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The Use of Machine Learning and Internet of Things Technologies in Maternal Healthcare: A Systematic Review

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Background and Purpose: There has been a recent increase in the use of the Internet of Things (IoT) and machine learning (ML) technologies in maternal healthcare. These technologies have enabled the design of wearable medical devices that can remotely monitor pregnant women's vital signs, predict impending pregnancy complications, and provide early warnings. This would necessitate timely, appropriate, and personalized care to improve the health of pregnant women. This review examines current trends and gaps in integrated IoT and machine learning technologies in maternal healthcare and provides recommendations for designing suitable models to improve personalized maternal healthcare.
Methods: We adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for systematic reviews to analyse 50 articles published between 2017 and 2024 covering the use of IoT and ML in maternal healthcare. The risk of bias of the included studies was evaluated using the Prediction Model of Bias Assessment Tool (PROBAST).
Results: We established the need for further studies to guide the design of IoT and ML frameworks that can capture both fetal and maternal vitals and transmit them directly to the cloud for analysis without an intermediary such as a smartphone. Furthermore, the use of tinyML technology for on-device sensor data analytics in real-time monitoring requires further consideration in maternal healthcare applications.
Conclusions: This review followed PRISMA guidelines to analyse trends in the use of integrated ML and IoT technologies in maternal healthcare. The evaluation highlighted gaps in the design of the devices for continuous monitoring of maternal and fetal vitals and predicting pregnancy complications. The review provides recommendations for further research work in the design of these intelligent devices.

Keywords: Machine Learning, Internet of Things, Pre-eclampsia, Pregnancy complications, Maternal healthcare.

1 Introduction

Pregnancy complications have continued to be a critical global health challenge, and it is estimated that they affect approximately 8% of all pregnancies [1]. The complications often result in increased rates of morbidity and mortality for both the mother and unborn child. Early diagnosis and prompt intervention can reduce the risk of severe complications, which, if not diagnosed in good time, are associated with poor birth outcomes such as miscarriage, pre-term birth, stillbirth, low birth weight, or birth deformities [2]. Every day, eight hundred women die due to preventable causes related to pregnancy and childbirth [3]. With the help of technology, some of these fatalities can be averted. In 2020, the maternal mortality rate was 223 deaths per 100,000 live births in low-income countries [4]. The use of advanced technologies can enable the development and implementation of tools for enhancing early detection of these pregnancy complications [5]. One of the main goals of the United Nations Sustainable Development Goals is to reduce the global maternal mortality ratio to fewer than 70 per 100,000 live births by 2030 [6]. The use of the Internet of Things (IoT) and advancements in machine learning (ML) and deep learning can help achieve this goal by enhancing

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real-time monitoring of health status and predicting pregnancy complications, enabling timely, appropriate intervention. However, optimizing models for early prediction and identification of maternal complications remains a major challenge in real-time pregnancy monitoring [7]. A decrease in self-perception of clinical signs related to maternal complications, challenges in accessing the healthcare system, and poor quality of healthcare leads to delays in the diagnosis of the complications and poor prognosis as well [8]. Developing a non-invasive ANC tool to identify maternal signs and symptoms of illness during pregnancy can provide a significant opportunity to detect abnormal patterns early and manage them, thereby minimizing severe complications [2].

Health information systems in many African countries face various challenges that hinder their ability to deliver evidence-based healthcare effectively. According to [9], challenges include reliance on paper-based record-keeping, inadequate ICT infrastructure, poor internet connectivity, and limited electrical supply, especially in rural areas. Additionally, inadequate numbers of qualified health informatics personnel and fragmented, non-interoperable digital platforms that limit real-time data capture and sharing. This results in fragmented, unreliable, insecure, and poor-quality data, which impedes informed clinical decisions, leading to missed diagnoses and repeated testing that are costly and time-consuming [10]. These challenges can be addressed by integrating ML and IoT technologies, especially in maternal healthcare, to improve maternal and neonatal outcomes in limited-resource settings. The technologies can be harnessed to implement a real-time monitoring system that continuously collects patient vitals to facilitate data-driven decisions, early risk detection, early warning of impending complications, and timely, personalized interventions [11]. These systems would transform African health systems from reactive, paper-based systems to a proactive, data-driven, patient-centered approach.

Easy access to personalized information related to pregnancy, high-quality health services, and effective interaction with healthcare providers is necessary for all pregnant women. To facilitate these services for pregnant women quickly and efficiently, intelligent devices, communication systems, and e-health applications should be implemented and used to help prevent many pregnancy-related complications [12]. The potential for global e-health growth has increased as communication and information technologies advance. In Rwanda, for example, a monitoring system for pregnancy and newborn information was implemented using a mobile application. The project tracks the number of pregnancies and their associated complications through instant messaging in the community [13].

The adoption of emerging technologies such as IoT and machine learning in maternal healthcare can improve maternal and fetal health outcomes. The technologies have been utilized extensively in implementing information systems tools for early detection of complications, identification of pregnant women who are at high risk, and provision of continuous data on the health status of pregnant women and their unborn child to make informed decisions on appropriate and timely intervention to reduce maternal health risk [14].

This review aims to present a systematic review of the literature on the integration of Internet of Things (IoT) and machine learning (ML) technologies in maternal healthcare to gain a better understanding of the research trends and critical research concerns in this area by analyzing the common ML algorithms, features, and IoT frameworks used in remote monitoring and prediction of pregnancy complications. Additionally, we seek to provide a roadmap for future research on the effective integration of technologies to address complex pregnancy complications by proposing a conceptual model for maternal healthcare monitoring. The remainder of this article is organized as follows: Section 1.1 presents the machine learning process and the algorithms used for predicting pregnancy complications. Section 1.2 provides the IoT technologies used in maternal healthcare. Section 2 compares this study with other related previous reviews. Section 3 explains the systematic review methodology used to answer the research questions, while Sections 4 and 5 present the results and discussion. Sections 6 and 7 provide limitations, a summary of the study, and opportunities for future research.

1.1 Machine learning in maternal healthcare

Machine learning is an artificial intelligence branch that enables machines, through the use of smart software, to perform their jobs skillfully [15]. Statistical learning methods are the backbone of intelligent machines. The machine learning technique is based on mathematical procedures and algorithms that describe the relationships between variables [16]. The technique is used to extract complex patterns from existing datasets to make predictions or decisions. In the healthcare system, machine learning algorithms provide an efficient means to extract knowledge by constructing predictive models from diagnostic medical datasets. For instance, extracting knowledge from data collected from diabetic patients can help predict diabetic progression [17]. Machine learning comprises the following phases: data collection, data preprocessing, model training, model evaluation, and model deployment and performance monitoring [18]. The machine learning steps are iterative and vary based on the problem being solved and the data set being used, as illustrated in Figure 1.

Obtaining the dataset needed to train the models is the first step in the machine learning process. Since this affects the model's correctness, the data set gathered ought to be accurate and relevant. An important aspect to consider is where the data is collected, as it should come from a reliable source, as this can affect the model's outcome. For instance, in maternal healthcare, data can be collected from e-health records, wearable devices such as sensors and wristwatches, and surveys [19].

The data preprocessing phase involves data cleaning, including handling missing values, inconsistent data, and duplicate data. Additional tasks include combining data from different sources, converting the dataset into a suitable format, reducing dimensionality, and extracting relevant features. Understanding the data and the issue to be solved is part of the problem definition phase, for instance, in maternal healthcare, determining the specific maternal health issues like gestational diabetes, pre-eclampsia, or pre-term birth.

During the model development phase, the training data set is split into training and test sets, and the appropriate algorithm for the particular problem is evaluated. Then the model is trained on the training data set to extract hidden patterns; for example, training a model to predict the risk of pre-eclampsia based on the selected features [20].

The next phase is the model evaluation phase, in which the model's hyperparameters are fine-tuned on a validation dataset to avoid overfitting. The model's performance is evaluated using appropriate metrics such as sensitivity, accuracy, precision, and F1 score [19].

The last phase is model deployment, which involves using the model to predict unseen data. It can include integrating the model into a maternal healthcare system. Then, continuously monitor the model and retrain it periodically to ensure its accuracy and relevance [20].

