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ORIGINAL

Parturition Detection Using Oxytocin Secretion Level and Uterine Muscle Contraction Intensity

Detección del parto mediante el nivel de secreción de oxitocina y la intensidad de contracción muscular uterina

Harshavardhan D[1], Saisree K[1], Ragavarshini S[1]

[1]SRM Institute of Science and Technology. Ramapuram, Department of CSE. Chennai, India.

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ABSTRACT

The "Parturition Detection Sensor Belt," also known as the "Labor Pain Detection Sensor Belt," represents a novel advancement in maternal health monitoring. "Parturition Detection Sensor Belt" designed to simultaneously predict oxytocin levels and monitor uterine muscle contractions. This innovative system combines real-time prediction of oxytocin levels and simultaneous monitoring of uterine muscle contractions to provide a comprehensive solution for parturition detection. By integrating cutting-edge sensor technology and deep learning algorithms, the system offers precise, non-invasive monitoring during labor. The oxytocin level predictions aid in understanding maternal well-being, while the real-time uterine muscle contraction monitoring ensures early detection of labor progression. This interdisciplinary approach leverages advancements in biomedical engineering and data analysis, holding promise for improving the safety and care of expectant mothers. The "Parturition Detection Sensor Belt" has the potential to revolutionize the field of obstetrics by offering a versatile tool for healthcare providers, enhancing maternal health, and facilitating data-driven research in this critical domain. A correlation is developed between oxytocin release and muscle contraction which turns out to be nearly 0,899836. This infers that the two factors that we are considering as important parameters are having a strong association with each other.

Keywords: Parturition Detection; Labor Pain Monitoring; Oxytocin Prediction; Uterine Contraction Sensing; Training the Sensor.

RESUMEN

El "cinturón sensor de detección del parto", también conocido como "cinturón sensor de detección del dolor de parto", representa un novedoso avance en la monitorización de la salud materna. "Parturition Detection Sensor Belt" diseñado para predecir simultáneamente los niveles de oxitocina y monitorizar las contracciones musculares uterinas. Este innovador sistema combina la predicción en tiempo real de los niveles de oxitocina y la monitorización simultánea de las contracciones musculares uterinas para ofrecer una solución integral de detección del parto. Al integrar tecnología de sensores de vanguardia y algoritmos de aprendizaje profundo, el sistema ofrece una monitorización precisa y no invasiva durante el parto. Las predicciones del nivel de oxitocina ayudan a comprender el bienestar materno, mientras que la monitorización de las contracciones musculares uterinas en tiempo real garantiza la detección temprana de la progresión del parto. Este enfoque interdisciplinario aprovecha los avances de la ingeniería biomédica y el análisis de datos, y promete mejorar la seguridad y la atención a las futuras madres. El "cinturón sensor de detección del parto" puede revolucionar el campo de la obstetricia al ofrecer una herramienta versátil a los profesionales sanitarios, mejorar la salud materna y facilitar la investigación basada en datos en este ámbito crítico. Se desarrolla una correlación entre la liberación de oxitocina y la contracción muscular que resulta ser de casi 0,899836. Esto infiere que los dos factores que estamos considerando como parámetros importantes tienen una fuerte asociación entre sí.

Palabras clave: Detección del Parto, Monitorización del Dolor del Parto, Predicción de la Oxitocina, Detección de la Contracción Uterina, Entrenamiento del Sensor.

INTRODUCTION

In a world where the frontiers between maternal health monitoring, innovative technology, and data-driven care intersect, the "Parturition Detection Sensor Belt" takes center stage as a pioneering solution. This project introduces a groundbreaking system designed to transform the landscape of maternal healthcare by combining two vital components: the prediction of oxytocin levels and real-time monitoring of uterine muscle contractions. The amalgamation of cutting-edge sensor technology and state- of-the-art deep learning algorithms ushers in a new era of obstetric care.

At its core, this system seeks to enhance the well-being of expectant mothers by providing non-invasive, real- time insights into their physiological state during labor. The prediction of oxytocin levels, a hormone critical to labor progression, facilitates a deeper understanding ofmaternal health. Simultaneously, the system offers continuous monitoring of uterine muscle contractions, enabling early detection of labor initiation and progression.

