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MACHINE LEARNING APPROACH FOR THE EARLY DETECTION OF STRESS AND HYPERTENSION IN PREGNANT WOMEN: A REVIEW

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Abstract

The paper presents a review of machine learning approaches for the early detection of Stress and Hypertension (SH) in pregnant women. It discusses the management of SH in pregnant women and its causes, such as psychosocial stressors, anxiety and depression, pregnancy-related concerns, physiological changes, gestational diabetes, poor lifestyle, complications, and medical concerns. Existing methods for managing SH among pregnant women, such as stress questionnaires, psychological assessments, urine protein testing, symptom assessment, blood pressure monitoring, fetal monitoring, biochemical markers, and ambulatory blood pressure monitoring, are also presented. Furthermore, the paper discusses the challenges encountered in adopting these conventional methods, including the subjectivity of self-reported data, limited access to healthcare services, diagnostic challenges, cost and resource constraints, interpretation and variability, patient compliance and engagement, and the complexity of multifactorial conditions. The study suggests that addressing these challenges requires efforts to improve healthcare infrastructure, increase access to prenatal care services, enhance diagnostic capabilities, and promote patient education and engagement. By addressing these barriers, healthcare systems can better detect and manage SH in pregnant women, ultimately improving maternal and fetal outcomes. Additionally, the paper explores the implementation of various intelligent methods based on machine learning and deep learning for the early detection of stress and hypertension. It reviews various works on the implementation of intelligent techniques, which have shown more satisfying and adaptive results. However, despite the extensive discussion on the impact and management of SH among pregnant women, the paper notes the absence of a solution for a cost-effective software model for the management of SH among pregnant women.

Keywords: Stress; Hypertension; Pregnant Women; Machine Learning; Deep Learning; Diagnosis

1. INTRODUCTION

Pregnancy is a critical period characterized by physiological and psychological changes among women, making them vulnerable to stress-related complications such as hypertension and preeclampsia. These conditions not only pose significant risks to maternal health but also increase the likelihood of adverse outcomes for the developing fetus, highlighting the importance of effective management strategies (Zhang et al., 2021).

Traditional approaches to managing SH in pregnant women rely heavily on clinical assessments, periodic monitoring, and standard interventions. While these methods are valuable, they did not fully capture the complexity of individual risk profiles and dynamic physiological changes experienced during pregnancy (Hussain and Borah, 2020). Moreover, existing healthcare systems face challenges such as limited access to specialized care, inadequate resources, and disparities in healthcare delivery, underscoring the need for innovative and scalable solutions (Beksac et al., 2018).

Machine learning (ML) offers a promising framework for enhancing the management of SH in pregnant women by leveraging computational algorithms to analyze multifaceted datasets and extract actionable insights. ML is type of artificial intelligence with the capability to learn from data and solve classification or regression problem (Akbulut et al., 2018). ML algorithms can integrate diverse sources of data, including physiological measurements, electronic health records, behavioural indicators, and environmental factors, to develop personalized risk prediction models and decision support systems. By considering individual patient characteristics and dynamic interactions between risk factors, ML-based approaches can enable early detection of stress-related complications and facilitate targeted interventions tailored to the specific needs of pregnant women (Neocleous et al., 2018).This study aims to advance medical field by developing and validating ML-driven tools and applications specifically designed for the management of SH in pregnant women (Lu et al., 2020). Through collaboration with healthcare providers, researchers, and technology developers, the study seeks to harness the potential of ML to improve clinical decision-making, optimize intervention strategies, and ultimately enhance maternal and fetal health outcomes (Salehi et al., 2018).

Ultimately, the successful implementation of ML approaches for the management of SH in pregnant women holds the promise of revolutionizing prenatal care delivery, reducing the burden of stress-related complications, and improving overall maternal and fetal well-being.

2. RESEARCH METHODOLOGY

Qualitative research technique was chosen as the approach for carrying out the investigation. Qualitative research methods aim to collect data that is frequently inexpressible non numerical form. When gathering data by observation, coded survey or interview answers, and other methods, these approaches frequently include some degree of interpretation on the part of the researchers. In a single study, researchers may employ a variety of qualitative techniques in addition to a theoretical or critical framework to aid in the interpretation of their findings (Fulton Library, 2024).

3. SH MANAGEMENT IN PREGNANT WOMEN

SH during pregnancy present significant concerns for both maternal and fetal health, necessitating comprehensive understanding and management throughout the gestational period. Stress, whether psychological or physiological, can trigger a cascade of hormonal responses that may adversely affect pregnancy outcomes. Similarly, hypertension, characterized by elevated blood pressure levels, poses substantial risks such as preeclampsia and eclampsia, both of which can lead to severe complications for both mother and baby (Hassan et al., 2020).