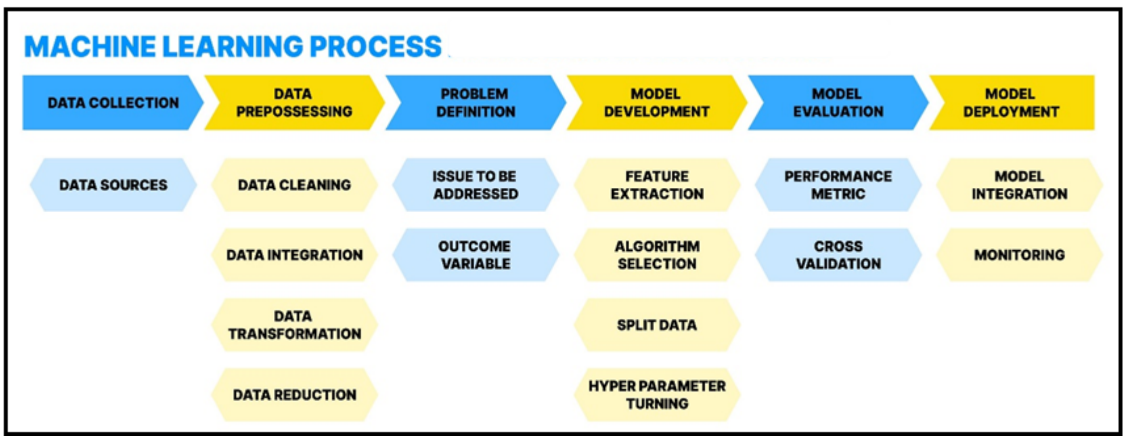

Figure 1. Machine-learning process

Deep learning models have shown higher predictive performance when using electronic health record data, which has increased massively. Due to the lack of transparency in deep learning models, it is difficult to interpret their patterns; as a result, there is a lack of trust in using them for real-world decision-making, since it is difficult to explain how predictions are generated. This problem may be solved by using Bayesian neural networks to predict the effects of data noise. The uncertainty is initiated to ensure the provision of model prediction, which

also provides an extra level of confidence [21]. However, high uncertainty may undermine model predictions. Furthermore, investigating the distributions of model predictions and uncertainties enables the identification of patient groups to ensure timely intervention, such as reducing data noise, thereby improving predictive accuracy [22].

Some of the machine-learning techniques used for predicting pregnancy complications include artificial neural networks (ANNs), deep learning, naïve Bayes, support vector machines (SVMs), k-nearest neighbors (KNNs), decision trees, random forests, and gradient-boosted decision trees [23].

The ANN algorithm usually mimics how the brain's cell tissue works, with the computational trick lying in the relationships among the neurons. This algorithm consists of at least two layers, namely: the input layer and the output layer. The input layer consists of the input value nodes, while the output layer consists of the output value nodes after processing using the activation function. In a multivariate neural network, hidden layers contain output-value nodes that serve as inputs to the other side nodes [24]. An artificial neural network is a biologically inspired computer simulation that performs particular tasks such as clustering, classification, and design recognition [25].

Deep learning is an advanced machine learning subfield that enables computational models structured into multiple layers to analyse data at various levels of abstraction. The layers are represented by a neural network structure, stacked in a literal layer-by-layer manner. In contrast, deep learning has several hidden layers, each representing a higher level of abstraction, unlike neural networks and multiple-layer perceptrons. The technique is used to extract additional hidden features that may not be visible to the human eye, thereby increasing its predictive accuracy. The technique is widely used across domains such as image processing, image identification and retrieval, natural language processing, and search engine information retrieval [26]. Commonly used deep learning approaches include multilayer perceptron (MLP), recurrent neural networks (RNN), and convolutional neural networks (CNN) [27].

Naïve Bayes is a supervised learning method that is adaptable and uses conditional probabilities to classify an instance based on the characteristics of the test data set and assign it to the same class [28]. Naïve Bayes is a simple classifier that uses probabilistic techniques based on the application of Bayes' theorem and is independent of assumptions about the relationships between the characteristics used for classification. The algorithm calculates probabilistic outcomes and matches dataset values by computing frequencies. The Bayesian theorem assumes that all attributes are independent. The conditional independence assumption is seldom correct in real-world applications and yields better, more advanced classification results [17].

The support vector machine (SVM) is a supervised algorithm used for classification and regression analysis, though it is primarily used for classification. In this algorithm, every data element is represented as a point within an n-dimensional space, where n is the number of characteristics, with each characteristic corresponding to a specific coordinate [29]. This algorithm is a popular classification method that categorizes data into multiple classes using binary classification. Unlike other machine learning algorithms, SVMs use a hyperplane as a decision boundary between classes. The algorithm searches for the hyperplane with the highest range. It is an exclusionary classifier that formally characterizes the data by separating a hyperplane between specific classes and isolating entities. It is also involved in identifying and classifying instances that are not data-supported but do not involve distributing data collected for each class [17].

K-Nearest Neighbor (KNN) is a simple algorithm for classification and regression that uses a non-parametric method, where the input comprises k closest training instances in the parameter space to give an output t, depending on whether the algorithm is geared towards classification or regression. The algorithm searches for the nearest data neighbors, records each logical element, and categorizes the current elements according to their similarity. The value of k is always a positive integer representing the number of nearest neighbors in a classification technique. Class or object property values are selected from the closest neighbors [17]. The KNN algorithm assumes that similar things exist near one another. The advantages of KNN are that its implementation is simple and straightforward, and that no model needs to be built; only features need to be tuned or additional assumptions made; however, it becomes slower as the number of parameters increases [30]. The decision tree algorithm consists of an internal node and one class-labeled node. The classification issues in this algorithm are addressed by repeatedly splitting the input space to create a tree with pure, straightforward node points associated with a single class. Moving down the tree, the classification of new data elements is performed by selecting a single branch at each point. Developing a decision tree is dependent on the type of target in the current model. This algorithm uses a reduction-in-variance approach to build a tree model for continuous target variables at the test point, rather than the Gini impurity approach used for categorical target variables. In the Decision tree technique, initiation occurs at the root node and termination at the last node, which is the leaf node of the tree. Internal nodes are located between the root and leaf nodes and are used to test data-point features; each internal node has one possible outcome. This algorithm is used in real-world applications across sectors. For instance, the health sector is used for early diagnosis of cognitive disability, which increases the efficiency of screening positive cases as well as predicting pregnancy complications for pregnant women. The advantage of this algorithm is that it is easy to interpret, handles both continuous and categorical attributes, and requires little or no information processing. In addition, it is highly significant for classification and prediction. However, when the data set is imbalanced, this algorithm shows poor overall performance and is noise-sensitive, which can lead to overfitting if the training dataset contains noise [27].

Random forests are ensemble models that integrate multiple models and are compatible with a wide range of data sets for classification or regression. The random forest model overcomes high conflict even beyond the decision trees. In a random forest model, there are several decision trees, each with a slight disparity from the others. Integration of the outcomes from each decision tree is performed for a specific data point. During the integration process, a majority vote is used for classification, and the average value is used for regression tasks. The performance of the combined trees is better than that of a single tree when it comes to predictions. This is because separate training is used for all the decision trees on a random sample drawn from the training data set. This model is called a random tree because it builds random trees, ensuring that all trees are different [27]. Although complex and time-consuming, the model is suitable for feature importance analysis and has been successfully applied to the early detection of various pregnancy complications.

