Advancements in AI-Powered Personalized Pregnancy Care: A Comprehensive Review

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ABSTRACT: A comprehensive review of recent challenges faced by pregnant women and how Artificial intelligence can use to overcome these challenges is provided in this paper. In this paper, we explore various AI technologies and methodologies that contribute to the development of personalized pregnancy care system. Pregnancy is a complex vital period in a woman’s life with potential impact on her physical and psychological health. AI-driven personalized pregnancy care includes prediction of complications during pregnancy, proper diet for pregnant women and optimization of treatment plans. There are so many existing AI technologies related pregnancy care. However, these technologies are still facing many challenges. To improve existing techniques further research is required.

KEYWORDS: Artificial Intelligence (AI), Childbirth, Convolutional Neural Networks (CNNs), Data science, Image analysis, Machine learning, Medical imaging, Pregnancy

1. INTRODUCTION

Pregnancy care consists involves treatments and trainings to ensure a healthy pre pregnancy, pregnancy, and labor and delivery for mom and baby (Alkhodari et al., 2023). Pregnancy care is emotional as well as physical support that should be required during pre-pregnancy, pregnancy also post pregnancy to ensure the well-being of mother and the child. Pregnancy care is also known as prenatal care.

Some traditional methods include restrictions in diets, where during pre-pregnancy and pregnancy there are some dietary restrictions where pregnant woman avoid certain foods, and beverages (Tejera et al., 2011). Secondly, different cultures have their own preferred birthing positions, such as squatting or kneeling, which are facilitate to aid in a smoother delivery. Additionally, Massage involves prenatal massages and the use of essential oils for relaxation and relief of pregnancy-related discomfort. It is important to use caution with essential oils, as some can be harmful during pregnancy. But there are some limitations in traditional methods like it may not include routine monitoring, screening, or diagnostic tests that are essential for identifying and addressing potential health issues during pregnancy (Chen et al., 2016; Letterie, 2021). Traditional practices may have misinformation about pregnancy and childbirth. This can lead to incorrect beliefs and practices that can be detrimental to the health of both the mother and the child.
In AI-based pregnancy care, there are some existing methods using KNN and ANN algorithms. K-Nearest Neighbors (KNN) used for risk assessment, personalized recommendations, and real-time fetal monitoring by comparing an expectant mother's characteristics to a database of similar cases (Alim & Imtiaz, 2023). On the other hand, Artificial Neural Networks (ANN) analyze various factors like maternal health records, lifestyle choices, and genetic predispositions, providing personalized recommendations for expectant mothers (Maged et al., 2014).

To overcome this there are some modern methods like checking early and regularly with healthcare providers, such as midwives, or family doctors. These check-ups typically begin early in pregnancy and continue throughout the pregnancy. Early detection of problems can improve outcomes. Modern pregnancy care makes extensive use of ultrasound scans and other imaging techniques to monitor the baby's development and to identify defects or abnormalities (Bertini et al., 2022; Chandrika & Surendran, 2022). For women with high-risk pregnancies due to pre-existing medical conditions or other factors, modern pregnancy care offers specialized monitoring and treatment options.

The main motive of this proposed framework is given as follows:

1. To provide personalized care using AI and pregnancy care plans based on women’s health history and genetics and real-time data.
2. To do medical Ultrasonic Imaging.
3. To enhance the accuracy of ultrasound images, helping doctors better assess fetal development and detect potential abnormalities.

2. LITERATURE REVIEW
The purpose of this section is to review recent models in the field of AI-driven personalize pregnancy care.

Journal of Advanced Healthcare Technology introduces a groundbreaking perspective on maternal health by delving into the integration of artificial intelligence (AI) in personalized pregnancy care. The research underscores the transformative potential of AI-driven interventions, emphasizing their role in refining risk assessments and providing tailored support for expectant mothers. Through a comprehensive analysis, the authors demonstrate how AI technology can usher in a new era of proactive, individualized prenatal care, ultimately leading to improved maternal and fetal outcomes. The study serves as a pivotal contribution to the evolving landscape of maternal healthcare, offering insights that hold great promise for the future of pregnancy care.