Firstly, stress in pregnant women can arise from various sources, including personal, social, and environmental factors. High levels of stress may activate the body's fight-or-flight response, leading to increased secretion of stress hormones like cortisol and adrenaline. These hormonal fluctuations can disrupt the delicate hormonal balance necessary for maintaining a healthy pregnancy, potentially resulting in adverse outcomes such as preterm birth or low birth weight. Additionally, stress can contribute to unhealthy coping mechanisms such as substance abuse or poor dietary habits, further exacerbating the risks associated with pregnancy (Naik et al., 2021).

Secondly, hypertension, particularly when occurring during pregnancy, requires vigilant monitoring and management to mitigate potential complications. Chronic hypertension predating pregnancy or gestational hypertension emerging during pregnancy can both pose risks. Preeclampsia, a condition characterized by high blood pressure and organ damage, is a significant concern and can escalate to eclampsia, which involves seizures. These conditions not only endanger the mother's health but also compromise fetal growth and development, potentially leading to intrauterine growth restriction or premature birth (Zhu et al., 2015). The figure 1 presents a diagram of pregnant woman showcasing the fetal behaviour during normal and abnormal Bp condition.

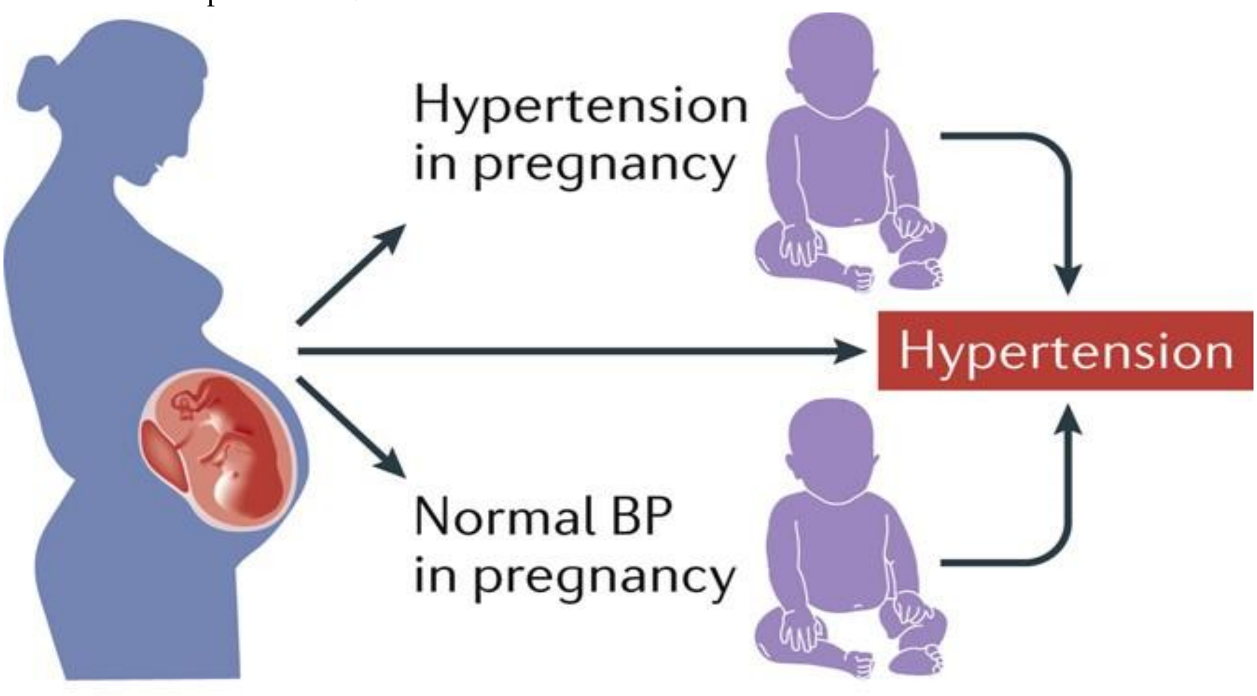

Figure 1: Pregnant woman showcasing fetal behaviour (Zhu et al., 2015)

The figure 1 presents a diagram of pregnant woman condition due to diverse BP condition. The relationship between SH during pregnancy is complex and bidirectional. Chronic stress can contribute to the development or exacerbation of hypertension, while hypertension itself can induce stress responses in the body (Pawar, 2014). This interconnectedness underscores the importance of holistic approaches to managing both conditions concurrently. Comprehensive prenatal care that includes regular monitoring of blood pressure, stress assessment, and appropriate interventions such as lifestyle modifications, counselling, or medical treatment, when necessary, is crucial for optimizing maternal and fetal well-being (Ishak et al., 2017).

