we managed to rectify 26 articles. These 26 studies were further rectified through quality assessment statements, from which 19 articles were extracted. Finally, based on these 19 articles further mapping of the RQs were established according to the context and objective of this study. Subsequently, these studies were classified and reported in terms of key findings, and the key findings are discussed in the perspective of different challenges and future opportunities. The short outcomes of this study are highlighted below:

1) Exploring the impact of trustworthy intelligent healthcare systems in the context of early detection of life diseases.
2) Highlighting the challenges which are faced in current healthcare systems.

Highlighting the taxonomical view of intelligent healthcare systems for an intra-patient hospital setting.

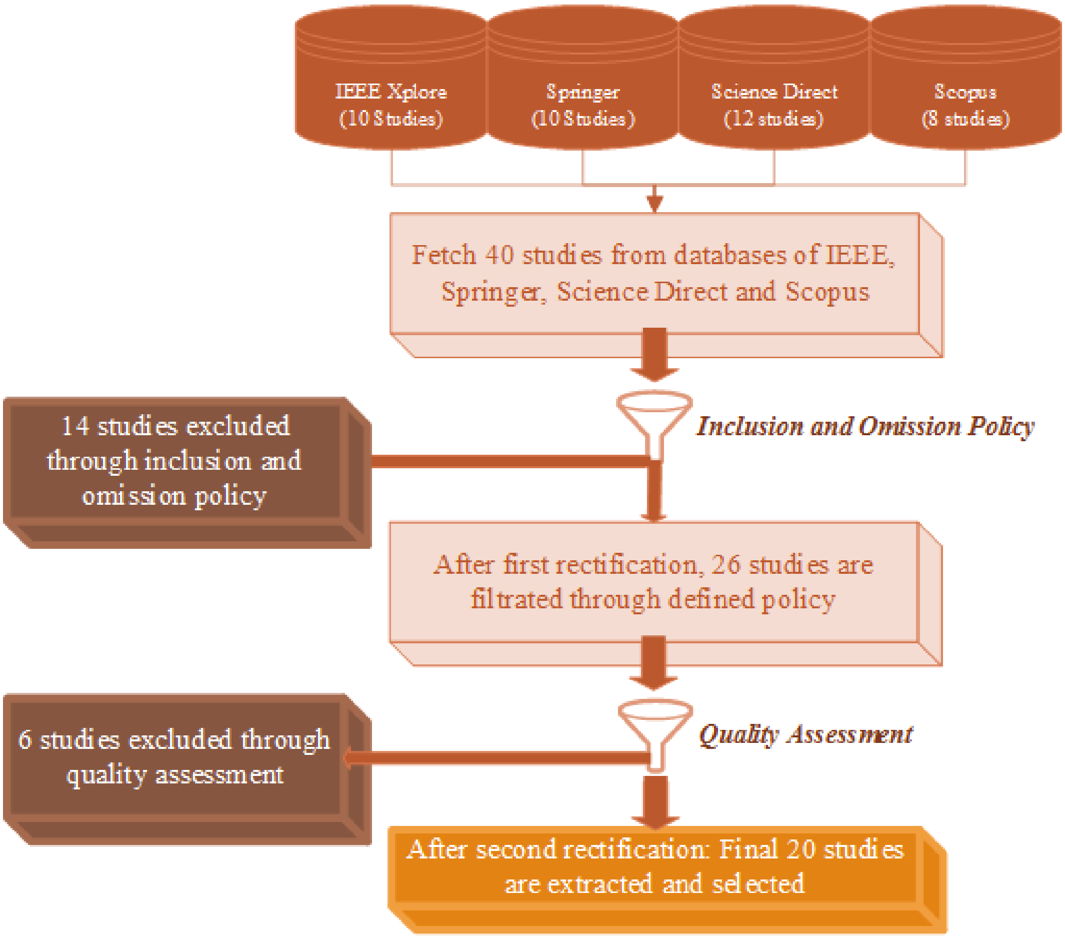

Fig. 2: Extraction of high-quality udies

4.0 QUALITATIVE MEASUREMENT AND DEMOGRAPHICAL VIEW

The significance of the selected studies was analyzed in the context of bibliometric measurements. These studies were recorded according to their past track citations record and subsequently matched according to the three defined RQs. Table 5 narrates the bibliometric information of selected articles as well as the matching up according to the RQs.