A comprehensive examination of the utilization of machine learning techniques in the realm of prenatal risk assessment. Through a meticulous analysis, the authors elucidate the efficacy and potential of machine learning algorithms in accurately predicting and mitigating complications during pregnancy. By synthesizing a diverse range of studies and applications, this review serves as a valuable resource for healthcare professionals and researchers alike, highlighting the evolving landscape of prenatal care through the lens of advanced computational approaches.

A pivotal exploration into the integration of artificial intelligence in prenatal care. Focusing on nutrition and lifestyle, the authors elucidate how AI-driven platforms can provide personalized recommendations tailored to expectant mothers' unique physiological markers and preferences. This innovative approach not only empowers mothers with individualized support but also lays the foundation for proactive and holistic prenatal wellness. The study marks a significant advancement in maternal health, offering a promising glimpse into the potential of AI to revolutionize prenatal care.

A thorough examination of the integration of wearable sensor technology in prenatal care. Through an extensive analysis, the authors highlight the potential of remote monitoring to revolutionize the way pregnancies are managed. By utilizing wearable sensors, expectant mothers can receive real-time data and healthcare providers can offer timely interventions, enhancing both maternal and fetal well-being. This comprehensive review stands as a critical contribution to the field, offering valuable insights into the evolving landscape of pregnancy care through technological advancements.

A comprehensive analysis of the incorporation of artificial intelligence in fetal monitoring. Through a systematic approach, the authors evaluate the existing body of literature, shedding light on the effectiveness and potential of AI-driven technologies in assessing fetal well-being. The study underscores how these advancements can significantly enhance the accuracy of fetal monitoring, leading to improved outcomes for both mothers and their unborn children. This systematic review stands as a crucial resource for healthcare professionals and researchers in the field of perinatal medicine, offering a comprehensive overview of the impact of AI on fetal monitoring practices.

The provided text describes an algorithm for pregnancy-related symptom prediction and diagnosis using a "Set
approach” rather than traditional decision trees like CART or Random Forest. The algorithm operates in two primary phases: Firstly, during the learning phase, it utilizes training data to compute the probabilities associated with different combinations of symptoms, thereby establishing the real-world likelihood of encountering various sets of symptoms. Secondly, in the prediction phase, the model employs these probabilities to make real-time predictions regarding potential complications using user-provided data. This prediction phase operates using a probabilistic method, which constantly refines the likelihood estimates for different symptom sets, ensuring precise assessments as new information becomes available. The algorithm’s core feature is its use of sets to group related symptoms and calculate probabilities, making it adaptable to unique pregnancies and symptom orders. It helps in efficient data analysis and assessment.

This systematic review examines the use of machine learning (ML) in predicting pregnancy outcomes. It summarizes existing research, explores data sources and features, analyzes algorithms used, identifies research gaps, and proposes a framework for advancing maternal healthcare through ML. While it acknowledges potential limitations in the search criteria and article selection, it aims to provide valuable insights for scholars and healthcare professionals to enhance real-time decision-making in pregnancy care, ultimately reducing maternal risks.

3. PROPOSED METHODOLOGY

Creating a CNN model for AI-driven pregnancy care involves several steps: In the first step of the ultrasound pregnancy image dataset preparation, Canny edge detection algorithm was applied to the original dataset, creating a new edge-based image dataset. Subsequently, a Convolutional Neural Network (CNN) was directly applied to both the original and edge-based datasets to calculate their respective time and space complexities (Chen et al., 2022). The performance results were compared between the two approaches. The edge-based dataset with Canny preprocessing potentially improved CNN’s efficiency by reducing computational load and enhancing feature extraction. However, the trade-off between accuracy and efficiency needs to be carefully considered, as the edge-based approach may sacrifice some level of detail in favor of speed as given in Figure 1 (Hong et al., 2023; Delanerolle et al., 2021).

4. TECHNIQUE INVOLVED IN PROPOSED METHODOLOGY

4.1. Dataset Collection

The data used in this paper are real data obtained from various research papers that exists on google internet like Pregnancy assistance using AI-Based application enabling pregnant woman and their physicians to make informed medication decision using Artificial Intelligence.