Overall, SH represent significant challenges during pregnancy, requiring comprehensive management strategies to mitigate adverse outcomes (Aktas et al., 2017). Recognizing the multifaceted nature of SH in pregnancy is essential for healthcare providers to implement effective interventions tailored to individual needs. By addressing these issues through integrated approaches encompassing medical, psychological, and lifestyle interventions, it is possible to promote healthier pregnancies and improve maternal and neonatal outcomes.

3.1 Causes of SH Among Pregnant Women

SH in pregnant women can arise from various factors, both physiological and psychosocial. Understanding the underlying causes is essential for effective management and intervention. Here are some common causes in figure 2:

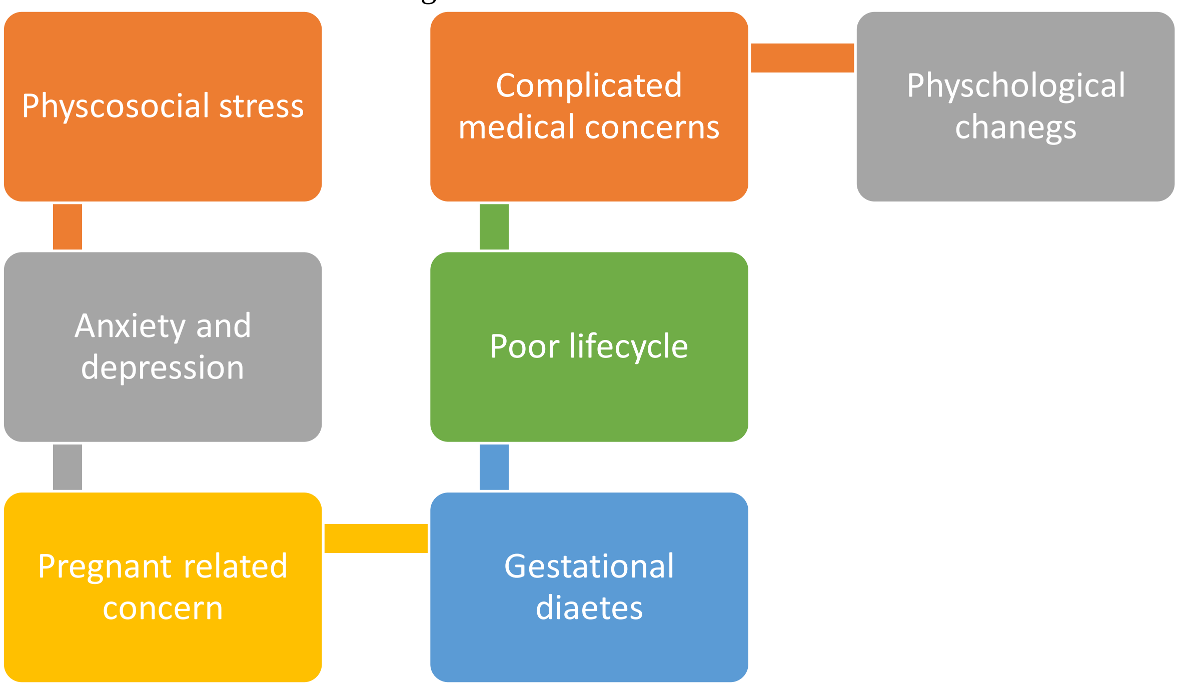

Figure 2: Causes of SH among pregnant women

a. **Psychosocial Stress:** Pregnant women may experience stress due to various psychosocial factors such as financial concerns, relationship issues, work-related stress, or family dynamics. These stressors can be particularly challenging during pregnancy when women may already be experiencing physical discomfort and hormonal changes (Lee et al., 2016).

b. **Anxiety and Depression:** Pre-existing anxiety disorders or depression can exacerbate stress levels during pregnancy. The hormonal fluctuations and life changes associated with pregnancy can exacerbate these mental health conditions, leading to increased stress levels and potential complications (Zakaria et al., 2018).

c. **Pregnancy-Related Concerns:** The natural anxieties and worries associated with pregnancy, such as concerns about childbirth, parenting, or the health of the baby, can contribute to stress. Women may also experience stress related to previous pregnancy complications or traumatic birth experiences (Hussain et al., 2019).