A gradient-boosted decision tree is another ensemble model, similar to a random forest, because it uses multiple decision trees and supports both classification and regression. However, this model differs from the random forest in that it doesn't use randomization when developing model trees. Instead, pre-pruning is used, in which trees are constructed serially and each attempts to rectify the mistake of the preceding tree. In this model, the death of the trees is small, with depth values ranging from 1 to 5. The basic concept of this algorithm is to mix several simple models. The most extensive application of this model is in supervised learning, where it is naturally robust. The main drawback of this model is that it requires carefully standardized parameters, typically takes longer to train, and is ineffective when the data points are in high-dimensional space [27]. The model has been widely used in building predictive models in maternal healthcare. The algorithm was used by [31] to implement a perinatal mortality prediction model that had an accuracy of 90.24%

1.2 TinyML

TinyML is a machine learning subdomain involving developing and deploying machine learning models on small, low-power devices such as microcontrollers, embedded systems, and sensors. This is a fast-expanding research area, driven by a growing demand for intelligent devices that can process data at the edge rather than relying on cloud or remote servers. The main aim of TinyML is to bring the power of machine learning to a wide range of edge devices, enhancing their ability to handle complex tasks such as voice recognition, object detection, and predictive maintenance. The recent proliferation of TinyML can largely be credited to improvements in the hardware and software ecosystems that support its implementation. With the prospect of deploying low-energy systems such as sensors and microcontrollers, machine learning can be effectively brought to the edge, enabling these applications to operate in real time and allowing machine learning practitioners to achieve more with less. As pointed out by Warden & Situnayake [32], the tinyML technology has several advantages, particularly

- Reduced latency: Data transmission to the server is unnecessary because the model runs on the edge device. In a typical data transfer, there is latency; hence, avoiding the transfer to the server reduces latency.
- Saves Energy: The microcontrollers require low power, enabling them to run for a long time without charging. No vast infrastructure is needed either, since there's no data transfer.
- Improved security and data privacy: - Since the data is kept on the model that runs on the edge, there is no need to transfer the data to servers, and this increases the guarantee of data privacy
- Reduction of bandwidth: The on-device sensors read and process the data locally, so no raw sensor data needs to be transmitted to the server.

1.3 Monitoring Pregnancy Complications Using IoT Technology

Internet of Things (IoT) technology enables smart devices to gather and share data by communicating with one another. However, these smart devices face challenges in data storage, processing power, and power shortages, among others. To overcome these challenges, IoT technologies are implemented using different communication protocols based on factors like data rate, power consumption, and communication range. According to [33], communication

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protocols are classified into low-power wide-area networks (LPWAN) and short-range networks. LPWAN is a cost-effective wireless technology that can use licensed or unlicensed frequencies. It provides long-range connectivity with low power consumption and low data rates. The LPWAN protocols include Sigfox, long-range (LoRa), and Narrow-band IoT, among others. Short-range networks provide reliable, low-power connectivity that supports high data rates over short distances. Some short-range network protocols that can be used include Bluetooth, which provides a secure short-range low-power device connection; others are Zigbee, Z-Wave, RFID, and near-field communication NFC [34].

Monitoring women's vital signs during pregnancy and labor is very important. It helps in the early identification of high-risk pregnancies for the caregivers to provide more targeted and appropriate treatment, follow-up care, and monitor fetal well-being in both low and high-risk pregnancies. Proper management of maternal and fetal risk and labor complications detected in pregnancy can prevent 3.2 million deaths and reduce maternal and neonatal morbidity and mortality to a large degree throughout the world [35]. The prenatal supervision of intrauterine growth enhances the detection of growth-restricted fetuses, which are exposed to an increased risk of death [36].

Ninety-nine percent of maternal deaths occur in developing countries. This is mainly attributed to the inability of the majority of pregnant women to undergo customary checkups at the onset of their pregnancies, increasing the chances of infant deaths, especially in rural areas [37]. With the use of IoT technologies, this can be minimized; for instance, the researchers proposed using sensors to measure vital parameters of the pregnant woman and the baby, such as temperature, fetal movement, blood pressure, and heart rate. The measured parameters were then transferred through IoT and viewed on a mobile phone. These sensors provide high-quality, timely health care for the mother and the unborn child, thereby enabling regular monitoring that reduces infant mortality [38].

A 24-hour monitoring system for pre-eclampsia was developed by [39]. They used a smartwatch in conjunction with a mobile device and a cloud-based application. The smartwatch measures the pregnant mother's blood pressure and sends real-time data to the caregiver for appropriate action. The target population was women at 20 weeks or more into their pregnancy. The researchers sampled 30 pregnant women from two level-five hospitals in Kenya. The system was based on Internet of Things architectures, which comprised a FI smart wristwatch, a pregnant mother's smartphone, a blood pressure monitoring application, a cloud data center, and the caregiver's smartphone. Various parameters were used to evaluate the system, including content richness, perceived usefulness, user satisfaction, and perceived ease of use. The use of a smartwatch integrated with mobile and cloud applications showed great potential for being adopted in health systems, especially in developing countries.

Maternal mortality for women living in rural areas and poor communities is very high [3]. The ultrasounds used in these areas are insufficient; additionally, there are inadequately skilled personnel to use and interpret the scans, leading to high scan costs and potentially undetected pregnancy complications [40]. Thus, there is a need for continuous monitoring using IoT-based technology. An IoT-based healthcare monitoring system for rural pregnant women was proposed by [37]. They used sensors to measure parameters such as fetal temperature and fetal heart rate in their study.

Additionally, an Arduino controller board was used to integrate the temperature and the accelerometer sensor. The controller analyzed the sensor data, and the results were then simulated. The regular monitoring of the vital parameters of the fetus and the pregnant woman in rural areas greatly reduced infant mortality, with IoT providing quality and timely health assistance for both fetus and woman [37].

A routine checkup for pregnant women is vital, as it ensures that women receive appropriate maternal health care services, and it reduces maternal morbidity and mortality rate to a great extent [40]. A real-time monitoring system using IoT techniques to monitor the fetus's heart rate, temperature, and motion, as well as labor symptoms, was proposed by [41]. The parameters are measured using sensors such as an accelerometer to monitor fetal motion, a temperature sensor to measure temperature, and a pulse rate sensor to measure heart rate. Other sensors and devices used included a force sensor, a microcontroller, and a sweat sensor. The device is designed as an abdominal belt with the mentioned sensors, which are connected to the microcontroller. The microcontroller is programmed to send an alert message via GSM when the set threshold parameters are exceeded, and to store all measured data in the cloud using IoT [41].

Maternal health requires a comprehensive framework that enables continuous monitoring of pregnant women. The framework is essential in addressing the diverse health needs of pregnant women, which differ from pregnancy to pregnancy and from woman to woman [42]. Additionally, the monitoring framework assists in early identification of pregnancy complications and provides an opportunity for appropriate intervention to minimize the risks associated with them. Moreover, continuous monitoring offers pregnant women support and informational empowerment, leading to improved outcomes for both the mother and her unborn child. To support this monitoring framework, [43] presented an IoT-based system for ubiquitous maternal health monitoring during pregnancy and the postpartum period. The system consisted of multiple data collectors to track the mother's condition, including stress, sleep, and physical activity. The researchers sampled 28 women from southern Finland with high-risk pregnancies who were monitored during pregnancy and three months postpartum using the system. The women had smartphones with the study app installed and wore a smartwatch for three months after delivery. They were required to measure their blood pressure at least once a week and send the data through the mobile application to the server. The system's feasibility, energy, and data reliability were also evaluated, whereby the results indicated that the system implementation was feasible in terms of system usage over the nine months. It was also concluded that the smartwatch used had acceptable energy efficiency for long-term monitoring, enabling the collection of photoplethysmography data [43].

For any pregnant woman, it is a good practice to perform routine screening for hypertensive disease; certain parameters need to be monitored during pregnancy, such as blood pressure, respiratory rate, glucose levels, and fetal heart sounds, to ensure they remain within normal limits [44]. Ansari & Ansari [45] proposed a smart system for monitoring pregnant women and analyzing the biological factors during pregnancy. The system enabled fast decision-making and treatment by enabling high-speed transfers of medical information to doctors and over mobile devices for consultation and remote medical examinations. Various sensors were used to capture parameters such as blood pressure, temperature, hemoglobin level, heart rate, and kicking rate, enabling real-time monitoring of the pregnant woman.

Remote, continuous monitoring during pregnancy provides healthcare professionals with significant opportunities to observe key parameters and detect pathological signs at an early stage. Grym et al. [46] conducted a study to evaluate the feasibility of continuous monitoring of health parameters, including physical activity, sleep, and heart rate, in nulliparous women throughout the nine months and one month postpartum. During pregnancy, a smart wristband connected to a cloud server was used to measure parameters in a sample of 20 women. The physical activity, sleep, and heart rate were collected with a smart wristband, which was integrated with a photoplethysmogram bio-sensor to measure the heart rate and an inertial measurement unit for tracking physical activity and sleep. The study confirmed that the IoT-based system was feasible for monitoring health parameters during pregnancy when large amounts of data were collected. The study concluded that a smart wristband with an IoT solution was a feasible system for collecting representative data on continuous variables such as sleep, physical activity, and heart rate.