Table 5: Bibliometric Information of Selected Studies

Std_ID	Reference	Year	Citation Count	Avg. Citations Count/Year	RQ1	RQ2	RQ3
St-1	[40]	**2019**	**97**	48.5	✓	✓	✓
St-2	[41]	2020	0	0	✓	✗	✓
St-3	[42]	2019	6	3	✓	✓	✓
St-4	[16]	2017	161	40.25	✓	✓	✗
St-5	[24]	2019	15	7.5	✗	✓	✓
St-6	[43]	2018	231	77	✗	✓	✓
St-7	[23]	2019	9	4.5	✓	✗	✓
St-8	[44]	2018	79	26.33	✓	✗	✗
St-9	[22]	2019	15	7.5	✓	✓	✓
St-10	[28]	2018	20	6.66	✓	✓	✗
St-11	[45]	2019	14	7	✓	✓	✓
St-12	[12]	2019	2	1	✓	✓	✗
St-13	[46]	2017	37	9.25	✓	✓	✓
St-14	[47]	2017	89	22.25	✓	✓	✓
St-15	[30]	2018	392	130.66	✓	✓	✓
St-16	[9]	2016	72	14.4	✓	✗	✗
St-17	[8]	2020	0	0	✓	✗	✓
St-18	[25]	2020	21	21	✓	✗	✓
St-19	[48]	2018	78	26	✓	✓	✓
St-20	[57]	2022	55	3.23	✓	✗	✓

Table 5 represents the construction of bibliometric measurements of 20 studies ranging from 2016 to 2022. The bibliometric attributes of this study are, st_id(study id), published year, citation count, average citation count per year, and mapped RQs. The ✓ sign narrates the RQs matched up to the satisfied level and ✗ defines the unsatisfactory unmapped result.

The tabular representation of the selected studies was helpful for further analysis and discussion. According to Table 6, the study of st-15[30] is the most cited article in the databank as well as matched all the defined RQs in the domain of technology-oriented healthcare systems. St-15 has the highest impact with 392 citations and a 130.66 average citation count per year. The second most cited article in the list is st-6[43] with 231 citations and 77 average citations count per year. Meanwhile, st-4 [16] highlights the third leading study in the context of citations and mapping up of all RQs, with 161 citations and 40.25 average citations per year, clearly reflecting a strong record study. Table 7 highlights the bibliometric comparison of the selected articles.

Table 6: Publication Venue of Selected Studies

Std_ID	Reference	RS	ES	IF	Quarterly (Q)
St-1	[40]	YES	*NO*	*NO*	*NO*
St-2	[41]	NO	YES	YES	YES
St-3	[42]	NO	YES	YES	YES
St-4	[16]	NO	YES	YES	YES
St-5	[24]	NO	YES	YES	YES
St-6	[43]	NO	YES	YES	YES

St-7	[23]	NO	YES	YES	YES
St-8	[44]	NO	YES	YES	YES
St-9	[22]	YES	NO	YES	YES
St-10	[28]	YES	NO	NO	YES
St-11	[45]	NO	YES	YES	YES
St-12	[12]	NO	YES	YES	YES
St-13	[46]	YES	NO	YES	NO
St-14	[47]	YES	NO	YES	YES
St-15	[30]	NO	YES	YES	YES
St-16	[9]	YES	NO	YES	YES
St-17	[8]	NO	YES	YES	YES
St-18	[25]	NO	YES	YES	YES
St-19	[48]	NO	YES	YES	YES
St-20	[57]	YES	NO	YES	YES

**RS(Review study),ES(Experimental study),IF(Impact factor)

The effectiveness of Table 6 is analyzed through the attributes of quarterly (*Q)* and IF. The high level of these attributes narrates that the convergent of IoT, cloud computing, machine leaning, and big data analytics are truly integrated in digital healthcare unit which mean these technologies are supportable for the detection and prediction of daily life diseases. The collective finding of this study narrates that emerging technologies are completely correlated with daily life diagnostic solutions. The modern healthcare systems should embody the integral of these emerging technologies that supported the parameters of robust, accurate, reliable, and early diagnosis of highly impacted diseases. These 19 selected studies are segmented into two categories namely, review studies and experimental studies. These two categories explicitly demonstrated how the power of technology-oriented healthcare units such as mobile and intelligent healthcare units support the diagnosis of different neurological disorders, cardiac malfunctions, dental issues, and other common life diseases. Table 7 shows the demographic of selected review mode studies and Table 8 highlights the demographic of selected experimental studies.