d. **Physiological Changes:** Pregnancy itself induces significant physiological changes in the body, including hormonal fluctuations, increased blood volume, and changes in cardiovascular function. These changes can predispose some women to develop hypertension, especially if they have pre-existing risk factors such as obesity, diabetes, or a family history of hypertension.

e. **Gestational Diabetes:** Gestational diabetes, a condition characterized by high blood sugar levels during pregnancy, can contribute to stress and hypertension. Managing blood sugar levels through diet, exercise, and sometimes medication can be stressful for some pregnant women, especially if they feel overwhelmed or anxious about the condition's impact on their health and the health of their baby (Marin et al., 2019).

f. **Poor Lifestyle Habits:** Unhealthy lifestyle habits such as smoking, excessive alcohol consumption, poor diet, lack of exercise, and inadequate sleep can increase the risk of both SH during pregnancy. These habits can exacerbate physiological changes and contribute to poor overall health outcomes.

g. **Complications and Medical Concerns:** Women with pre-existing medical conditions such as chronic hypertension, kidney disease, or autoimmune disorders may be at higher risk of developing complications during pregnancy, including stress and hypertension. Managing these conditions alongside pregnancy can be challenging and stressful (Manoochehri et al., 2021).

Addressing these underlying causes requires a multifaceted approach, including comprehensive prenatal care, mental health support, lifestyle modifications, and medical interventions when necessary. By identifying and addressing the specific stressors and risk factors affecting pregnant women, healthcare providers can help mitigate the impact of SH on maternal and fetal health.

3.2 Methods for Management of SH (SH) among Pregnant Women

Detecting SH in pregnant women involves a combination of clinical assessments, physiological measurements, and self-reported data. Here are some existing methods used to detect these conditions in figure 3:

a) **Stress Questionnaires and Psychological Assessments:** Various validated questionnaires and psychological assessments are available to assess stress levels in pregnant women. These tools evaluate factors such as perceived stress, anxiety, depression, and coping mechanisms. Self-report measures, combined with clinical evaluation, help healthcare providers identify women at risk of stress-related complications (Salehi et al., 2018).

b) **Urine Protein Testing:** Proteinuria, or the presence of protein in the urine, is a hallmark sign of preeclampsia. Healthcare providers often perform urine protein testing alongside blood pressure monitoring to screen for preeclampsia in pregnant women. Elevated protein levels may indicate kidney damage, a common complication of preeclampsia.

c) **Symptom Assessment:** Pregnant women are often asked about symptoms such as headaches, visual disturbances, abdominal pain, or swelling, which can be indicative of preeclampsia or other pregnancy-related complications. Self-reported symptoms play a crucial role in identifying potential issues and guiding further evaluation and management (Pawar, 2014).

d) **Blood Pressure Monitoring:** Regular blood pressure measurements are essential for detecting hypertension in pregnant women. Healthcare providers typically use a sphygmomanometer to measure blood pressure at prenatal visits. Elevated blood pressure readings may indicate gestational hypertension or preeclampsia, necessitating further evaluation and monitoring.

e) **Fetal Monitoring:**Fetal well-being can be affected by maternal stress and hypertension. Non-invasive methods such as fetal heart rate monitoring using Doppler ultrasound or electronic fetal monitoring during prenatal visits help assess fetal health and detect signs of distress or intrauterine growth restriction associated with maternal complications.

f) **Biochemical Markers:** Research is ongoing to identify biochemical markers associated with SH during pregnancy. Biomarkers such as cortisol, inflammatory markers, and endothelial function markers may provide insights into the physiological pathways involved in these conditions and aid in early detection and monitoring (Salehi et al., 2018).

g) **Ambulatory Blood Pressure Monitoring (ABPM):** In cases where traditional blood pressure measurements may not provide a comprehensive assessment, ambulatory blood pressure monitoring allows for continuous blood pressure monitoring over a 24-hour period. ABPM can provide valuable data on blood pressure variability and nocturnal dipping patterns, aiding in the diagnosis and management of hypertension in pregnant women.