When a pregnant woman is under too much stress, it can have negative effects on both her and her unborn child. These prolonged high levels of stress can lead to high blood pressure, heart disease, pre-term birth, or low birth weight, as well as disrupt the normal maternal adaptation process [47]. Oti et al. [48] developed a personalized, automated health system for real-time stress monitoring based on IoT technology to support conventional clinical methods for maternal stress management. The researchers suggested a stress-level estimation algorithm based on heart rate and heart rate variations during pregnancy. The algorithm was distributed in an edge-based IoT system. The algorithm was tested using supervised and unsupervised learning on an unlabeled dataset for 7 months. A sample of twenty pregnant women was used. The women wore a wearable smart wristband for seven months. Data was collected in two categories, first using a Garmin vivosmart 2 device, capturing heart rate, activity, and sleep information with 60,000 data points. The second data set was obtained using a Garmin vivosmart 3 device, which has a stress level classification ranging from 0 to 100. Heart rate, sleep activity, and stress classification were extracted with 600 data points. An online k-means clustering algorithm was used classification of the stress levels. The edge-based IoT architecture consisted of sensors, edge devices, and a cloud server. A 97.9 % accuracy was obtained using a 10-cross-fold validation.

2 Previous Review Studies

Recent reviews and meta-analyses have greatly contributed to the domain knowledge of using Machine learning and the Internet of Things (IoT) in maternal healthcare. This section highlights the recent systematic reviews related to the current study. A summary of the previous reviews is shown in Table 1.

Based on these reviews, it is evident that IoT and machine learning technologies have garnered substantial attention in recent years, primarily aimed at enhancing the overall health of a mother and her unborn child. Reviews of studies on the application of ML and IoT technologies in maternal healthcare have been conducted. Nevertheless, the framework of integrating ML IoT technologies to facilitate early diagnosis of pregnancy complications has not been the main focus of the evaluation. Thus, this research endeavors to provide a systematic evaluation of the existing frameworks that integrate ML and IoT technologies in maternal healthcare. The review focuses on the features, ML algorithms, and IoT frameworks used to identify existing gaps and to provide a roadmap for future research. It is also worth noting that most previous reviews used the PRISMA methodology and that databases such as PubMed, Springer, and Emerald were frequently used. This information has significantly informed the conceptualization of the current review paper.

Table 1. Previous Review

Study	Methodology	Database	Machine learning	IoT	Contribution	Relationship with current research
[49]	PRISMA	PubMed, Africa Journal Online(AJOL), Google Scholar, Scopus	Yes	Yes	Researchers noted that there were no data-driven models for emerging technologies in maternal care.	The review focused on the existing data model, whereas current research focuses on frameworks for integrated IoT and ML technologies in maternal healthcare.
[50]	Systematic literature review	ACM, Emerald, Hindawi, Science Direct, IEEE, SAGE, Springer	No	Yes	Provided a comprehensive taxonomy of IoT in healthcare	The review focused on the application of IoT in healthcare; our review focuses on maternal healthcare
[51]	Not mentioned	PubMed, IEEE, Science Direct, Springer,	No	Yes	Research provided a taxonomy of IoT-based sensors in healthcare	Review focused on IoT in healthcare, our research is on both IoT and machine learning in healthcare
[52]	RISMA	Scopus, Science Direct, Google scholar, web of science, ACM	No	Yes	Reviewed the state of the art in the adoption of 4.0 technologies in maternal healthcare	The review focused on the application of 4.0 technologies in mental healthcare, whereas our research focused only on IoT and ML technologies.
[53]	Not mentioned	PubMed, Semantic Scholar, National Center of Biotechnology Information(NCBI)	Yes	Yes	Reviewed the sensors and AI algorithms for maternal health.	The review focused on issues common in the use of AI and IoT in maternal health, such as security and energy. The current review focuses on the framework of integrated technologies in maternal healthcare.
[54]	Systematic review, design with a narrative method	PubMed, EMBASE, Scopus, Cochrane database	Yes	No	The review focused on issues in wearable devices in healthcare	The review did not provide the application of AI in maternal healthcare
[55]	PRISMA	Google Scholar, IEEE Xplore, MDPI, Science Direct, IOP Science, PubMed, and ACM	Yes	Yes	Reviewed description, data processing, and performance of sensors used in maternal healthcare.	The review did not focus on appropriate features and IoT frameworks in maternal healthcare.

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3 Materials and methods

The review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [56]. The framework for categorization and coding was borrowed from [57] and [58]. Four major research phases: Article identification, Inclusion and exclusion, Quality check, and classification and coding were carried out. The review sought to answer the following research questions (RQs)

- RQ1: What is the trend in the use of IoT and ML in maternal healthcare?
- RQ2: What are the commonly used machine learning algorithms in the prediction of pregnancy complications?
- RQ3: Which model specifications are most suitable for developing prediction models of pregnancy complications?
- RQ4: Which IoT frameworks are commonly used in maternal healthcare?
- RQ5: What are the best practices for transmitting data from IoT devices to cloud storage?

3.1 Article Identification

The initial stage of this review was to identify relevant research studies using the terms IoT, Machine learning, and maternal healthcare, guided by the research questions. Based on the availability and thorough coverage of the systematic review objectives, five electronic databases were selected: PubMed, Emerald, Springer, IEEE, ScienceDirect, and BioMed, to provide access to a range of relevant articles. These electronic databases were selected because they contain peer-reviewed research and are commonly used by diverse scholars.

The following search string was used, the string was made as broad as possible to capture all the relevant articles:

(Iot[All Fields] AND Machine Learning[All Fields] AND ("mothers"[MeSH Terms] OR "mothers"[All Fields] OR "maternal"[All Fields]) AND ("delivery of health care"[MeSH Terms] OR ("delivery"[All Fields] AND "health"[All Fields] AND "care"[All Fields]) OR "delivery of health care"[All Fields] OR "healthcare"

3.2 Inclusion and Exclusion Criteria

A total of 527 articles were retrieved from all selected databases, with 313 from PubMed (the highest percentage), 114 from ScienceDirect, 5 from Emerald, 21 from IEEE Explorer, and 74 from Springer, as illustrated in Figure 2.

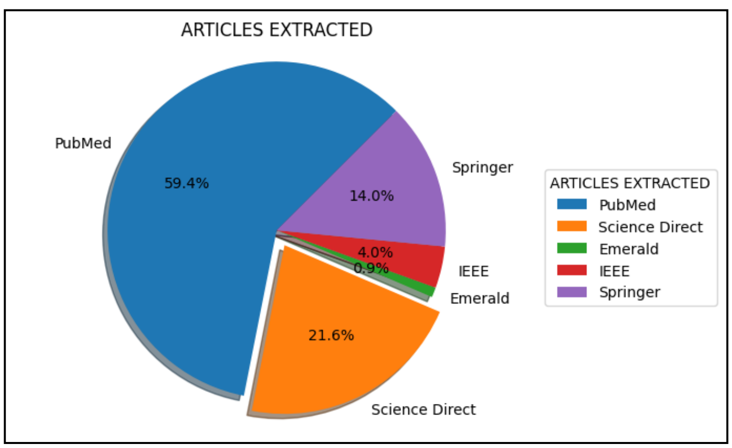

Figure 2: Articles extracted

The inclusion criteria adopted in this research were based on:

- English language as the original publication
- Access to the full-text
- Research employing machine learning and IoT approaches to monitor and predict pregnancy complications.
- Experiment-based articles.
- Papers published between 2017 and 2024 because research focused on recent trends

Duplicated articles from the databases were excluded in the second phase based on a review of the titles and abstracts. If the abstract was unclear, the introduction and conclusion were read. The articles were excluded based on the following criteria:

- Book chapters
- Articles on comparative studies
- Articles that were not accessible
- Case reports and systematic reviews
- Articles on medical image detection
- Articles that discussed impact assessment studies

The initial search retrieved 527 articles. After checking for duplicate studies, 78 articles were excluded, leaving 449. A further 399 irrelevant articles were excluded. Finally, only 50 articles were analyzed in the study. The summary of the findings after excluding the articles is presented in a PRISMA flow chart Figure 3.

