A Review on Internet of Medical Things (IoMT): A Case Study for Preeclampsia

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Abstract. Preeclampsia detection research has started exploring some methods to diagnose and predict preeclampsia. Machine learning (ML) methods and the Internet of Things (IoT) have been successfully implemented in medical research to improve the diagnosis and prevention of complex diseases and syndromes. The goal of this work is to undertake a review of the most recent work on preeclampsia detection. The research focused on articles related to the keywords 'machine learning, 'Internet of Things, 'IoT', 'medical', and preeclampsia in five main databases, namely IEEEXplore, ScienceDirect, SpringerLink, ResearchGate, and ACM Digital Library, etc. We selected and reviewed 90 articles in the end. The final discussion highlights research gaps that remain to be investigated in the cognitive approach to IoT. The study found that preeclampsia detection based on the internet of Medical things (IoMT) was not found, so it became a big opportunity to develop this research in the future.

1 Introduction

Preeclampsia, classically defined as proteinuric gestational hypertension [1], is characterized by hypertension and organ disorders caused by pregnancy or affected by the current pregnancy. However, preeclampsia can occur even without symptoms of high blood pressure and the presence of protein in the urine, hypertension is the main cause of maternal death [2]. When the disorder advances cause seizures, which is a condition known as eclampsia [3]. Until now, preeclampsia is to be one of the leading causes of maternal death, so professionals must know how to deal with and take action [4].

Based on a survey by the National Health Portal of India, almost 8-10% of pregnant women have preeclampsia [5]. Preeclampsia is a leading cause of maternal death [6], the second leading cause of maternal death in the UK [7], in Europe [8], in several developing countries [8], and the main contributors to maternal mortality in the world [9], and also responsible for 75,000 maternal deaths worldwide each year [10]. Globally, 10–15% of all

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maternal deaths are attributable to preeclampsia or eclampsia [11]. Maternal deaths occur in developing countries higher than in developed countries [12], and up to 99% of these deaths occur less developed countries [7].

Several factors that cause preeclampsia such as first pregnancies, twins, and teenage pregnancies have high risk [12]. Traditionally, the diagnosis of preeclampsia depends directly on the health professional. [13]. This diagnosis can be improved with the use of e-health methods. These can support the prevention of the disease, avoiding the problems that happen once it has been diagnosed. The current focus of health care researchers is to promote the use of e-health technology in developing countries to support medical decisions [14]. Health expert will be enable to take preventative steps and offer continous monitoring to the high-risk pregnancy group, Especially for preeclampsia, so decreasing the incidence of serious diseases [15].

The prediction of preeclampsia and its disorders has received much attention during the last two decades [3], [4]. Early detection and management of hypertension in pregnancy is required. The initial diagnosis of preeclampsia is based solely on blood pressure and urine tests for proteinuria, and can be remotely 16]. Early diagnosis and treatment of high blood pressure can reduce maternal morbidity and consequently mortality [17].

In this international issue, now, the medical personnel and researchers are looking for to early detection of preeclampsia. The fast prediction and detection of the preeclampsia disease is important not only for healthcare professionals to decreased sum of preeclampsia disease patients but also for their patients. Several model for predicting the risk of preeclampsia have been done and validated in several studies [16, 17].

In this scenario, advanced computing research such as Internet of Things (IoT) and Machine learning (ML) are now digital technologies that can be implemented to solve health problems. ML algoritms have been applied in several approaches that include risk factors datasets metabolites, images analyses, to diagnose and to predict preeclampsia. ML algroritms have been used to support the doctor in the prevention of preeclampsia. These techniques have been successfully applied to medical research to improve the diagnosis and the prevention of complex diseases and syndromes.