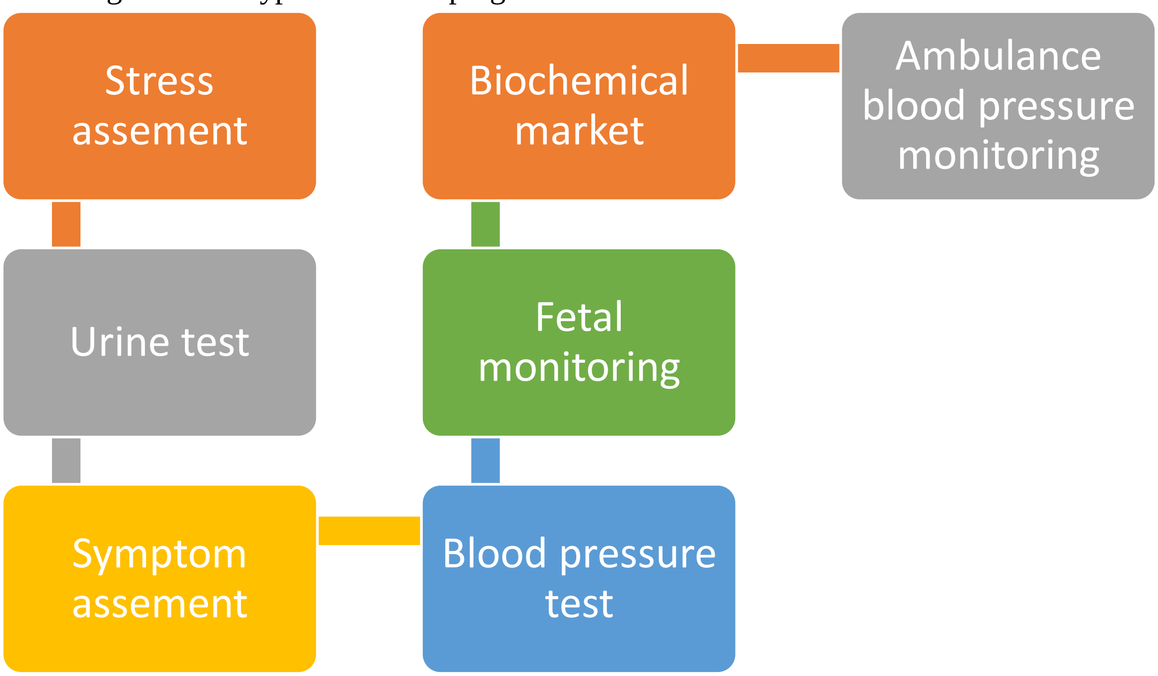

Figure 3: Method of managing SH among Pregnant Women

4. CHALLENGES ENCOUNTERED IN DETECTING SH IN PREGNANT WOMEN

Existing methods for detecting SH in pregnant women are valuable, they also face several challenges that can impact their effectiveness and reliability. Some of these challenges include:

a. **Subjectivity of Self-Reported Data:** Self-reported data, including symptom assessments and psychological questionnaires, are inherently subjective and may be influenced by factors such as individual interpretation, recall bias, and social desirability bias. This subjectivity can limit the accuracy and reliability of these measures, particularly in cases where women may underreport symptoms or stress levels due to stigma or fear of judgment (Schmidt et al., 2020).

b. **Limited Access to Healthcare Services:** Inadequate access to prenatal care and healthcare services can hinder timely detection and management of SH in pregnant women, particularly in underserved or remote communities. Limited access to trained healthcare providers, diagnostic tools, and monitoring equipment can delay diagnosis and increase the risk of complications (Tahir et al., 2018).

c. **Diagnostic Challenges:** Diagnosing conditions such as preeclampsia and gestational hypertension can be challenging due to overlapping symptoms and variable presentation. Differentiating between normal pregnancy-related symptoms and signs of complications requires careful clinical evaluation and diagnostic testing, which may not always be readily available or accessible.

d. **Cost and Resource Constraints:** Some diagnostic tests and monitoring methods, such as ambulatory blood pressure monitoring and biochemical marker assays, can be costly and resource-intensive. Limited healthcare budgets and infrastructure constraints in certain settings may restrict access to these diagnostic tools, particularly in low-resource or developing countries.

e. **Interpretation and Variability:** Interpreting diagnostic results and monitoring data requires expertise and clinical judgment. Variability in interpretation among healthcare providers can lead to inconsistencies in diagnosis and management approaches, potentially impacting patient outcomes. Standardized protocols and guidelines for screening, diagnosis, and management can help address this challenge but may not always be uniformly implemented (Zakaria et al., 2018).

f. **Patient Compliance and Engagement:** Patient compliance with recommended monitoring and follow-up protocols can be variable, particularly in cases where women face socioeconomic or cultural barriers to healthcare access. Factors such as transportation issues, childcare responsibilities, language barriers, and distrust of healthcare providers can impact patient engagement and adherence to recommended interventions.

g. **Complexity of Multi-factorial Conditions:** SH during pregnancy are multi-factorial conditions influenced by a combination of genetic, environmental, behavioural, and socioeconomic factors. Addressing these complex interactions requires a comprehensive, multidisciplinary approach that may be challenging to implement within existing healthcare systems (Naik et al. 2021).