Table 7: Demographic of Selected Review Mode Studies

Author	Diagnostic Application	Technology	Description	Map	Outcome
[40]	MRI	Deep Learning: Convolution Neural Network (CNN)	Extensive level of review the medical image analysis with different frames od CNN models for detection of these diseases	RQ1, RQ2	MRI data processing with well-trained CNN models
[43]	Cardiac and neurological diseases (ECG, EEG, EDG)	Deep Learning	Detail review of 53 studies of ECG, EEG and EDG. The finding of this review indicates that, deep learning models are performed well on large size of datasets	RQ2, RQ3	Perfect linkage the online and offline healthcare systems
[44]	General Healthcare systems	IoT platform	Detail discussion of e-health and mhealth via IoT platform	RQ1	Highlight the fragments of efficient IoT based healthcare systems.

[22]	Medical Data handling	Integration of Machine learning and BIG data analytics	Extensive integration analysis of machine learning and biomedical big data. Moreover, thoroughly discuss different Feature extraction and, feature selection techniques	RQ1, RQ2, RQ3	Integral of machine learning approaches in medical data analytics through versatile set of feature extraction and selection methods
[28]	Medical Data handling	IoT platform inclusion cloud computing and fog computing	Critical observations on different architectural levels, like cloud-based architecture of healthcare system, fog-based architecture of healthcare system	RQ1	Big data and IoT in healthcare system
[46]	General lifestyle diseases during pregnancy	Mobile health technology: IoT platform, Cloud computing, Machine learning	Digital health solution via mobile health technology during Pregnancy.	RQ1, RQ2, RQ3	1. Perfect mobile app for prevention of diseases in Pregnancy 2. Mobile app technology for data transfer through server in case of heart rate changes in pregnancy
[47]	General healthcare system	Big data analytics	Detail discussion on smart health concept with inclusion of intelligent agent, text mining and conceptual framework for a big data enabled healthcare system	RQ1, RQ2, RQ3	The classic Big data based conceptual framework healthcare system
[9]	General healthcare system	Medical data analytics of healthcare systems	BIG data issues in context of major challenges in the healthcare systems that can be effectively tackled via recent advancement in ICT technologies	RQ1	Narrate the issues of medical big data analytics
[57]	General healthcare system	Edge health technology, IoMT platform, Machine learning	Workflow of Intelligent healthcare systems with IoMT devices and Cloud transfer	RQ1, RQ3	Highlight the key paramters of IoMT devices along with policies of cloud trasnfer

Table 8: Demographic of Selected Experimental Mode Studies

Author	Diagnostic Application	Technology	Description	Map	Outcome
[41]	Brain Tumor Segmentatio n	Deep Learning and IoT	Brain tumor segmentation approach through Conditional Radom Fields (CRF) and heterogeneous CNN and further internet of medical things (IoMT)	RQ1, RQ3	Accurate results of brain tumor detection with technology of CNN and IoT
[42]	MRI for Brain diseases detection	Deep Learning	Clinical brain studies of 40 patients: use a novel Deep learning model (DL-AdvSS) for brain part through MRI.	RQ1, RQ2 ,RQ3	Efficient result in MRI segmentations and prediction with use of Deep learning model
[16]	ECG	Cloud computing (Human	Introduce Smart clothing for health monitoring via integration of human and cloud computing	RQ1, RQ2	Efficient integration of cloud computing with sensors of ECG