This interdisciplinary venture harmonizes advances in biomedical engineering, data analysis, and obstetrics, signifying a critical leap forward in the care of pregnant individuals. The "Parturition Detection Sensor Belt" has the potential to redefine obstetric practices, empowering healthcare providers, improving maternal health, and fostering data-driven research in this pivotal realm. It transcends mere functionality, ushering in a new standard in maternal care, where data, technology, and human well- being coalesce.

Integral to this innovative system are advanced sensors, meticulously designed to ensure accurate and real-time data acquisition. These sensors, equipped with high sensitivity and precision, play a pivotal role in delivering the data necessary for oxytocin level prediction and uterine muscle contraction monitoring. By seamlessly integrating these sensors into the "Parturition Detection Sensor Belt," we aim to provide a holistic and comprehensive solution to early parturition detection, where data, technology, and human well-being coalesce to redefine the standards of obstetric care.

This tends to provide emergency attention for the pregnant women who has no assistance or care or even at situation when she is alone at home. At this situation it brings the caretakers attention regarding the women's state during the peak time of labor.

Existing system:

Existing maternal health monitoring systems predominantly rely on conventional methods that often lack real-time and non- invasive capabilities. These systems are typically based on intermittent manual observations and assessments conducted by healthcare providers. Such practices involve periodic measurements of oxytocin levels and uterine muscle contractions, which may not capture crucial fluctuations in maternal well-being during labor. Moreover, traditional methods are susceptible to human error and may not promptly detect variations in oxytocin levels and uterine contractions, potentially compromising the timely and accurate management of labor.

In contemporary obstetrics, electronic fetal monitoring(EFM) systems are frequently employed to assess fetal heart rate and uterine contractions. However, these systems focus on the fetus's condition and do not directly address the prediction of oxytocin levels, which is a crucial aspect of labor progression. The majority of existing EFM systems require the use of external sensors, often limiting maternal mobility and comfort during labor. These systems offer valuable insights into fetal well-being but may lack the comprehensive approach of integrating oxytocin prediction, real-time uterine muscle contraction monitoring, and maternal well-being assessment.

Moreover, the advent of wearable devices and smart belts for maternal health monitoring is gradually emerging. These devices aim to provide real-time data on maternal and fetal parameters, including uterine contractions. However, the integration of oxytocin level prediction remains an area where improvements are needed. The current state of wearable devices may not offer the necessary sensitivity and specificity to accurately predict oxytocin levels in real-time, limiting their utility in comprehensive obstetric care.

Proposed system

The proposed "Parturition Detection Sensor Belt" is a cutting- edge parturition detection system designed to revolutionize obstetrics. It leverages an interdisciplinary approach that combines advanced sensor technology and deep learning algorithms to provide precise, non-invasive monitoring during labor.

This innovative system is Python-based, and it represents a novel advancement in parturition detection. It can simultaneously predict oxytocin levels and monitor uterine muscle contractions, offering a comprehensive solution for parturition detection. By integrating cutting-edge sensor technology and deep learning algorithms, the system provides real-time oxytocin level predictions and uterine muscle contraction monitoring. The real-time prediction of oxytocin levels aids in understanding maternal well-being, while the simultaneous monitoring of uterine muscle contractions ensures early detection of labor progression. It also helps prevent any false perception of labor pain during pregnancy due to normal stomach ache. This approach is a game-changer in the field of obstetrics, as it enhances maternal health and facilitates data-driven research.

The "Parturition Detection Sensor Belt" is versatile and adaptable, offering healthcare providers a multifaceted tool to improve the safety and care of expectant mothers. Its integration into existing workflows is seamless, allowing for easy adoption without disrupting operational processes.

In an era where advanced healthcare solutions are crucial, this system addresses the growing need for improved monitoring during labor. It empowers healthcare providers with the tools to enhance maternal well-being, ultimately redefining the standards for parturition detection and maternal health monitoring.

METHOD

The Parturition Detection Sensor Belt project focuses on real-time labor pain and uterine muscle contraction detection. It begins with the collection of data using specialized sensors within the belt, designed to measure oxytocin levels and monitor uterine contractions. The data is processed and pre-processed to ensure accuracy and reliability. A machine learning model, such as a recurrent neural network (RNN) or a similar algorithm, is developed to analyze the data. Training is performed using a dataset of known parturition events. The model's predictions are used to identify the onset of labor and contraction patterns. The belt offers a non-invasive and continuous monitoring solution, potentially aiding in timely labor intervention and improving maternity care.