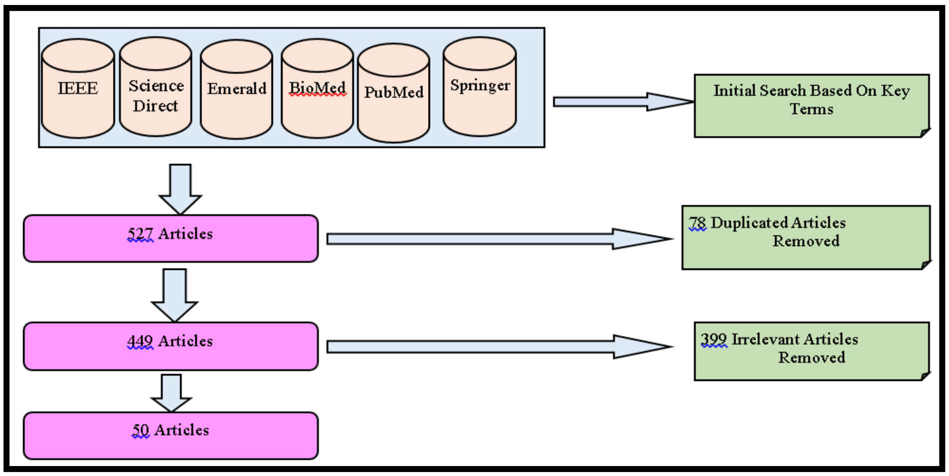

Figure 3: Research resources and article screening

3.3 Quality Check

The quality of the studies was assessed based on whether they addressed the use of IoT and machine learning in maternal healthcare, the clarity of the research objectives and questions, and the clarity of the methodology used. The risk of bias of the included articles was assessed independently by two reviewers (MMM) and (EMM) using the Prediction Model Risk Tool (PROBAST). The conflicts were resolved through discussion and consultations with the third reviewer (AW). The bias in each article was reported per domain and summarized in a risk-of-bias table (Table 2). Based on the risk and bias evaluation, most studies had low risk for participants, predictors, and outcomes. However, 46.8% of the studies had a high risk of analysis, mainly because most studies didn't discuss preprocessing, handling missing data, normalizing data to avoid dominance by some features in machine learning algorithms, and handling categorical values. The overall risk of bias for the selected articles was 50%.

Table 2: Risk of bias table based on PROBAST.

Study	Participants	Predictors	Outcome	Analysis	Overall
[59]	Low	Low	Low	Low	Low
[60]	High	High	High	High	High
[61]	High	High	High	High	High
[62]	Low	High	High	High	High
[63]	Low	High	Low	High	High
[64]	High	Low	High	High	High
[65]	Low	Low	Low	High	High

[66]	High	Low	High	High	High
[48]	Low	Low	Low	Low	Low
[67]	Low	Low	Low	Low	Low
[68]	Low	Low	Low	Low	Low
[26]	Low	Low	Low	Low	Low
[24]	Low	Low	Low	Low	Low
[69]	Low	Low	Low	Low	Low
[70]	High	Low	Low	Low	High
[71]	Low	Low	Low	Low	Low
[72]	Low	Low	Low	Low	Low
[73]	Low	Low	Low	Low	Low
[74]	Low	Low	Low	High	High
[75]	Low	Low	Low	High	High
[76]	Low	Low	Low	Low	Low
[77]	Low	Low	Low	Low	Low
[78]	Low	Low	Low	Low	Low
[79]	High	Low	High	High	High
[80]	Low	Low	Low	High	High
[81]	Low	Low	Low	Low	Low
[82]	Low	High	Low	High	High
[83]	Low	Low	Low	High	High
[84]	Low	Low	Low	High	High
[85]	Low	Low	Low	High	High
[86]	Low	Low	Low	Low	Low
[87]	Low	Low	Low	Low	Low

3.4 Classification and Coding Frameworks

To improve the display of the systematic review results, a table was created based on the search terms, illustrating the input features for training the ML algorithm, the types of ML algorithms used, the performance metrics, and the IoT frameworks used in maternal healthcare.

4 Results

The selected studies were analyzed, and the results were presented in tabular format. The main focus was on IoT frameworks, including the data communication modules and the features/parameters used, the ML algorithm, and the evaluation metric. Table 3 summarizes the analyzed papers by whether IoT and ML technologies were integrated, the ML algorithms and parameters used, and the performance metrics.

Table 3: A summary of all the reviewed studies between 2017 and 2024

Study	Year	IoT/ML-Integrated	ML Algorithm used	Features captured using sensors	Wearables and embedded IoT	Evaluation metrics
[59]	2022	No	Decision Tree, Random Forest, SVM, KNN, Naïve Bayes, and Multilayer Perceptron	Static features	None	Accuracy Sensitivity Specificity
[43]	2021	No	None	Pregnant activities include; stress, sleep, and physical activity.	smart rings, smartwatches, Holter monitors, and PPG sensors	system's feasibility, energy efficiency and data reliability
[46]	2019	No	None	Heart rate	Biosensor, Activity tracer Smart wristband	Accuracy
[60]	2022	Yes	-Decision Trees -Naïve Bayes, -SVM, -Random forest, -Stochastic Gradient Boosting -Logistic Regression	Maternal parameters -Abdominal pain -Visual disturbances -Hyperreflexia - BP, Fetal parameter -Amniotic fluid volume -Feto-placental unit	Wireless CTG Blood pressure sensors Smartphones	-Sensitivity -Accuracy -Area Under curve (AUC)
[61]	2022	Yes	KNN Decision Tree	Blood pressure Heart rate Body temperature	PIC microcontroller (PIC16F877A Blood pressure sensor Heartbeat sensor, Temperature sensor	Not specified
[88]	2021	No	None	-fetal heart rate, -Blood glucose/sugar, -Uterine contraction, -Blood pressure	-Blood pressure sensors- GIS -Smartphone	Not specified
[62]	2020	Yes	Modified Decision Tree Algorithm	Blood sugar Blood pressure,	Not Implemented	Accuracy.
[89]	2018	No	None	Body temperature, glucose level, pulse rate, fetal movement	LoRa technology to interface the maternal monitoring system in the ambulance	Not specified
[90]	2022	No	None	Temperature, heart rate	Arduino microcontroller, pulse sensor, temperature sensor, GSM module	Not specified
[91]	2024	No	None	Fetal heart rate	FHR detector	Accuracy, Sensitivity, Specificity
[92]	2018	No	None	Blood pressure, heart rate, and patient steps	The V07 smart wristwatch used Bluetooth technology to transmit data to a mobile application.	Not specified

Study	year	IoT/ML-Integrated	Algorithm used	Features captured using sensors	Wearables and embedded IoT	Evaluation metrics
[63]	2021	Yes	SVM, boosted decision tree, logistic regression, Bayes point machines, decision forest	Static	Proposed to use Arduino with a heartbeat sensor, temperature sensor, blood sugar sensor, and Wi-Fi module	AUC, accuracy, recall, f1-measure
[93]	2017	No	None	Not mentioned	Proposed portable medical devices with multiple sensors, mobile devices, and cloud.	Not specified
[94]	2020	No	None	Body temperature, blood pressure, heart rate, pulse rate,	Arduino microcontroller, wireless RFID	Not specified
[64]	2021	Yes	Support Vector Machines	Heart rate, blood sugar, temperature, and uterine contraction	Sensor devices, smartwatches.	Not specified
[65]	2021	Yes	1-D convolutional neural network (CNN) classifier	uterine tonus activity, blood pressure, heart rate, temperature and oxygen saturation	IoT module to monitor FHR IoT module - (heart rate, oxygen saturation, blood pressure, and temperature) signs	Accuracy of F1- score
[39]	2019	No	None	Blood pressure	F1 smart wristwatch, IoT technology Mobile device	Not specified
[37]	2018	No	None	Temperature, blood pressure, fetal heart rate	Temperature sensor, blood pressure sensor, Accelerometer sensor, Arduino controller, Mobile technology	Not specified
[41]	2020	No	None	Heart rate, temperature, fetal motion, labor pain symptoms, excessive sweat	Abdomen belt with a temperature sensor, pulse rate sensor, sweat sensor, accelerometer, force sensor, and MPU 6050. Microcontroller, GSM, and cloud computing	Not Specified
[46]	2019	No	None	Physical activity, sleep, and heart rate	Smart wristband, cloud technology, IoT technology, photoplethysmogram biosensors, and an inertial measurement unit	Not specified
[66]	2023	Yes	Decision tree	Blood pressure, blood glucose level, ECG, temperature	Arduino Nano, ESP32 microcontroller module	Accuracy
[45]	2020	No	None	Blood pressure, Temperature Haemoglobin level,	Sensors, Cloud	Not specified