		cloud integration)			
[24]	MRI	Deep Learning (CNN) via Transfer Learning	Classification of brain tumor with accuracy of 98% via features-based CNN and transfer learning (accuracy 98%)	RQ2, RQ3	Accurate Brain tumors classification via well trained CNN transfer learning
[23]	MRI	Deep Learning and IoT	Online brain stroke detection through deep learning IoT system with accuracy of 100% and time taken 0.015s	RQ1, RQ3	High accurate detection of tomography images
[45]	Cardiac Malfunction (ECG) and Brian stroke (EEG)	Mobile Cloud Computing (MCC) and Machine learning: Multi-layer perceptron (MLP)	Proposed unique MCC architecture-based healthcare system for detection of stroke	RQ1, RQ2, RQ3	Reliable integral of MCC and MLP
[12]	Dental diseases	IoT platform and Deep Learning (CNN)	Intelligent dental healthcare platform worded on the bases of IoT and CNN of deep learning models	RQ1, RQ2	Dental diseases prediction via intelligent healthcare systems inclusion CNN model and IoT architecture
[30]	General healthcare system	IoT Platform, Cloud computing, Fog Computing	Fog computing approach: Smart healthcare system narrates considering IoT based edge healthcare	RQ1, RQ2	IoT based edge healthcare system
[8]	Brain CT image analysis	IoT platform and Machine learning in classification	IoT based accurate brain CT images analysis (accuracy level is 98.41%)	RQ1, RQ2	Reliable IoT platform for Analysis
[25]	General Intelligent healthcare systems	Quality of service (QoS) in medical data processing	he computation of medical data processing in intelligent healthcare systems with unique QoS	RQ1, RQ3	Intelligent QoS data computation healthcare system
[48]	Cardiac diseases (ECG)	Big data, Cloud computing, Machine learning	Big data analytics: classification of ECG signals using machine learning techniques on cloud computing	RQ1, RQ2, RQ3	Utilize the services of cloud computing and machine learning techniques of cardiac diseases classification

5.0 RESULTS AND DISCUSSION

This systematic review is based on the selected high-quality publications from March 2016 to June 2020 in the domain of medical data analytics using different technological factors. We noticed that the advancement of current diagnostic assessment in life diseases such as MRI for brain tumor detection, cardiac malfunction measurement through ECG tool, and diabetic diagnostic tool are dependent on different technologies, such as a huge e-health records through machine learning (ML) techniques or reliable IoT structure for the flow of patients information with the help of mobile edge cloud computing (MECC) [13], [26], [47]. However, it is observed through literature that there is still some gap for further improvement in modern healthcare systems. Therefore, the answers to the defined RQ's are discovered in the selected 19 studies which are the vital step towards reducing the improvement gaps in modern healthcare systems. Figure 3 showcased the mapping ratio of each research question.

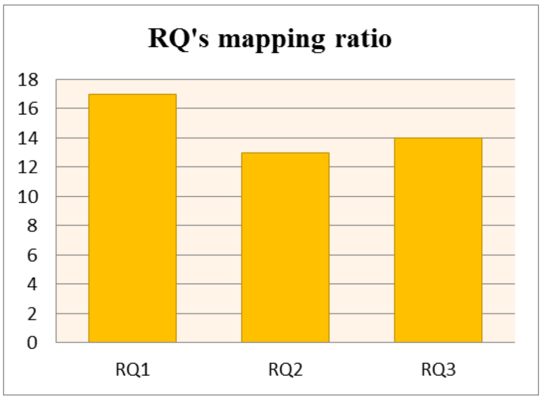

Fig. 3: Map ratio of each research question

RQ1: Accurate disease diagnostic provider

Early diagnosis of different neurological diseases, cardiac malfunction, and human body infected areas through MRI, ECG, CT scan diagnostic solutions help to improve human life survival [24], [48]. The upgradation of these diagnostic solutions on a timely basis with trusted technology of IoT platforms, MCC, MLP, CNN, and medical data analytics appear to be the leading cause for the success of early and accurate detection of diseases, especially neurological diseases and cardiac malfunctions[8], [41], [45]. Table 8 and Table 9 narrate the detail of RQ1 that matches the role of trusted technologies in different disease diagnostic applications.

RQ2: Life diseases mining via knowledge-based learning

Accurate estimation of the correlation of different diseases through the diagnostic application of MRI, Brian CT image analysis, ECG, and intelligent health monitoring units are quite helpful in the presence of trusted technologies[30], [47][48]. Additionally, brain tumor detection and cardiac diseases mining deliver the extraction of different features which are processed through MLP, and CNN via trusted IoT-based MCC architecture[8], [45]. The RQ2 mapping is clearly reflected in Table 8 and Table 9.