Addressing these challenges requires a concerted effort to improve healthcare infrastructure, increase access to prenatal care services, enhance diagnostic capabilities, and promote patient education and engagement. By addressing these barriers, healthcare systems can better detect and manage SH in pregnant women, ultimately improving maternal and fetal outcomes.

5. MACHINE LEARNING FOR MANAGEMENT OF SH

Machine learning (ML) offers promising avenues for the detection and management of SH in pregnant women, leveraging computational algorithms to analyze complex datasets and extract meaningful patterns. An overview of how ML can be applied in this context is showcased in figure 5:

a) **Data-Driven Detection Models:** ML algorithms can analyze diverse data sources, including physiological measurements, electronic health records (EHRs), and patient-reported data, to develop predictive models for SH detection. For instance, ML models can integrate data from wearable biosensors, such as heart rate monitors and activity trackers, to continuously monitor physiological parameters and detect patterns indicative of stress or hypertension. These models can provide real-time alerts to healthcare providers, enabling proactive interventions to mitigate risks and improve outcomes (Neocleous et al., 2018).

b) **Personalized Risk Stratification:** ML techniques allow for personalized risk stratification by considering individual patient characteristics, including demographics, medical history, lifestyle factors, and genetic predispositions. By analysing large-scale datasets, ML algorithms can identify complex interactions between risk factors and develop personalized risk assessment tools. These tools can assist healthcare providers in identifying pregnant women at higher risk of developing stress-related complications or hypertension, facilitating targeted interventions and resource allocation to those who need them most (Salehi et al., 2018).

c) **Decision Support Systems:** ML-based decision support systems can assist healthcare providers in clinical decision-making by synthesizing vast amounts of patient data and providing evidence-based recommendations. For instance, ML algorithms can analyze EHR data to predict the likelihood of developing preeclampsia or gestational hypertension based on early clinical indicators. These predictions can guide healthcare providers in implementing preventive measures, such as lifestyle modifications or pharmacological interventions, tailored to individual patient needs.

d) **Continuous Monitoring and Feedback Loops:** ML-driven monitoring systems can enable continuous tracking of patient health parameters and feedback loops to optimize intervention strategies over time. For example, ML algorithms can analyze trends in blood pressure measurements, symptom reports, and medication adherence patterns to adapt treatment plans dynamically. Additionally, ML-based chatbots or mobile applications can provide personalized recommendations for stress management techniques, such as relaxation exercises or mindfulness practices, based on real-time data inputs and user preferences (Martinez et al., 2018). However, several challenges must be addressed to effectively implement ML-based solutions for SH detection and management in pregnant women. These include ensuring data privacy and security, addressing algorithmic bias and interpretability issues, integrating ML models into existing clinical workflows, and validating the effectiveness of these models through rigorous clinical trials and real-world implementations. Despite these challenges, ML holds great potential to augment traditional healthcare approaches and improve outcomes for pregnant women at risk of stress-related complications and hypertension. The figure 4 presents the operation process of ML algorithms.

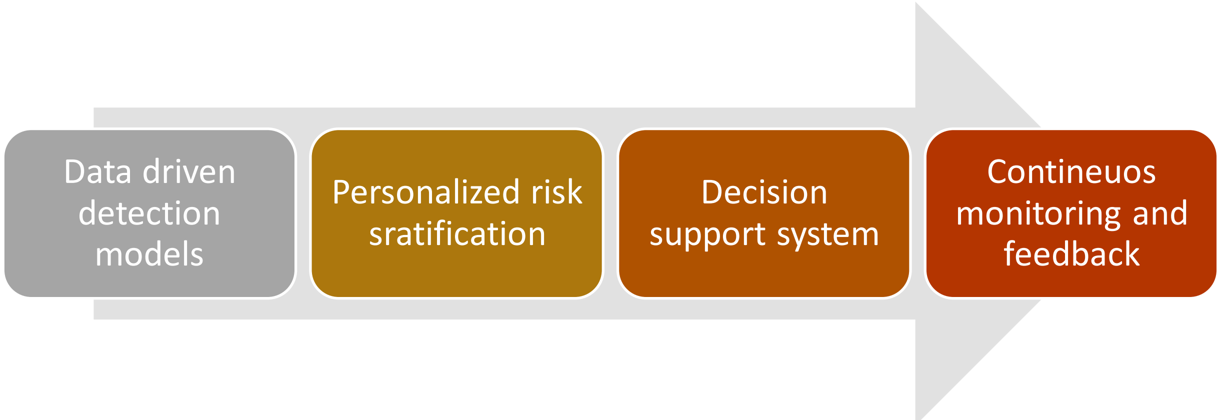

Figure 4: Operation of ML algorithms or processing of clinical data (Maric et al., 2020)