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Study	Year	IoT/ML-Integrated	Algorithm used	Features captured using sensors	Wearables and embedded IoT	Evaluation metrics
[48]	2019	Yes	K-means clustering algorithm Random forest	Heart rate, sleep information	Garmin Vivismart 2, IoT, Edge computing, cloud computing	Accuracy
[67]	2018	No	Naïve Bayes and Logistic Regression	None	None	ROC Curve, Accuracy, Sensitivity, Specificity
[68]	2020	No	ANN, Logistic regression, Decision tree, SVM, Random forest, and ensemble method	None	None	Precision, sensitivity, Specificity, ROC, and AUROC
[26]	2018	No	ANN, Naïve Bayes, KNN, Linear regression, and SVM	None	None	Accuracy
[24]	2018	No	ANN and Deep learning	None	None	Accuracy
[69]	2019	No	Decision tree	None	None	Accuracy, Precision, Recall, and F-Score.
[70]	2019	No	C4.5 Decision Tree and K Nearest Neighbor	None	None	Accuracy, precision, Specificity
[71]	2020	No	Logistic regression, ANN, Gradient boosting decision tree (GBDT), and ensemble learning were experimented with.	None	None	Accuracy
[72]	2024	No	Convolutional Neural Networks	None	None	Accuracy
[73]	2023	Yes	Random forest classifier	Heart Rate (HR), Systolic/Diastolic BP, Fetal Movements, and Temperature	a wearable device that consists of different sensing modules that collect data, i.e., BP, Temperature, Heartbeat	Accuracy
[74]	2024	Yes	ANN	Temperature, Heart rate, Blood pressure	Wearable sensing technology, Arduino Mega 2560, Smartphone	Sensitivity
[75]	2017	No	Random forest, Naïve Bayes, decision tree	None	None	Accuracy, averaged one-dependence estimator, true positive rate, positive rate.
[76]	2021	No	Gradient boosting, Logistic regression	None	None	Area under the curve, Specificity, sensitivity, positive predicted value.
[77]	2018	N0	SVM, Bayesian networks, Naïve Bayes, Neural Network, Random forest, C4.5 decision tree, Adaptive regression spline, Logistic regression	None	None	ROC, Accuracy, Sensitivity, Specificity, F1 score

Study	Year	IoT/ML-Integrated	Algorithm used	Features captured using sensors	Wearables and embedded IoT	Evaluation metrics
[78]	2019	No	Logistic regression, decision tree, naïve Bayes, SVM, random forest, stochastic gradient boosting.	None	None	ROC Curve, Area Under Curve, Accuracy, sensitivity, and Specificity
[79]	2019	Yes	Viterbi Machine learning algorithm	Blood pressure.	Smart Bracelet	Accuracy, Sensitivity, Specificity
[80]	2018	No	A hybrid of Multivariate adaptive regression splines (MARS) and Support Vector Machine	None	None	Accuracy, Sensitivity, and Specificity
[81]	2020	No	Naïve Bayes	None	None	Accuracy, AUC, and ROC curve sensitivity
[82]	2020	No	ANN, Random Forest, Naïve Bayes, Bagged Tree, Boosting, Linear regression	None	None	Accuracy Random forest had the highest accuracy of 87%.
[83]	2017	No	ANN with 50 hidden layers	None	None	The accuracy of the ANN
[84]	2019	No	Backpropagation ANN with 11 neurons	None	None	Not Specified
[85]	2020	No	Support vector machines (SVM)	None	None	Accuracy
[86]	2023	Yes	optimized single-dimensional Convolutional Neural Network KNN, Random forest(RF), SVM, Convolutional neural networks(CNN) and Extreme learning machines (ELM)	heart rate, temperature, blood pressure, blood glucose, oxygen saturation, and fetal heart rate	Accelerometers, respiration sensors, temperature sensors, heart rate sensors (Maternal and Fetus), Pulse Oximeters, esp8266 WIFI handsets	Accuracy, Precision Recall, Sensitivity F1-score
[87]	2024	Yes	Decision tree, K nearest neighbors, Extreme Gradient Boosting, Random Forest Adaptive boosting Multilayer perceptron	temperature, blood pressure, glucose levels, and heart rate	Raspberry Pi 4 Model B single-board computer, including heart rate, blood pressure, glucometer (HbA1c, Fasting hour-m), and temperature sensors	Accuracy, ROC, AUC

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5 Discussion

Integrated IoT and machine learning technologies can be used to implement systems capable of continuously monitoring maternal and fetal vitals and predicting the occurrence of pregnancy complications. This would aid early warning and prompt appropriate, timely intervention measures to improve the health of expectant women and their fetuses. Additionally, the technologies can support data-driven intervention and individualized maternal care. The use of these technologies can make maternal healthcare more proactive, accessible, and effective, ultimately improving birth outcomes. The goal of this review was to understand recent trends and gaps in the use of these integrated technologies in maternal healthcare and to provide recommendations for future design considerations. In the discussion that follows, we explore our findings guided by the review questions. The first research question sought to understand cutting-edge technologies commonly used in the early diagnosis of pregnancy complications to improve pregnant women's health. From the analysis, the research interest in the integration of IoT and ML in maternal healthcare began in 2019, marking the start of efforts to integrate IoT and Machine learning technologies to monitor pregnant women and predict pregnancy complications in real time. For the years 2023 and 2024, this review found only 3 and 4 research articles, respectively, that integrated the two technologies in maternal healthcare. This clearly shows that research on integrating these technologies into maternal healthcare is in its early stages and that there is significant potential for further research in this area. There is a great opportunity for innovations that involve monitoring pregnant women and predicting pregnancy complications, thus further studies in this field are necessary. Figure 4 shows the trends in the use of IoT and ML in pregnancy complications between 2017 and 2024. Table 4 contains details of the commonly used IoT frameworks in maternal healthcare.

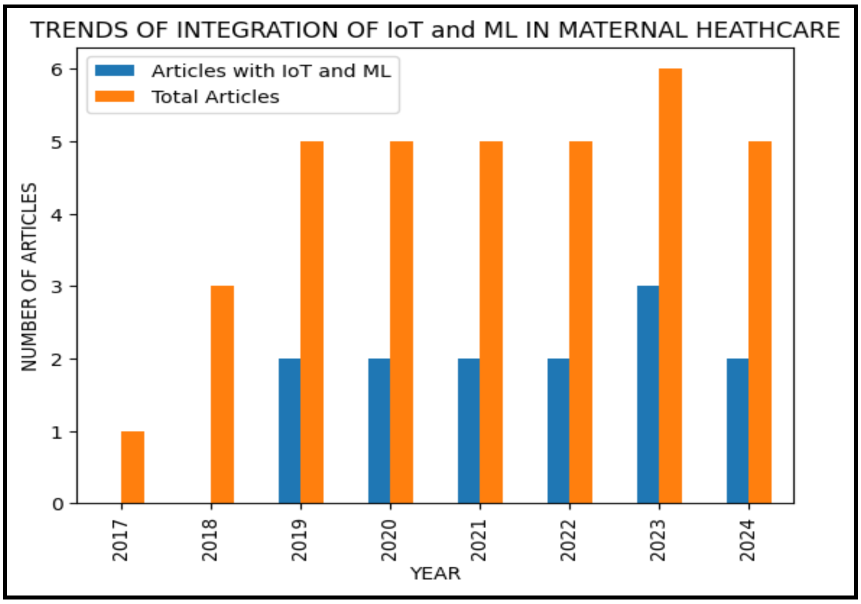

Figure 4: Trends of integration of IoT and ML in maternal healthcare

Table 4. Wearable and embedded IoT

Wearable and embedded IoT	Research article	Frequency
None	[59], [91]	2
Existing smart device	[43], [46], [92], [64], [48], [79], [39], [46], [73]	9
Arduino microcontroller,	[90], [63], [94], [37], [45], [66]	6
Microcontroller	[61],[41], [93], [89]	4