In this digital computing technology era, the recent developments in IoT are combine with several technologies such as artificial intellegence, machine learning, and cloud computing technology. These technologies can assisted to improve the diagnosis. The data collecting from persons form another locations using IoT can be done in real-time [18]. The IoT has proven to provide effective service [19]. To sum up, the following are the primary goals of this systematic review:

- highlight the most notable applications of ML in the field of IoT
- evaluate the time publication trend of ML applied to IoT;
- outline the research gaps still to be investigated.

2 Internet of Medical Things (IoMT)

IoT is a network of devices that interact with each other over the internet, enabling the collection and exchange of data [20-24]. IoT has became as one of the recent advances of information and communication technologies, and it is has big impact when combined with health services, especialy eHealth [25]. IoT is a system in which objects have identifying, sensing and processing capabilities that make it enable to communicate with each objects and with other devices and services through the Internet to achieve multiple purposes [26]. IoT refers to the connection to various devices and systems, which can be accessed by users anytime and anywhere, and to collect and exchange information [27]. IoT has been associated with various fields, one of which is health care [28]. IoT is a generally new concept that promising solution providing for healthcare monitoring continuously and supporting clinical decision making [29]. Health monitoring system is one of the popular IoT applications and many kinds of designs and patterns have been applied [30]. The IoT integrated with health services has a big impact, especially eHealth [31].

Nowadays, recent advances of several technologies such as mobile, wearable, and IoT make a novel opportunities for designing and developing new intelligent computing services that address various health and well-being issues [32], and that combines several components such as hardware, softwares, and animals or people throught a network enabling them to interact, communicate, collect and exchange data [33].

A large amount of data is produced by IoT application required for intelligent data processing [34]. IoT-based medical device for collecting patients' heart details before and after heart disease [35]. From a technical perspective, the IoT is gaining a rapidly growing attention in many disciplines, especially in personalised healthcare. Meanwhile, body area sensor network (BASN) under the IoT framework has been widely applied for ubiquitous health monitoring.

2.1 Internet of Medical Things (IoMT) and Machine Learning

Several researchs related with IoT and health care and medical analysis have done to decreased burden on the elderly population with chronic disease on the modern health care system. The burden on the healthcare system can be reduce by IoT [20]. The care monitoring system at Home using IoT enable the elderly can see about their health condition from home [36]. Internet of Medical Things (IoMT) enables continuous, remote and real-time patient monitoring [37], in hospitals and, most importantly, at home [38]. The aim of IoMT and digital healthcare systems is to provide human with the ease of receiving quality healthcare from their homes [39]. The IoMT develops the interconnection of communication enabled medical-grade technologies and their integration to wider-scale health networks in order to improve patients' health [40].

Recently, IoMT [41-43] played a vital role in remote healthcare monitoring (RHM) [44]. The IoMT is mainly used to collect the remote data for patient through wearable sensors/devices [45] and store them in the cloud databases. These data are made avaialble for real-time analysis and application by caregivers [46]. IoT for health consists of various wearables devices, such as fitness bands, smartwatch, and other wireless-enabled devices (i.e., blood pressure monitoring, heart rate monitoring, glucometer, etc.) [47].

IoT-enabled medical devices provide important data to support the performance of health care professionals [48]. In healthcare, the monitor and make quick decisions in critical situations is the most useful area for IoT [49]. Telemedicine [50], includes various points, such as medical care delivery, diagnosis [51], ECG monitoring has been commonly adopted as vital approach for diagnosing heart disease [52]. Healthcare-Internet of Things (H-IoT) is a complex system that includes microelectronics, medicine and health systems, computer science, and more [53].

Health sector is proving to be one of the most attractive fields for IoT applications. Wireless technology support supports real-time monitoring for chronic disease treatment and enables early diagnosis [23, 54]. IoT allows for distributed healthcare applications and makes a significant contribution to the reduction of healthcare costs, and required behavior change [55].

IoMT is the facility to transfer data over a network without demanding human to human or human to computer interaction [56], This a new paradigm, named Cognitive Internet of Things (CIoT), to empower the current IoT with a 'brain' for high level intelligence which objects should have the capability to learn, think, and understand both physical and social worlds by themselves and not only connected [57]. Intelligent processing and analysis of big data is the key to developing smart IoT [24].