5.1 Deep Learning Approach for Hypertension Prediction

Tahir et al. (2018) deploys a neural network (NN) to predict the likelihood of hypertension, aiming to match or exceed the performance of other algorithms such as Naive Bayes (NB) and linear regression. The dataset, comprising 239 samples from Surabaya Haji General Hospital and encompassing 17 risk factors, was utilized. To enhance accuracy, the researchers fine-tuned the neural model with a single hidden layer, determining that 17 neurons yielded the lowest error rate. Subsequently, the model underwent validation and comparison employing three distinct validation techniques. Notably, NN exhibited superior performance, achieving a 96.66% accuracy following validation using the leave-one-out (LOO) cross-validation method.

Sakinah et al. (2019) employed a variant of recurrent NN known as Long Short-Term Memory (LSTM). Finding an accurate prognosis through this method necessitated identifying the optimal combination of various parameters, including the count of neurons in hidden layers, maximum epochs, and the arrangement of training and testing data. Adaptive Moment Estimation (ADAM) optimization was employed in the LSTM network to iteratively adjust weight values, minimizing system error rates. Validation in this study utilized both LOO cross-validation and tenfold cross-validation. Data from Haji General Hospital in Surabaya constituted the dataset. The LSTM model yielded the best accuracy rates for both training data (96.62%) and testing data (90.22%).

Manoochehri et al. (2021) proposed the development of a data mining-based model serving as a screening tool. The study incorporated medical records of 1452 pregnant women from Hamadan City, Iran, spanning from April 2005 to March 2015, each record comprising nine features. Six data mining techniques, including Random Forest (RF), Logistic Regression (LR), Discriminant Analysis, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and C5.0 Decision Trees, were investigated. Results identified the number of pregnancies, age, and pregnancy season as the most significant risk variables for hypertension detection. Among the six methods, the SVM model achieved the highest prediction accuracy of 0.791.

Han et al. (2020) analyzed medical data from 568 women who received care at the Obstetrics Department of Fujian Maternal and Child Health Hospital. The sample included pregnancies with hypertension, normal-term pregnancies, and pregnancies with gestational hypertension (GH) from September 2014 to September 2018. A back-propagation (BP) neural network was employed to identify reliable hypertension indicators. Using TensorFlow software, a three-layer BP NN was constructed with 25 input features. Notably, albumin, mean platelet volume, blood urea nitrogen, lactate dehydrogenase, and triglyceride were identified as the most influential predictors of hypertension. The BP NN achieved an accuracy of 78.8%.

Bennett et al. (2022) leveraged extensive data resources from the Public Use Data Files (PUDF) for Texas, the Magee Obstetric Medical and Infant (MOMI) database, and the Oklahoma PUDF. Their study aimed to predict hypertension early using machine learning (ML) and the cost-sensitive deep neural network (CSDNN) method. Various network architectures were explored using Hyperband, Bayesian optimization, and random search hyper-parameter optimization algorithms. CSDNN with focal loss (CSDNN-FL) emerged as the top-performing model for the Oklahoma and Texas datasets, achieving AUCs of 64% and 66%, respectively. For the MOMI dataset, CSDNN-FL and CSDNN with weighted cross-entropy (CSDNN-WCE) outperformed other approaches, yielding an AUC of 76%. While some models showed high G-mean values, the AUC for Native Americans in Texas was 57.1% and for African Americans was 66.7%. For Oklahoma Native Americans, the best AUC was 58% using DNN and balanced batch, while for Oklahoma African Americans and the MOMI African American dataset, the top-performing models were either CSDNN-FL with a balanced batch approach or CSDNN-WCE.