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Not Implemented	[62], [88], [72]	3
IoT module	[65], [86], [87]	3

The answer to the second research question would guide the selection of appropriate machine learning algorithms to experiment with when designing pregnancy complication prediction models, as well as the evaluation metrics to use. This research found that decision tree algorithms were most commonly used to implement predictive models for pregnancy complications, followed closely by random forests and support vector machines. We observed that 65 pregnancy complication prediction models had been developed and implemented across the 50 articles we reviewed. Of the 65 models, 15 used the decision tree technique, 11 used the random forest algorithm, and 10 used the support vector machine algorithm. Decision trees are widely used for predicting pregnancy complications due to their ease of use and interpretability; they are also adaptable to both categorical and numerical datasets because they do not require data scaling or encoding [95]. Moreover, decision trees require minimal data preprocessing because they do not require data normalization. Furthermore, they successfully capture complex nonlinear inputs and output features, making them ideal for real-world applications [96]. These aspects make them suitable for use as a researcher can easily verify their decision-making process.

Random forests have also been widely used in predicting pregnancy complications. They work by averaging the decisions of multiple trees, thereby reducing the risk of overfitting and increasing the forest's accuracy. They are suitable for managing large datasets and data with missing values [97]. SVMs have the advantage of handling small datasets; they are ideal for high-dimensional datasets and are not prone to overfitting [98]. From the review, only a few studies integrated deep learning models with IoT technologies. Figure 5 summarizes the commonly used machine learning algorithms in maternal healthcare.

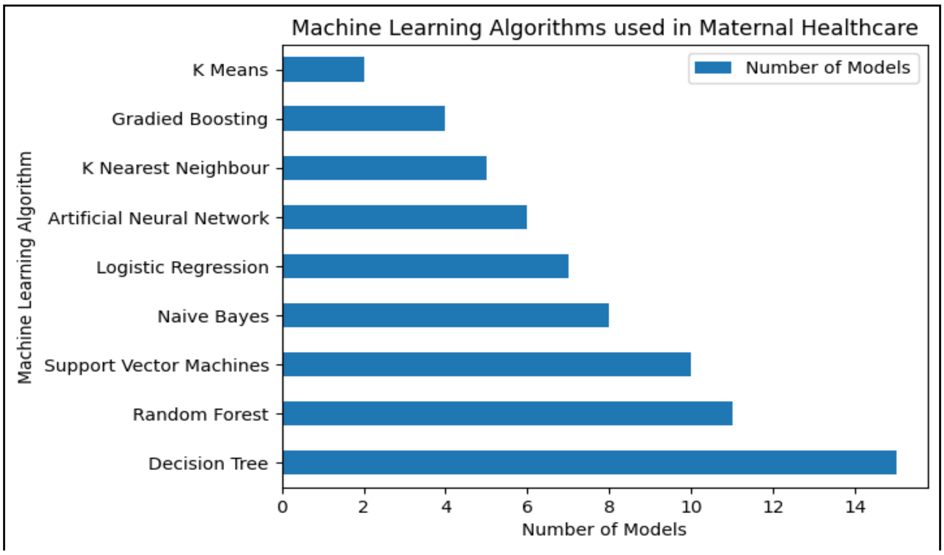

Figure 5: Machine Learning algorithms used in maternal healthcare

The review further established that the accuracy metric, a measure of correct predictions, is the most commonly used, as 26 of the 50 studies reviewed used it. The recall metrics followed this. The least-used evaluation metric for predicting pregnancy complications is precision, as shown in Figure 6. Although the accuracy metric is simple to understand, it can provide a quick overview of a predictive model's performance and is commonly used in predicting pregnancy complications, it has some challenges. The metric is not suitable for use with imbalanced data sets and doesn't account for the consequences of false positives or false negatives [99]. The sensitivity, or recall, metric focuses on the actual positive cases. It is a measure of the predictive model's ability to minimize false negatives. A high recall (sensitivity) implies that the predictive model doesn't miss women with pregnancy complications. The metric is appropriate because the cost of a false negative can be deadly. Aggregate metrics such as area under the curve, F1-score, and receiver operating characteristic (ROC) have also been used in maternal healthcare. The metrics combine various performance characteristics into a single figure [99] and provide a comprehensive

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understanding of the models' performance. The precision metric is the model's ability to minimize false positives among predicted positives, that is, incorrectly predicting a complication that does not exist; it measures the model's ability to avoid raising false alarms. The specificity metric emphasizes actual negative cases, that is, correctly identifying pregnant women without pregnancy complications, which is ideal for avoiding unnecessary interventions.

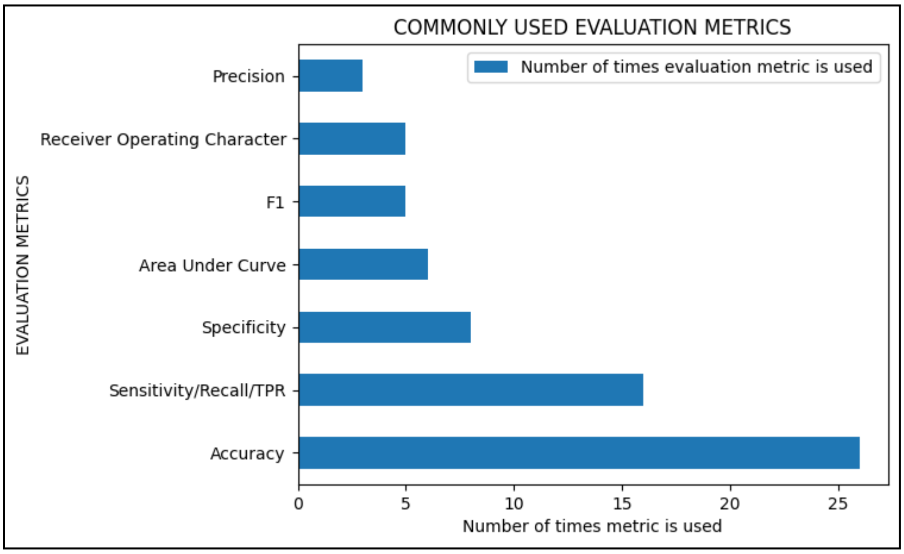

Figure 6: Commonly used evaluation metrics

The third research question aims to identify the most suitable features used in the design of an IoT framework for the remote monitoring of pregnant women's vital signs. The researchers established that the most commonly used features in monitoring pregnancy complications are blood pressure, temperature, and maternal heart rate. Additionally, initial research used blood pressure measurements. The researchers also found that, due to advancements in IoT technologies, other features such as blood oxygen levels, fetal heart rate, and uterine contraction values have recently been used to monitor the health status of pregnant women. Patients' steps and sleep patterns are the least used feature in monitoring the health status of pregnant women. Figure 7 shows the trends in the features used to monitor pregnancy complications.