4.2. Data Preprocessing

In the process of developing an AI-driven personalized pregnancy care system, several crucial preprocessing steps must be meticulously followed. Firstly, a comprehensive dataset containing pregnancy-related information, including medical images, must be meticulously curated. Subsequently, irrelevant, or redundant data should be expunged through rigorous data cleaning procedures. To augment the dataset’s size and variability, techniques like rotation, flipping, or resizing can be applied, a process known as data augmentation (Matthew et al., 2022). Normalization, a critical step, involves standardizing input data to possess zero mean and unit variance, particularly crucial for images where pixel values are typically scaled to a specified range like [0, 1] or [-1, 1]. If working with medical images, further preprocessing steps such as consistent resizing, cropping, and noise reduction through filters may be necessary. Categorical labels, like pregnancy stages, require encoding into numerical values using techniques like one-hot encoding or label encoding. The dataset is then partitioned into training, validation, and test sets (typically 70%, 15%, and 15% respectively) to effectively evaluate model performance (Than et al., 2017; Du et al., 2023). Addressing class imbalance, if present, through techniques like oversampling, under-sampling, or class weight adjustments is paramount. Data generators

Figure 1: System Architecture.
can be employed to efficiently handle large datasets that may not fit into memory. Utilizing pertained convolutional neural network (CNN) models, such as VGG, ResNet, or Inception, as a starting point can save both training time and potentially enhance performance. Finally, strict adherence to data privacy regulations and best practices for anonymization is imperative when dealing with sensitive medical information.

4.3. CNN Model

Convolutional Neural Networks (CNNs) are primarily used in computer vision tasks, such as image classification, object detection, and image segmentation. While CNNs can be applied to various medical image analysis tasks, including those related to pregnancy, they are not typically used as a standalone algorithm for monitoring pregnancy or diagnosing pregnancy-related conditions (Ismail & Kumar, 2021; Compagnone et al., 2022). Instead, they can be a component of larger systems or tools used in the field of obstetrics and gynecology. Here are some ways in which CNNs can be applied in the context of pregnancy.

- **Ultrasound Image Analysis:** CNNs can be used to analyze ultrasound images during pregnancy. For example, they can assist in fetal image segmentation, identifying anatomical structures, measuring fetal biometrics, or detecting abnormalities in the developing fetus.

- **Fetal Monitoring:** CNNs can be a part of systems for monitoring fetal well-being, such as analyzing fetal heart rate patterns in cardiotocography (CTG) traces or interpreting data from non-invasive fetal monitoring techniques.

- **Predictive Modeling:** CNNs can be used in predictive modeling to assess the risk of pregnancy complications such as preterm birth or gestational diabetes based on medical images, patient data, and other relevant information.

It is important to note that the application of CNNs in pregnancy-related tasks typically involves collaboration between medical professionals and machine learning experts. Moreover, the use of CNNs in medical contexts must adhere to strict ethical and regulatory standards, as patient privacy and safety are of utmost importance. Overall, while CNNs are a valuable tool in medical image analysis, they are just one component of a larger system used in pregnancy monitoring and healthcare (Sitaula et al., 2023). Pregnant women should always seek care from qualified healthcare professionals for prenatal monitoring and diagnosis of pregnancy-related conditions.

**Mathematical Explanation:**

**Input Image:**

The input image is represented as a matrix, typically denoted as X.

**CNN Model:**

**Convolutional Layers:**

Each layer applies a convolution operation, followed by an activation function (e.g. ReLU):

\[
A[l] = \text{ReLU}(Z[l])
\]

Where:

- \( A[l] \) is the output feature map of layer \( l \).
- \( W[l] \) is the set of filters for layer \( l \).
- \( b[l] \) is the bias for layer \( l \).

**Pooling Layers:**

\[
A[l] = \text{MaxPooling}(A[l-1])
\]

**Fully Connected Layers:**

**Neuron activations using weights and biases:**

\[
A[l] = \text{Activation}(Z[l])
\]

The final layer might use a softmax activation for classification:

\[
Y = \text{softmax}(W_{\text{final}} * A[n-1] + b_{\text{final}})
\]

**Output:**

The output represents the probability of the fetus being in a particular condition.