5.2 Machine Learning Approaches for Hypertension Prediction

Several studies have employed machine learning (ML) techniques to predict hypertension. Maric´ et al. (2020) developed an ML model to predict hypertension early, automatically selecting the most relevant features from a multitude of variables. They analysed routine prenatal visit data from 16,370 deliveries at Lucile Packard Children's Hospital, using gradient boosting and elastic net algorithms. The model considered 67 factors, including medication intake, medical records, and prenatal laboratory outcomes. Cross-validation assessed the model's performance, with the elastic net algorithm achieving optimal results: an AUC of 0.79 (95% CI 0.75–0.83), an FPR of 8.1%, and a sensitivity of 45.2%.

Jhee et al. (2019) utilized hospital electronic medical records from Yonsei University Hospital, encompassing 11,006 pregnant women, to predict late-onset hypertension. Various ML models were developed, including LR, decision tree (DT), random forest (RF), stochastic gradient boosting (SGB), support vector machine (SVM), and Naive Bayes (NB). The SGB model exhibited the best performance, with an FPR of 0.009 and an accuracy of 0.973.

Marin et al. (2019) employed ML algorithms, particularly the Viterbi algorithm, to predict hypertension using data such as blood pressure, age, and weight. Participants wore smart bracelets containing sensors, and the Viterbi algorithm analysed this data to estimate the probability of developing hypertension, achieving an overall accuracy of 80%, specificity of 72%, and sensitivity of 92.5%.

Liu et al. (2022) constructed prediction models for hypertension using clinical and laboratory information from early pregnancy prenatal screening. Their dataset included medical records for

11,152 pregnant women, utilizing LR, SVM, deep neural network (DNN), DT, and RF models. The RF model exhibited the highest accuracy, with an AUC of 0.86 (95% CI: 0.80–0.92).

Li et al. (2021) developed a prediction model using RF, extreme gradient boosting (XGBoost), LR, and SVM, identifying the most influential features with XGBoost. The XGBoost model achieved the best performance, with an AUC of 0.955, an f1_score of 0.571, and an accuracy of 0.920.Carreno et al. (2020) assessed time-series summary methods and feature size reduction methods for hypertension prognosis, employing RF and SVM classifiers. SVM paired with feature clustering achieved the highest accuracy of 93%.Martínez-Velasco et al. (2018) utilized common ML algorithms to estimate hypertension occurrence, with RF and LOO cross-validation showing the highest accuracy, specificity, and sensitivity. Bosschieter et al. (2022) focused on Explainable Boosting Machines (EBMs), demonstrating the highest accuracy in predicting hypertension compared to other ML methods such as RF and XGBoost.Schmidt et al. (2022) developed ML models for predicting unfavourable outcomes in suspected hypertension cases, achieving high accuracy with gradient-boosted trees and RF classifiers

6 CONCLUSION

Despite advancements in prenatal care, stress-related complications such as hypertension and preeclampsia continue to pose significant risks to maternal and fetal health. Current methods rely heavily on periodic monitoring and standard interventions, which may not adequately capture individual risk profiles or dynamic physiological changes experienced during pregnancy. Additionally, challenges such as limited access to specialized care, resource constraints, and disparities in healthcare delivery further exacerbate the problem, highlighting the urgent need for innovative and scalable solutions. The problem to be address in this study revolves around the inadequacies of existing approaches in effectively addressing SH during pregnancy.

The paper discusses the management of SH in pregnant women, the causes of the SH among them such as psychosocial stressors, anxiety and depression, pregnancy-related concerns, physiological changes, gestational diabetes, poor lifestyle and complications and medical concerns. The existing methods for management of SH among pregnant women are also presented, the methods identified in the study are stress questionnaires and psychological assessments, urine protein testing, symptom assessment, blood pressure monitoring, fetal monitoring, biochemical markers and ambulatory blood pressure monitoring. Furthermore, the challenges that are encountered for adopting these conventional methods such as subjectivity of self-reported data, limited access to healthcare services, diagnostic challenges, cost and resource constraints, interpretation and variability, patient compliance and engagement and complexity of multifactorial conditions. According to the study, addressing these challenges requires a concerted effort to improve healthcare infrastructure, increase access to prenatal care services, enhance diagnostic capabilities, and promote patient education and engagement. By addressing these barriers, healthcare systems can better detect and manage SH in pregnant women, ultimately improving maternal and fetal outcomes. As a result, the work further presents the implementation of various intelligent methods based on machine learning and deep learning for the early detection of stress and hypertension. Various works was reviewed on the implementation of the intelligent techniques, which in turn presented a more satisfying and adaptive result on implementation. But, from the review presented in this paper, many works were discussed on the impact and management of SH among pregnant women, however solution have not been obtained for a cost-effective software model for the management of SH among pregnant women.

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