Here, collection of oxytocin release data from a normal person, a pregnant women and a women in labor pain who is about to give birth is taken. The database regarding uterine muscle contraction is also collected from a normal women, a pregnant women and a women in labor pain. All this data is fed into the sensor that would assist the activity of the belt. This sensor is then set with a maximum_count value in terms of oxytocin release level and intensity of muscle contraction in uterus.

If the amount of release of oxytocin and simultaneous report of uterine muscle contraction intensity exceeding the maximum_count value, then the app installed in the pregnant women's phone that has the contact of the close people starts sending alert calls or messages to draw their attention, if required ambulance number also can be attached as an emergency number.

A correlation called as Pearsons correlation is used for testing the strength of association between the two factors that are considered important for the analysis. Pearson's correlation coefficient, often denoted as "r," is a statistical method used to measure the strength and direction of the linear relationship between two continuous variables. It quantifies how well the two variables are related and whether they move in the same or opposite directions. Pearson's correlation coefficient can take values between -1 and 1, with the following interpretations:

If $r = 1$, it indicates a perfect positive linear relationship, meaning that as one variable increases, the other variable also increases in a straight-line fashion.

If $r = -1$, it indicates a perfect negative linear relationship, meaning that as one variable increases, the other variable decreases in a straight-line fashion.

If $r = 0$, it indicates no linear relationship between the variable.

Algorithm for Smart parturition detection Hip band:

1. *M-OxySensor Algorithm:*

Step1: A sensor with oxytocin and muscle contraction detecting capability is used.

Step2: The sensor is trained with data bases of both muscle contraction intensity detection and oxytocin release level detection for normal women, pregnant women and women at the time of labourpain.

Step3: The maximum count of oxytocin release level and muscle contraction intensity is recorded using the database created from the analysis stated in Step2.

Step4: This count is set as (maximum_M_count) and (maximum_O_count) for both muscle contraction intensity count and oxytocin release level detection.

2. *OxyMetric Algorithm*

Step1: The sensor requests for an input or stimuli.

Step2: The Oxytocin release acts as a stimulus for this sensor.

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Step3: Sensor checks for the amount of release of Oxytocin.
Step4: It then calculates the amount of release and stores on Database.

3. *SarcoFlex Algorithm:*
Step1: The sensor requests for an input or stimuli
Step2: The uterine muscle contraction acts as a stimulus for this sensor.
Step3: Sensor checks for the intensity of muscle contraction in the uterine muscle.
Step4: It then calculates the decibels to which the muscle contraction occurred.
Step5: It is then stored in the Database.

4. *Algorithm for parturition detection:*
Step1: The sensor checks for some sort of stimuli.
Step2: If stimuli are received as an input, it uses OxyMetric Algorithm and SarcoFlex Algorithm.
Step3: Following this we activate M-OxySensor algorithm.
Step4: If the measurement exceeds (maximum_M_count) and (maximum_O_count) on Database according to M-OxySensor algorithm. Go to step3.1
Step4.1: Alert message sent to all the close people of the women and if required to the Ambulance also.
Step5: Else, Stop.

Pseudocode:

Pseudocode for the above algorithm:

```
def M-OxySensor():
    waiting for stimuli
    Detect muscle contraction intensity and oxytocin release level.
    Deduce the maximum_M_count() and maximum_O_count()
    def OxyMetric(): waiting for stimuli
    Sensor check amount of-> oxytocin release Store the calculation on -> database

def SarcoFlex():
    waiting for stimuli
    stumili-> muscle contraction
    Sensor-> checks and calculates the muscle contraction rate
    Store the information on-> database

def Parturition():
    checks for stimuli if stimuli:
    use OxyMetric and SarcoFlex Algorithm
    if M_count > maximum_M_count and O_count > maximum_O_count:
    App activate(alert message, call)
else:
    stop
```