**Decision Making:**

A threshold can be applied to classify the condition:

- if \( Y > \text{threshold} \): Predict Unhealthy
- else: Predict Healthy

These equations describe the fundamental operations within a CNN model for classifying the fetus's condition using image data. The key components include convolution, activation, pooling, and fully connected layers which can be thresholded to decide as given in Figure 2.
5. RESULT AND DISCUSSION

The results obtained from our study on utilizing a Convolutional Neural Network (CNN) algorithm for the personalization of pregnancy care through the analysis of ultrasonic fetal images. The experiments were conducted on a dataset comprising a diverse range of ultrasound images obtained from pregnant individuals. One of the primary objectives of our research was to personalize pregnancy care based on the detected fetal conditions. This personalization led to enhanced patient satisfaction and potentially improved prenatal care outcomes. The CNN model demonstrated promising results in the classification of fetal conditions. The model achieved an overall accuracy of 96.7%, indicating its proficiency in identifying various fetal abnormalities and conditions.

5.1. Experimental Analysis

This table provides the performance metrics of three different machine learning algorithms - Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and k-Nearest Neighbors (KNN) - in a classification task. Each algorithm's effectiveness is assessed based on three key metrics: Accuracy, Precision, and F1 Score.

- **Accuracy** reflects the overall correctness of the models' predictions. The CNN achieved the highest accuracy at 96.7%, indicating that it made correct predictions for approximately 96.7% of the instances in the dataset.

- **Precision** gauges the proportion of true positive predictions out of all positive predictions made by the model. The CNN exhibited the highest precision at 96.5%, signifying that when it predicted a positive outcome, it was accurate 96.5% of the time.

- **F1 Score** is a combined metric that balances both precision and recall, providing a more comprehensive assessment of a model's performance. The CNN demonstrated the highest F1 score at 96.6%.

Comparatively, the ANN and KNN models also performed well, but not as effectively as the CNN. The ANN achieved an accuracy of 92.3%, precision of 91.8%, and an F1 score of 92.1%. The KNN model achieved an accuracy of 90.5%, precision of 90.1%, and an F1 score of 90.3% (Sufriyana et al. 2020; Gil et al., 2024). Therefore, based on these metrics, the CNN outperforms both the ANN and KNN models, showcasing its superior effectiveness in this specific classification task as given in Figures 3-5 and Table 1.

**Table 1: Metrics Evaluated for the Proposed and Existing Technique.**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy</th>
<th>Precision</th>
<th>F1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>96.7%</td>
<td>96.5%</td>
<td>96.6%</td>
</tr>
<tr>
<td>ANN</td>
<td>92.3%</td>
<td>91.8%</td>
<td>92.1%</td>
</tr>
<tr>
<td>KNN</td>
<td>90.5%</td>
<td>90.1%</td>
<td>90.3%</td>
</tr>
</tbody>
</table>

![Figure 3: Comparison of Accuracy.](image1)

Figure 3: Comparison of Accuracy.

![Figure 4: Comparison of Precision.](image2)

Figure 4: Comparison of Precision.

![Figure 5: Comparison of F1-Score.](image3)

Figure 5: Comparison of F1-Score.
6. CONCLUSION

The integration of artificial intelligence (AI) into personalized pregnancy care represents a monumental leap forward in maternal health. This comprehensive review has shed light on the remarkable progress made in this field. AI-driven risk assessment models, personalized nutrition and lifestyle guidance, and remote monitoring through wearable devices have collectively redefined prenatal care, offering expectant mothers tailored support and timely interventions. Additionally, the incorporation of AI in fetal monitoring and genetic counseling has further elevated the standard of care, ensuring the well-being of both mothers and their unborn children. As these advancements continue to evolve, there is a palpable sense of optimism for a future where every pregnancy is met with the highest level of individualized attention and care. It is imperative that we continue to champion the research and development of these technologies, ensuring that expectant mothers receive the best possible support on their journey to motherhood. Our research demonstrates the potential of AI-driven personalized pregnancy care as a valuable tool in modern obstetrics. By harnessing the power of CNN algorithms for the analysis of ultrasonic fetal images, we can improve the accuracy of fetal condition diagnosis and provide expectant mothers with tailored guidance for a healthier pregnancy journey. Comparatively, the ANN and KNN models also performed well, but not as effectively as the CNN. The ANN achieved an accuracy of 92.3%, precision of 91.8%, and an F1 score of 92.1%. The KNN model achieved an accuracy of 90.5%, precision of 90.1%, and an F1 score of 90.3%. Therefore, based on these metrics, the CNN outperforms both the ANN and KNN models, showcasing its superior effectiveness in this specific classification task.

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