Smart wearable devices are one of different major types of IoT services can be used for patients who need to collect data about their health status such as heartbeat, blood pressure and glucose level through sensors on the wearable technologies, which are sent to smartphones. The health status of patients can be monitored by realtime [58]. The industry of wearable devices for pregnancies has been developing rapidly. The monitoring and management of maternal health indicators in the home for pregnant women and obstetricians used several factors such as fetal heart rate, blood glucose, and blood pressure [59]. We have summarized the results of analyzing IoT for Medical analysis in **Table 1**.

Table 1. IoT & Machine Learning for General Medical Analysis

Author	Function	Technology	Object
Singh et al. [60]	Identify thyroid patients	Fog computing and artificial intelligence	Thyroid patients
Guan et al. [36]	Home care monitoring system	IoT	Elderly
Li et al [59]	The monitoring and management of maternal health	IoT	Pregnant women and obstetricians
T. Zhang et al. [61]	The cardiac image processing of remote elderly patients.	A Joint DL and IoT platform (Deep-IoMT)	Elderly patients
N. Jin et al. [62]	A real-time detection framework for analysing the level of stress	IoT	A particular sports person
Gupta et al.; Iyda et al.[63], [64]	Early-warning architecture for remote monitoring in wards and at home	IoT, cloud-&Amazon Web Services (AWS)	COVID-19 patients
S. Wu et al. [65]	To help chronic disease patients	IoT-AAS	Chronic disease patients
Hossain et al.,; Naseer et al.[66], [67]	Feature extraction and predictive model for cardiovascular disease	Android-based applications and machine learning	Cardiovascular disease
Qin et al. [68]	Prediction of the health status of the elderly	Machine learning	Elderly patients
Bao et al. [69]	Predicting HIV and the diagnosis of sexually transmitted infections (STIs)	Machine learning	HIV patients

2.2 Internet of Medical Things (IoMT) for Pregnancy

Several studies related to the detection of preeclampsia using different methods have been carried out, ranging from simple methods to methods using machine learning. The prediction model using an elastic net [70].

The detection system for patients with preeclampsia uses a fuzzy decision tree. 4.5 The fuzzy linguistic model uses two main steps. First,a linguistic transformation to improve interpretability and flexibility in the analysis of preeclampsia was applied to the data sets. Second, knowledge extraction to classify data sets is done by inferring the decision tree rules. The linguistic rules obtained provide an understandable monitoring of preeclampsia based on application [71].

Prediction of preeclampsia using maternal medical record data at the beginning of the second trimester at the hospital for the prevention of preeclampsia using machine learning based on pattern recognition and cluster analysis. the prediction model using logistic regression, decision tree model, naïve bayes classification, support vector machine, random forest algorithm, and stochastic gradient boosting were used to build the prediction model. Statistics C was used to assess the performance of each model. Features of systolic blood pressure, serum blood urea nitrogen and creatinine levels, platelet counts, serum potassium level, white blood cell, serum calcium, and urinary protein were the most influential variables included in the prediction model. Machine learning algorithms can be used to effectively predict preeclampsia using a combination of maternal factors and laboratory data from the beginning of the second trimester to the beginning of the third trimester [16].

Prediction of preeclampsia using the BPJS Health dataset with a machine learning model. The number of datasets used is 95 features consisting of demographic variables and medical history was processed first using a nested case control design into preeclampsia/eclampsia (n = 3318) and normotensive pregnant women (n = 19,883) of all pregnant women. The best model consists of 17 predictors extracted by the random forest algorithm [8].