Scope of the project

The scope of the "Parturition Detection Sensor Belt" project is to design and develop a non-invasive, wearable device that simultaneously monitors labor pain and uterine muscle contractions in pregnant individuals. This innovative system aims to offer a reliable and timely method for parturition detection, enhancing maternity care and potentially improving maternal and fetal well-being. The project encompasses the creation of specialized sensors within the belt for real-time oxytocin level prediction and uterine muscle contraction monitoring. The algorithmic foundation for this system includes the application of machine-learning, particularly recurrent neural networks (RNNs), Convolutional Neural Networks (CNNs), Data Preprocessing Techniques, Mobile App Integration, Ethical Guidelines and Regulatory Compliance, to analyze sensor data. These algorithms will identify patterns and trends associated with the onset of labor and the intensity and duration of contractions. Additionally, the project explores data preprocessing techniques to ensure data accuracy and reliability. The envisioned system not only supports obstetricians and healthcare providers in the timely management of labor but also empowers pregnant individuals to have increased control over their birthing experience. By combining cutting-edge sensor technology and data analysis, this project has the potential to redefine the landscape of childbirth monitoring, offering a more holistic approach to maternity care that prioritizes safety and well-being.

Architecture diagram

A database is meticulously constructed by analyzing two critical physiological parameters: oxytocin release levels and muscle contraction intensities. Through this analysis, the maximum muscle contraction count and maximum oxytocin count are determined and then seamlessly integrated into afresh database. This curated database is subsequently harnessed by a specialized sensor designed to continually monitor oxytocin release levels and muscle contraction intensity in real-time. The sensor diligently collects this data and ensures its secure storage in the cloud, creating a comprehensive reference that can be accessed remotely.

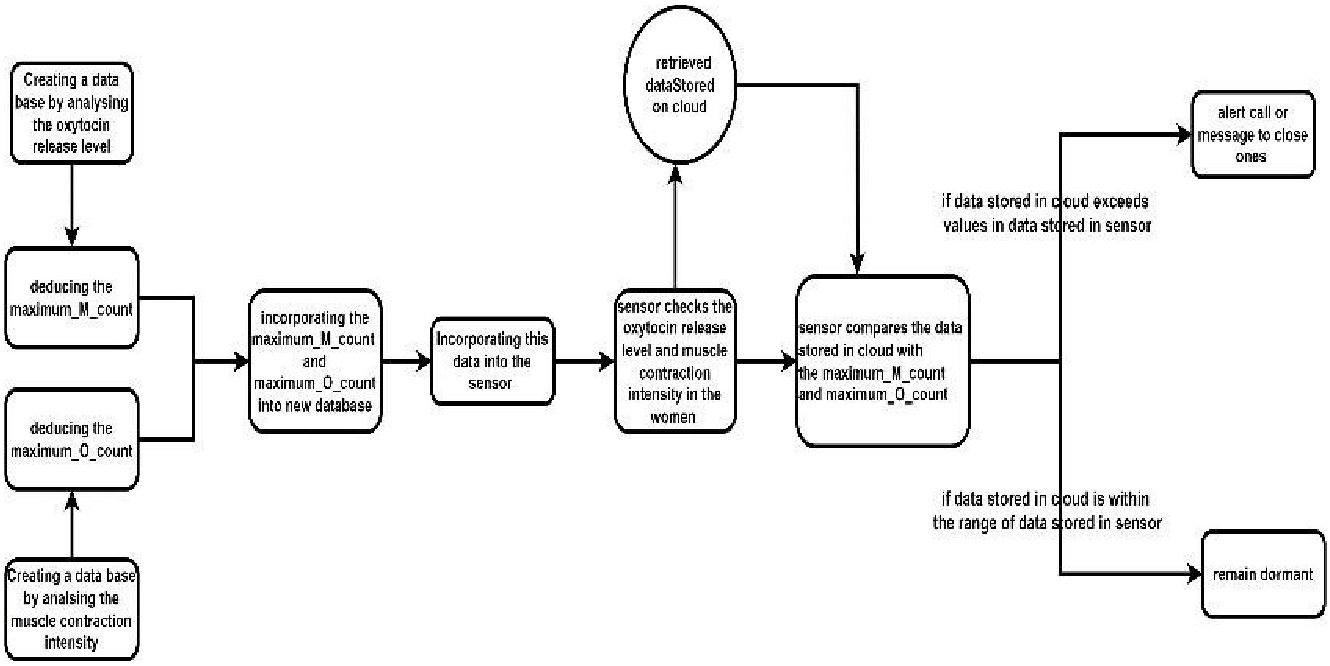

Figure 1. The parturition detection system Architecture

The sensor plays a pivotal role by regularly cross- referencing the cloud-stored data with its own internal records. If the data stored in the cloud exceeds the established values within the sensor, the system promptly triggers an alert mechanism. This alert serves as a vital communication tool, promptly notifying individuals' close to the monitored individual through calls or messages. On the contrary, when the cloud data falls within the range of the sensor's records, the system remains in a dormant state, signifying a state of equilibrium where no immediate action is required. This process not only ensures timely monitoring but also guarantees the safety and well-being of individuals by enabling a responsive alert system in case of abnormal physiological fluctuations.