RQ3: Quality Intelligent computation and reliable flow of e-health records

Trustworthy technology refines the performance efficiency of diagnostic applications via reliability and traceability parameters [41], [43]. Smart and digital health is the core diagnostic applications that depend on reliable online diseases detection, health quality intelligence via ML techniques, and reliable mobile technologies namely, MCC and mobile edge computing(MEC) [23], [25], [45]. However, the progressions of these factors are continuously evolving in hybrid form due to the enhancement of daily lifestyle diseases[57]. Table 8 and Table 9 highlighted the details of different selected studies mapped with RQ3.

The significance of deep learning models in intelligent diagnostic systems have been highlighted in many studies for an example the convolution neural network (CNN)[3], [23], [24]. In figure 4, MRI images have been used to detect brain tumor via CNN based intelligent diagnostic system [40]. Moreover, the robustness and reliable factors of these intelligent systems are constantly improved through reliable technologies namely, mobile cloud computing (MCC) and mobile edge computing (MEC).

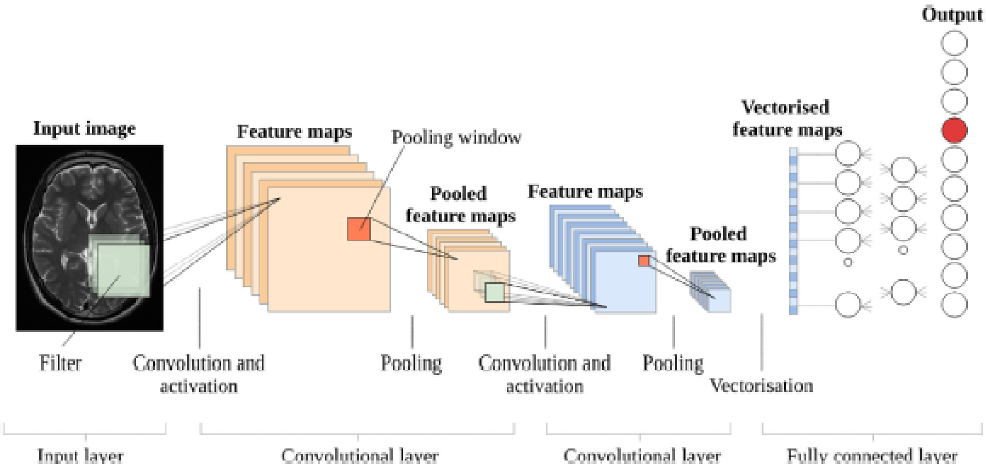

Fig. 4: Typical CNN based MRI for brain tumor detection [40]

Over the last few decades, digital and smart healthcare systems have largely used the versatile set of technologies for diagnosis of different sort of diseases. Current trend of different technology is continuously evolving with different sort of uncertainties in lifestyle related diseases. The lifestyle of daily living is the main cause for the development of these diseases like sudden cardiac arrest with multiple cardiac malfunctions and neurogenic injuries [39], [49][50], [51], and sometimes the life diseases could vary according to different lifestyles. At times unusual lifestyle would create uncertainties in context of unique nature of diseases for example extreme mental stress could lead to neuro-cardiac injuries which may cause sudden human death [39], [52]. Hence, in these uncertain cases the positive responses of technology-oriented diagnostic applications could not be utilized and it remains as a challenging task [3], [24]. Despite immense contribution of ML, cloud computing, medical Big data analytics, and IoT platform in diagnosis of common life diseases, there are still some areas where further improvement are required especially if we are dealing with human with risky diseases [19], [40][53], [54]. Figure 5 highlighted the reliable intelligent digital diagnostic system [55].