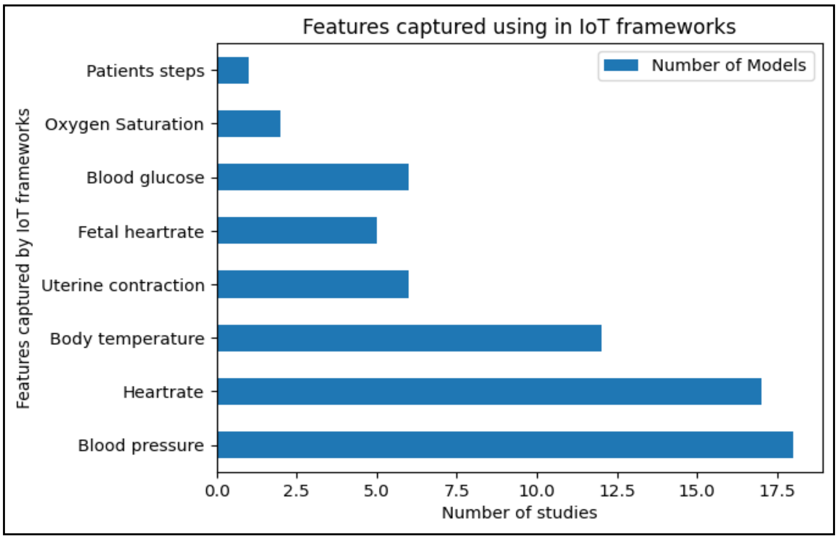

Figure 7: Features captured using IoT frameworks

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The fourth research question would help in understanding the research gap in the design and implementation of models that integrate ML and IoT technologies in maternal healthcare. As shown in Figure 8, this review found that 47% of the studies examined did not monitor the vital signs of pregnant women. Further analysis of the studies revealed that 21% used existing smart devices, such as smartwatches, while 16% used Arduino, which is likely inappropriate given its size. Only about 10% of the studies used microcontrollers to design a custom-made PCB-based monitoring device. This implies that further research is necessary on appropriate IoT frameworks for real-time monitoring of pregnant women using suitable biosensors, powerful microcontrollers, and integrating them with ML. Additionally, the analysis revealed that none of the reviewed studies used tinyML models to predict pregnancy complications. Consequently, there is a need to explore further the use of tinyML technology to build lightweight predictive models that can be embedded in IoT devices to predict pregnancy complications in real time.

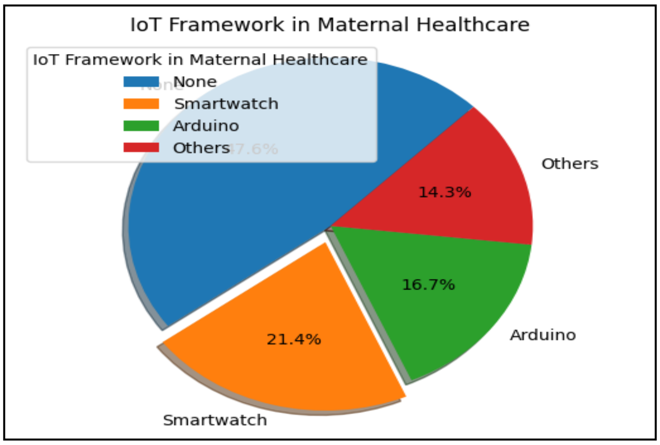

Figure 8: IoT frameworks in maternal healthcare

The last research question sought to understand how data from IoT monitoring devices in maternal healthcare was transmitted to the cloud for analysis and storage. The question focused on the communication modules used in the devices for monitoring the vital signs of pregnant women. The research found that 44% of the studies relied on smartphones as intermediaries to transmit the captured vital sign values to the cloud for analysis and storage. In 36% of the studies, the data transmission model was not mentioned. Data transmission was done using a Wi-Fi communication module in only 12% of the studies, while LoRa technology was implemented in monitoring devices in 4% of the studies, as shown in Table 5. Though most of the reviewed studies used smartphones as intermediaries for data transmission, smartphones are costly and difficult to access in lower- and middle-income countries, and it is also not easy to customize their firmware to suit specific research needs. Moreover, they may be difficult to integrate with existing electronic healthcare systems, and, above all, users may lack technical support for device use, and data security is not guaranteed [100].

Table 5. Data transmission module

Data transmission module	Research articles	Frequency
Smartphone Intermediary	[43], [46], [61], [88], [92], [93], [64],[41], [90], [48], [79]	11
LoRa	[89]	1
Wi-Fi	[63], [66], [86],	3
Not mentioned	[62], [94], [45], [45], [91], [101], [73], [74], [87]	9

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Fog computing	[65]	1

This demonstrates the need to empirically evaluate appropriate microcontrollers, biosensors, communication modules, and ML-based maternal risk prediction models. This can be used to design and develop a custom-made maternal health monitoring device with edge computing capabilities to preprocess captured vital signs and securely transmit the vital data directly to the cloud for analysis and storage, without the need for intermediaries such as smartphones. This model can be integrated with a mobile application to provide timely user alerts, feedback, and personalized recommendations. Further, a clinical dashboard for remote monitoring that is accessible to clinicians could also be developed. Large language models can also be used to generate clinician-friendly messages for expectant women. A proposed conceptual model for maternal health monitoring is shown in Figure 9.

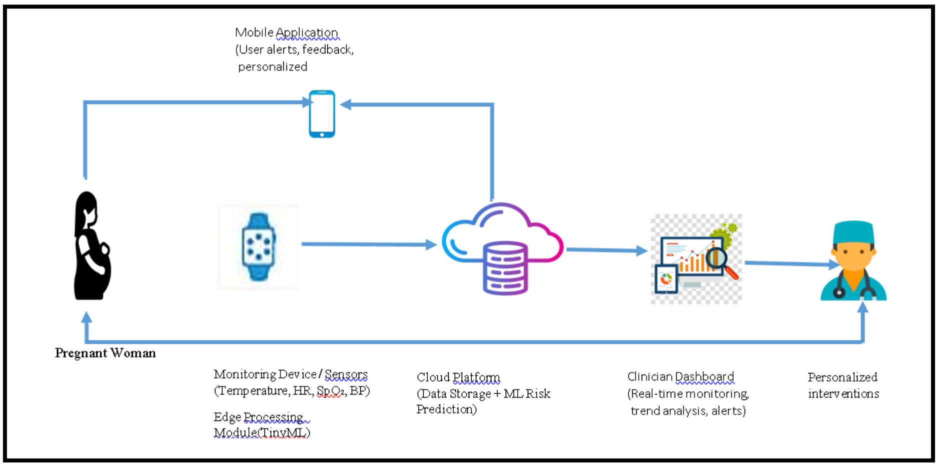

Figure 9: IoT ML Maternal Health Monitoring Conceptual Model

6 Limitations of the Study

The limitations of the study included the following:

1. Whereas the 50 articles analyzed in this study were carefully selected, a few studies on the use of machine learning and IoT in maternal healthcare might have been missed. This oversight might be due to several reasons, including but not limited to the inclusion criteria selected for this study.
2. The examined studies demonstrated different performances of the same machine learning technique, making it difficult to determine the best-performing technique.

7 Conclusion

In recent years, the integration of IoT and ML technologies has demonstrated tremendous potential in transforming maternal healthcare. These technologies have enabled the implementation of applications for remote monitoring and forecasting pregnancy complications. The rising number of pregnancy-related problems is still a major concern, with serious consequences for both maternal and fetal health. This review explores the integration of IoT and ML, examining their collaborative role in maternal healthcare by enabling continuous and remote monitoring of vital signs to enhance early diagnosis of pregnancy complications. This would allow for timely intervention measures to be put in place to improve the health status of pregnant women. The review focuses on existing gaps in integrating these technologies into maternal healthcare. It explores appropriate features, an IoT framework, ML algorithms, and evaluation metrics, and provides recommendations for further research work.

The ability of IoT devices to gather more detailed physiological data, such as blood oxygen levels, fetal heart rate, and uterine contractions, enhances remote monitoring. Despite these advances, there are still

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challenges in developing comprehensive frameworks that can capture the entire range of maternal and fetal vital signs and securely transmit the values to cloud storage for analysis. Previously, ML studies on maternal health were distinct from studies on maternal health monitoring. This review has established that the integration of IoT and machine learning in healthcare has recently become a focus for many researchers. Nonetheless, further research can be carried out on IoT frameworks that capture both fetal and maternal vital signs using powerful microcontrollers that integrate multiple communication modules, allowing the captured values to be transmitted directly to the cloud without the use of intermediary expensive smartwatches. These IoT ML frameworks may also be integrated with the pregnancy complication ML prediction model to monitor and classify pregnant women at risk of pregnancy complications in real time. This would ensure that appropriate and timely intervention is implemented in maternal healthcare to reduce poor birth outcomes. The gathered vitals can be analyzed using ML techniques to design a personalized care plan for different pregnant women. Furthermore, the evaluation of tinyML for on-device sensor data processing, which offers promise for real-time monitoring, requires further research.

Acknowledgments

None

Statement on conflicts of interest

No conflict of interest

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