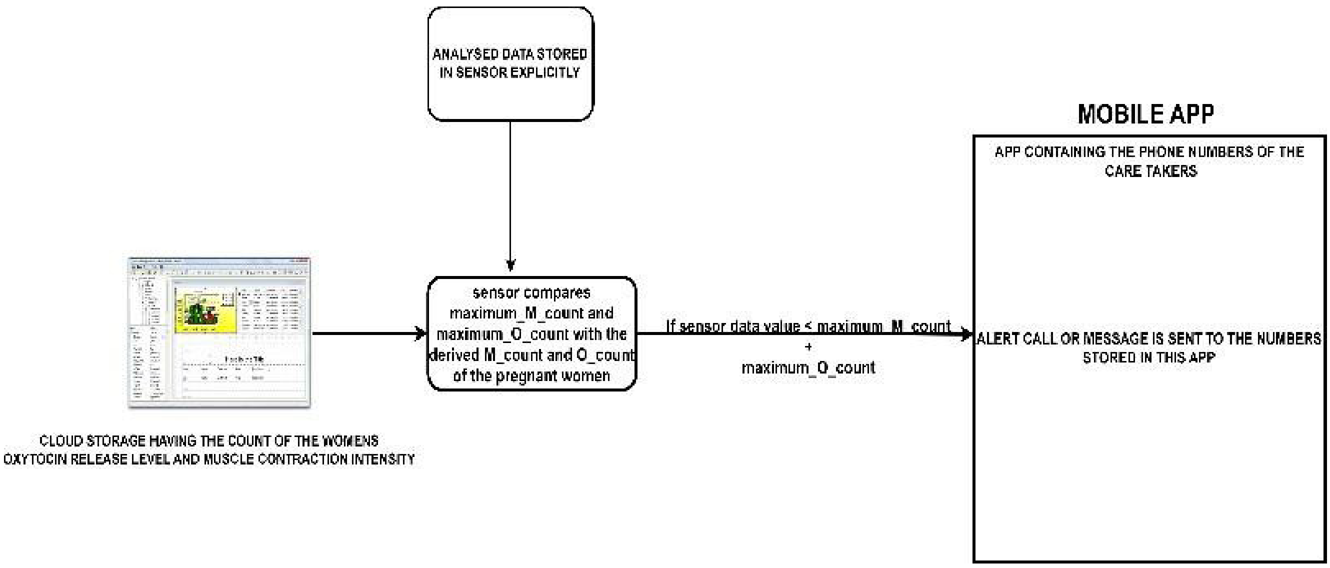

Figure 2. The working of the app system in the model

The flow in fig-2 above states the app activation process where the sensor compares the data stored in it and the data that it stored in cloud after examining the women.

If the sensor detects that the data value in the cloud (stored by the sensor) is lesser than data value stored in the sensor (maximum_M_count and maximum_O_count) created by the analysis initially, then there is not reaction. But, if the value in cloud exceeds the value in sensor database then the APP gets activated. It contains the contact of people whom the women have stored as care taker. Then the activated app sends a alert call or message to the care takers regarding the emergency.