3 Research Methods

3.1 The primary databases utilized in the search for papers were the eight listed below:

1. IEEEXplore, the Institute of Electrical and Electronics Engineers' (IEEE) database that houses technical literature in the fields of electrical engineering, electronics, computer science, and other related disciplines
2. ScienceDirect, which offers access to journals and technical and scientific articles published by Elsevier
3. SpringerLink, which provides access to scholarly articles published by the Springer Nature editorial team
4. The ACM Digital Library, a collection of published resources in the computing field maintained by the Association for Computing Machinery.
5. The National Library of Medicine is a leader in research in biomedical informatics and data science and the world's largest biomedical library
6. Elsevier is a Netherlands-based academic publishing company specializing in scientific, technical, and medical content.
7. ResearchGate is a popular online hub for disseminating academic publications, as well as a social networking and academic profile site.

Table 2. The study applied both inclusion (IC) and exclusion criteria (EC)

No.	Criteria	Status
1	Studies that are included in a journal's print or online edition.	IC
2	Studies will be published between 2015 and 2022.	IC
3	There has been a review of the literature.	EC
4	IoT AI, Cognitive are used in the inquiry.	EC

3.2 Search process and filtering criteria

The search and filtering process is shown in detail in Fig. 2. The inclusion (IC) and exclusion (EC) standards are summarized in Table 2. The queries that are described in Section 3.1 have been applied to the databases that are listed in Section 3.2. The papers we selected were those released between 2015 and 2022. This range was selected because, previous to 2015, ML approaches had not yet appeared in the preeclampsia disease. Additionally, the study limited itself to either published or in-press journal papers, excluding conferences and pre-prints. This choice complies with the quality criteria we sought for the systematic review we carried out.

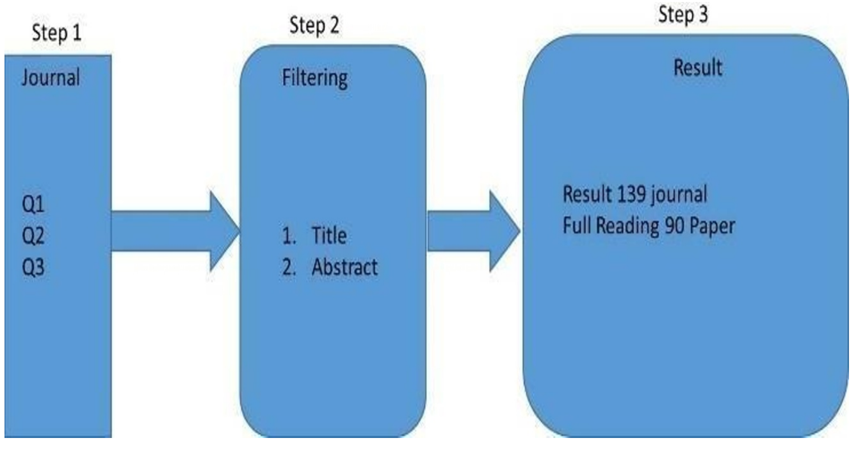

Fig 1. The selection of the paper's research process

4 Result and Discussion

In this paper, we show that researchers have shown a strong interest in developing preeclampsia detection systems using ML and IoMT in recent years. The Internet of Things (IoT) has infiltrated our daily lives but IoMT itself has limited capabilities. To reap the real benefits of IoT, it must be intelligent [72, 57]. The current IoT lacks sufficient intelligence and cannot achieve the expected application performance improvements. By integrating intelligent thinking into IoT, we are presenting a new concept of Cognitive Internet of Things (CIoT) [73].