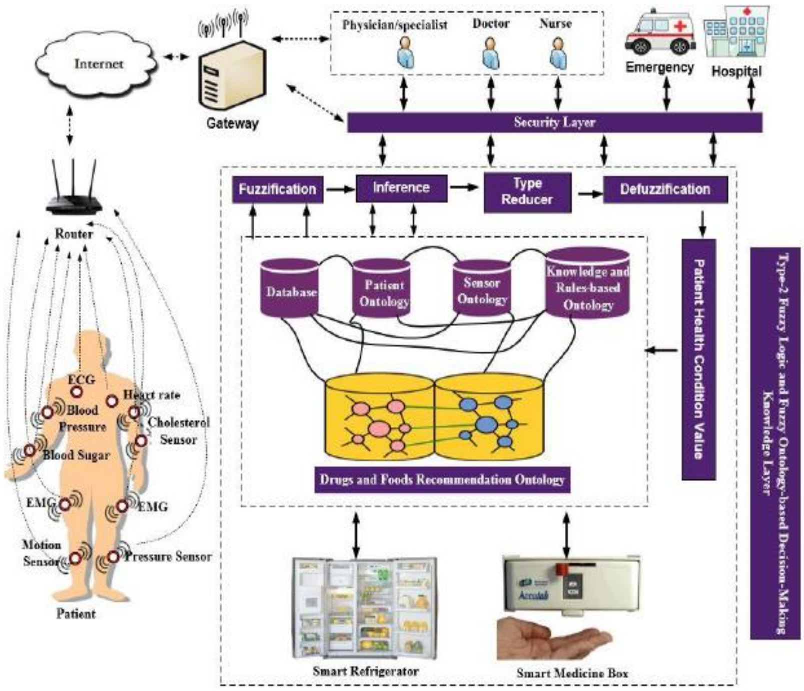

Fig. 5: Smart healthcare system via IoT platform [55].

Figure 5 in study[55] supports the intra-patient hospital concept in smart healthcare systems for diagnosis of different human diseases through intelligent edge nodes but the margin of improvement still exist in this smart healthcare system. Robust and secure synchronization between online-offline edge nodes is still challenge for research communities[56]. Modern diagnostic applications for different kind of diseases are based on the integrated emerging technologies in healthcare systems[57][58]. The segmentation of selected studies in reviews mode and experimental mode shown in respective Table 8 and Table 9 represent the significance of emerging platforms of IoT, cloud computing, and ML techniques. The upgraded emerging platforms of the diagnostic tools like MRI, ECG, EEG, and general health monitoring units are continuously evolving to conform with the concept of smart health to specifically cater the intra-patient hospital settings [16], [43]. Additionally, Table 8 and Table 9 provide useful findings of current research areas which are related to the crucial situations of human health like early brain tumor detection, accurate prediction of different cardiac malfunctions, and a reliable e-health transfer [2], [22], [40]. The mapping of defined RQ's of this study presented in table 8 and table 9 findings are the actual gain of this study.

5.1 Taxonomical Overview

The core parts of current technology oriented healthcare systems are the flexibility and scalability that continuously evolved with passage of time. This study delivers a quick review of half decade technologies which involved different diagnostic applications for the improvement of human health. Early diagnosis of diseases in intra-patient are highly demanded by many specialties of medical professionals[11], [59]. To treat a complex category of diseases or infections purely relies on these medical professionals, however, there is still a chance for human error to occur from the medical professionals' side[60]. Hence, it is best to mention that the next generation healthcare requires intelligent and rapid validation approaches which would help the medical professionals to treat humans with different type of life diseases effectively. Below is the proposed taxonomical overview of next generation healthcare:

1. Decision making Via Decentralized Trusted Technology Platforms.
2. Diseases Prediction Through Wearable Devices.
3. Robust Synchronization Between Online and Offline Mobile Edges [61]

6.0 CONCLUSION

The recent advancement of the innovations from the last few decades in different areas of human life disease are due to continuous upgradation of the technology. Flexibility and scalability parameters in current healthcare systems are regularly evolved with change of time. This systematic review is designed to identify the roles of trustworthy technologies platforms for early diagnosis of different diseases especially in the intra-patient setting. In intra-patient health sector, trustworthy platforms of technologies are the leading cause of efficient diagnostic solution of daily human life diseases. Agility in the evolution of these trusted technologies is purely based on early diagnosis requirements of the life diseases. Moreover, mapping of research questions in this systematic review highlighted the significance of different technologies platforms in intra-patient setting for early diagnosis of different diseases. Finally, the taxonomical overview emphasized in this study could be considered in the future for the formation of smart health next generation.

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