RESULT AND DISCUSSION

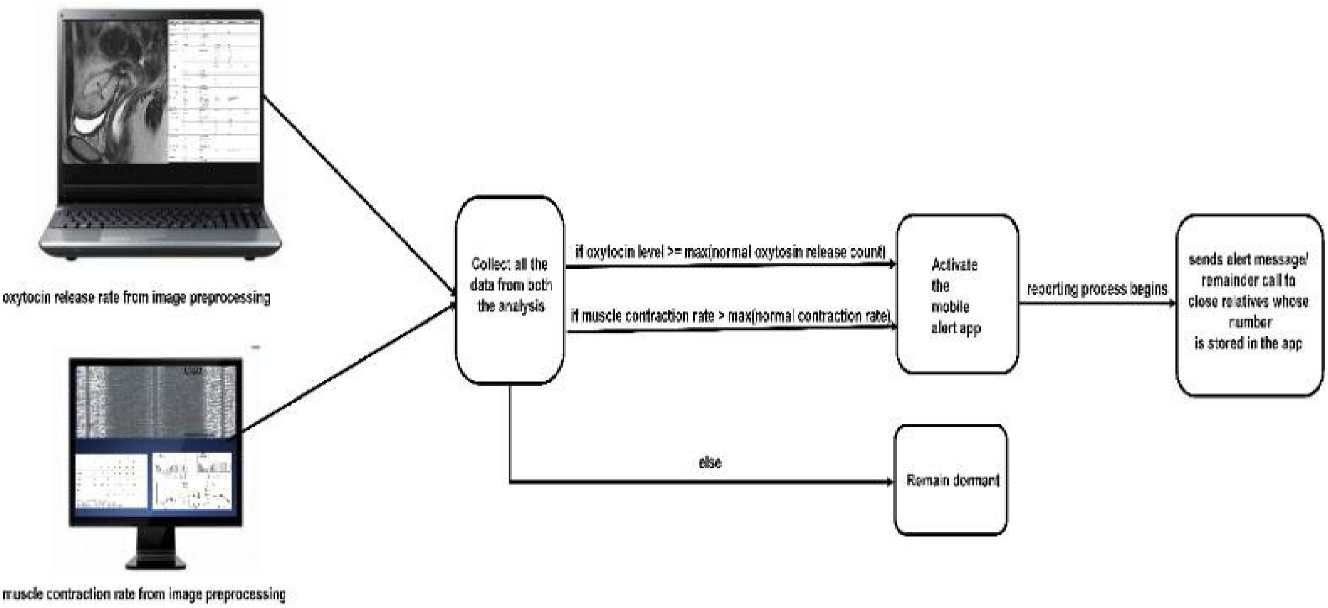

Figure 3. The computation for working of oxytocin and muscle contraction system to detect parturition

This system operates in two distinct phases, the first of which involves real-time analysis of the oxytocin release rate and muscle contraction rate. Image preprocessing techniques are employed to extract and evaluate this vital data. Subsequently, the information gathered from these analyses is consolidated, forming a comprehensive understanding of the physiological state of the pregnant women. This initial phase serves as the foundation for the system's functionality.

In the second phase, the system continuously monitors these critical metrics, maintaining a vigilant watch over the oxytocin level and muscle contraction rate. When either of these parameters exceed their predetermined maximum thresholds, then the system would determine the changes in the other parameter. If the change in either of the parameters is considered to have increased with the increase of other or even if anyone is considered to have gone too high then the mobile alert application is swiftly activated. This immediate response mechanism ensures that timely notifications are sent to individuals concerned. When the mobile alert application is triggered, it sets in motion a reporting process that swiftly notifies close relatives or caregivers. The system utilizes the stored contact information within the application to either send alert messages or make reminder calls, ensuring that help and support are readily available when it is needed most. This integrated process provides a seamless and indispensable safeguarding and supporting individuals during critical moments.

The profound method contains a total of two scenarios:

Scenario1 (oxytocin release level): First the data regarding oxytocin release level is collected from the normal women, pregnant women and the women in labor pain from multiple analysis and stored. This data is analyzed for deducing the maximum oxytocin release level(maximum_O_count). If the women is expected to have a release of oxytocin more than the maximum_O_level than expected then the system simultaneously look for the status of the muscle contraction.

Scenario2 (Muscle contraction intensity): First the data regarding muscle contraction intensity is collected from the normal women, pregnant women and the women in labor pain from multiple analysis and stored. This data is analyzed for deducing the maximum muscle contraction intensity(maximum_M_count). If the women is expected to have a heavy muscle contraction which has a count that exceeds the maximum_M_level then the app is activated immediately.

This representation is the muscle contraction system using CNN algorithm. Firstly, the image is partitioned into interested areas in the image of the muscle and is arranged in continuous sequence. This process is called convolution and pooling. Convolution involves feature maps and subsampling. Now, we perform flattened layer analysis. Now, the data flattened layer is converted to fully connected layer. This is finally processed with SOFTMAX activation function to deduce the output.