Combination between machine learning and IoT generate a revolution in human life and application industry that ability to connect and its intelligence, it makes people to create an intelligence device and capable to learn like human brain [72]. Several of methods and contributions provided in this review evaluation were highly accurate [35] shown the importance of adding inception layers to networks in order to improve performance. Summarize all the articles cited above, lists the ML method, performance, and the IoMT architecture model it can be seen in **Table 3.**

Table 3. Summarized IoMT In Maternal Object

Author	ML	Performance	IoMT	Object
Sufriyana et al. [8]	Logistic Regression, Decision Tree, Artificial Neural Network, Random Forest, Support Vector Machine, & Ensemble Algorithm	AUROC	No	Preeclampsia
Marić et al. [70]	Gradient Boosting, Elastic Net & Logistic Regression	AUROC	No	Preeclampsia
Jhee et al. [16]	Stochastic Gradient Boosting Method, Random Forest Algorithm Decision Tree Model, Naïve Bayes Classification, Support Vector Machine, & Logistic Regression	t-score & accuracy	No	Preeclampsia
Martinez-velasco & Miralles [13]	Random Forest & Decision Tree	Accuracy and F1-score	No	Preeclampsia
Simbolon [81]	Soft Voting-Based Ensemble Method,K-Nearest Neighbors, Linear Support Vector Machine, RBF Support Vector Machine, Gaussian Process, Multi- Layer	Accuracy and F1-score	No	Preeclampsia

Author	ML	Performance	IoMT	Object
	Perceptron, And Ada Boost			
Ahmed & Kashem [82]	Decision Tree Classifier RBF Support Vector Machine, Naïve Bayes	Accuracy	Yes	Maternal
Oti et al. [15]	K-means clustering	Accuracy & Sum of Squared Error (SSE) on	Yes	Maternal stress
Amala & Mythili [83]	-	-	Yes	Maternal
Marques et al. [84]	K-Nearest Neighbors, Support Vector Machines with a radial basis functionkernel,Random Fores, One-dimensional Convolutional Neural Network	F1- score	Yes	Maternal & Fetal
Sarhaddi et al. [85]	No	No	Yes	Maternal
Dhivya et al. [86]	No	No	Yes	Maternal
Heuvel et al. [87]	No	No	No	Preeclampsia

5 Challenges & Implication

Today, the world faces serious challenges in tackling various problems related to human health and well-being, such as a rapidly increasing aging population, chronic diseases, child mortality, and poverty due to an increasing population. On the other hand, the health service model is still carried out traditionally by visiting health service centers such as hospitals or clinics for examinations. This of course will be an obstacle. Several of the challenges and obstacles of the problem :

- Data processing in Intelligent algorithms need more sufficient and big training data [73].
- Feature extraction and classification in intelligent algorithms require computational time [74].
- Accuracy and performance [75].
- Data loss is a common problem in this system, long-term monitoring can cause data acquisition to be interrupted, data is inconsistent and incomplete. Therefore, a holistic approach to match missing data in real-time health monitoring systems is needed [76].
- WSN is vulnerable to several types of attack [77] due to sensor.
- Node is part of a bidirectional sensor network as discussed in [78] describes several

possible attacks which include Jamming, tampering, Sybil, Flooding.
- Cloud computing is this shared resource can face many security threats like Man-in-the-middle attacks (MITM), Phishing etc. [79].
- Some of the possible insider threats include data loss, account hijacking, and massive use of shared computers, etc. [80].
- Primary Health Care Becoming More Accessible [90]
- Technology That Is Accessible and Easy to Use [89]

As shown in **Table 2 and 3**, the research about preeclampsia states has always been restricted to studying only the ML. Whereas, in fact, where people have more complex. This will motivate future researchers to work on IoMT architectures for preeclampsia. Protection and testing mechanisms are critical in the implementation of any IoT program [88].

6 Conclusion

This paper provides a review of recent research on IoMT on maternal objects using ML and IoT. The goal is that we can know the latest developments in this field and as an insight in considering analytical methods for preeclampsia. We have provided a brief description of the various IoT & ML model architectures in maternal health care proposed by the most cited researchers.

We have described the research methods we adopted in detail, we have described the results of a systematic review according to three main classifications reflecting the research question. Recent discussions have shed light on the many issues that are still open in our chosen topic, which proves that further research efforts are needed, in the near future, to make the use of machine learning a part of IoT.

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