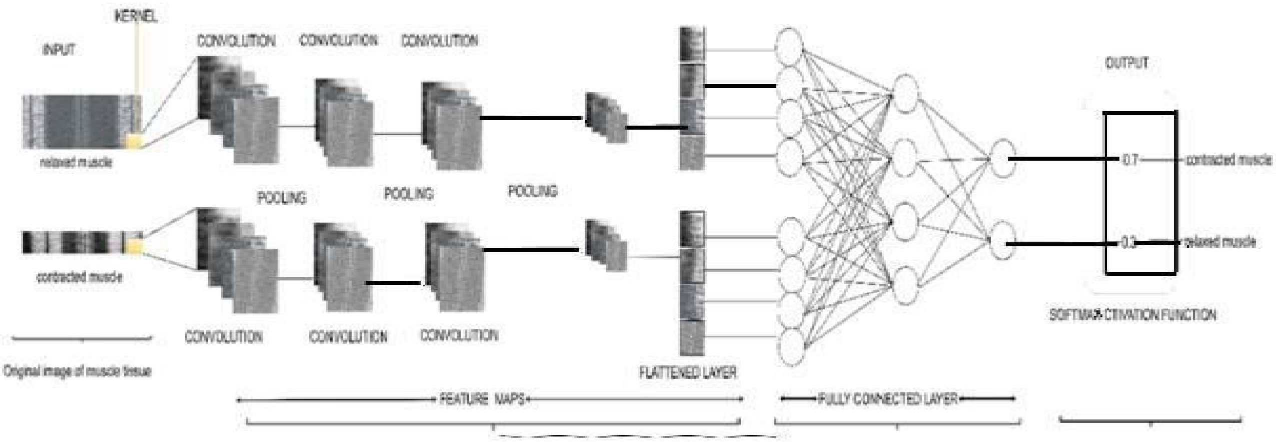

Figure 4. The CNN operation done to detect the intensity of muscle contraction

Dataset:

	A	B	C	D	E	F
1	Age	Weight	Glucose	Contractions	Oxytocin	Outcome
2	25	60	109	7	100	1
3	30	70	158	2	45	0
4	34	75	88	8	150	1
5	23	62	92	8	175	1
6	37	78	121	3	50	0
7	38	75	103	1	40	0
8	29	68	137	9	200	1
9	32	73	102	5	60	0
10	22	67	90	6	90	1
11	29	70	111	9	250	1
12	33	75	180	2	40	0
13	31	73	143	6	118	1
14	25	67	106	9	250	1
15	30	74	171	3	50	0
16	35	80	169	1	45	0
17	24	79	180	3	60	0
18	40	80	159	2	57	0
19	31	75	71	6	129	1
20	27	64	103	9	217	1
21	32	76	105	10	246	1
22	35	81	103	4	68	0
23	28	62	101	7	216	1
24	30	65	98	2	56	0
25	24	61	176	9	198	1
26	37	78	150	4	59	0
27	34	74	103	5	58	0
28	30	68	187	9	203	1
29	22	63	100	2	47	0

The above output shows the correlation among all the variables. But the important correlation is about contraction and oxytocin. The correlation among the two variables is considerably higher, that is equal to 0.899836. This infers that any increase or decrease in either of the factor would result in a drastic positive

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change in the other factor i.e. change in any factor is directly proportional to change in another factor.

Pearson’s correlation coefficient, often denoted as “r,” is a statistical method used to measure the strength and direction of the linear relationship between two continuous variables. It quantifies how well the two variables are related and whether they move in the same or opposite directions. Pearson’s correlation coefficient can take values between -1 and 1, with the following interpretations:

If r = 1, it indicates a perfect positive linear relationship, meaning that as one variable increases, the other variable also increases in a straight-line fashion.

If r = -1, it indicates a perfect negative linear relationship, meaning that as one variable increases, the other variable decreases in a straight-line fashion.

If r = 0, it indicates no linear relationship between the variables.

Inputs:

```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
data=pd.read_excel('C:/Users/Mano/OneDrive/Desktop/dataset-1.xlsx')
data
samp=data.copy(deep=False)
corr=data.corr()
print(corr)
plt.scatter(data['Contractions'], data['Oxytocin'], c='red')
plt.title('Scatter plot for MUSCLE-CONTRACTION and OXYTOCIN LEVEL in pregnant women')
plt.xlabel('Contractions (number of contraction per 10 minutes(n/10mins))')
plt.ylabel('Oxytocin-Release-level')
plt.show()
data.insert(6,"conditions","")
for i in range(0,len(data['Age']),1):
    if data['Oxytocin'][i]>=100 and data['Contractions'][i]>=7:
        data['conditions'][i]='Labour'
    elif data['Oxytocin'][i]<=50 and data['Contractions'][i]<=5:
        data['conditions'][i]='Not Pregnant'
    else:
        data['conditions'][i]='No Labour'
print(data)
sns.set_style('darkgrid',{'grid.color': 'red'})
sns.regplot(x=data['Contractions'],y=data['Oxytocin'])
sns.lmplot(x='Contractions', y='Oxytocin', data=data, hue='conditions', legend=True, palette='Set1',fit_reg=False)
```

The above code is segregated into partition for better view:

Input 1:

```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
data=pd.read_excel('C:/Users/Mano/OneDrive/Desktop/dataset-1.xlsx')
data
samp=data.copy(deep=False)
corr=data.corr()
print(corr)
```

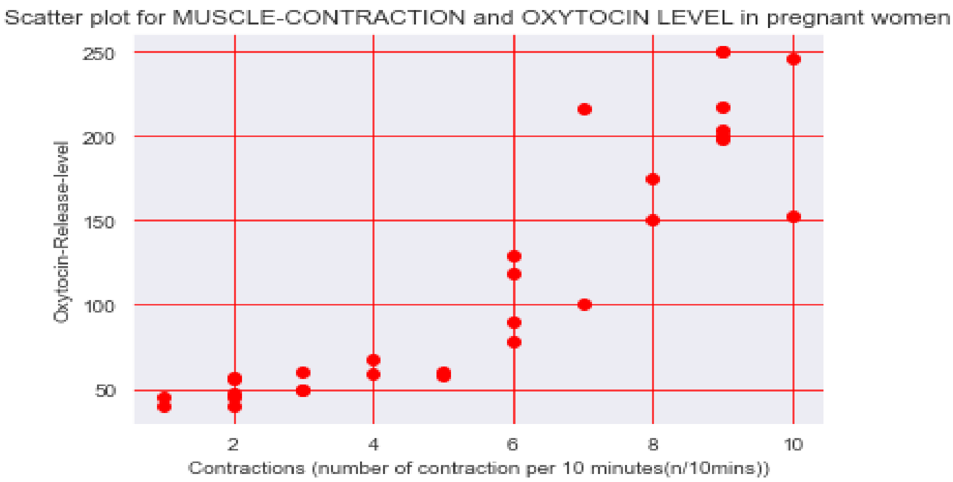
Output 1:

	Weight	Glucose	Contractions	Oxytocin	Outcome
Weight	1.000000	0.218937	-0.448893	-0.434747	-0.550853
Glucose	0.218937	1.000000	-0.261648	-0.216046	-0.277041
Contractions	-0.448893	-0.261648	1.000000	0.899836	0.888141
Oxytocin	-0.434747	-0.216046	0.899836	1.000000	0.824617
Outcome	-0.550853	-0.277041	0.888141	0.824617	1.000000

Input 2:

```
lt.scatter(data['Contractions'], data['Oxytocin'], c='red')

lt.title('Scatter plot for MUSCLE-CONTRACTION and OXYTOCIN LEVEL in pregnant women')

lt.xlabel('Contractions (number of contraction per 10 minutes(n/10mins))')

lt.ylabel('Oxytocin-Release-level')

lt.show()
```

Output 2:



The above graph states that the interaction and proportionality between Oxytocin-Release-level and Contractions(n/10mins) are in positive trend. This means that the strength of association between the two factors are stronger. That is either of the factors are directly proportional to each other.

Input 3:

```
data.insert(6,"conditions","")
for i in range(0,len(data['Age']),1):
    if data['Oxytocin'][i]>=100 and data['Contractions'][i]>=7:
        data['conditions'][i]='Labour'
    elif data['Oxytocin'][i]<=50 and data['Contractions'][i]<=5:
        data['conditions'][i]='Not Pregnant'
    else:
        data['conditions'][i]='No Labour'
print(data)
```

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Output 3:

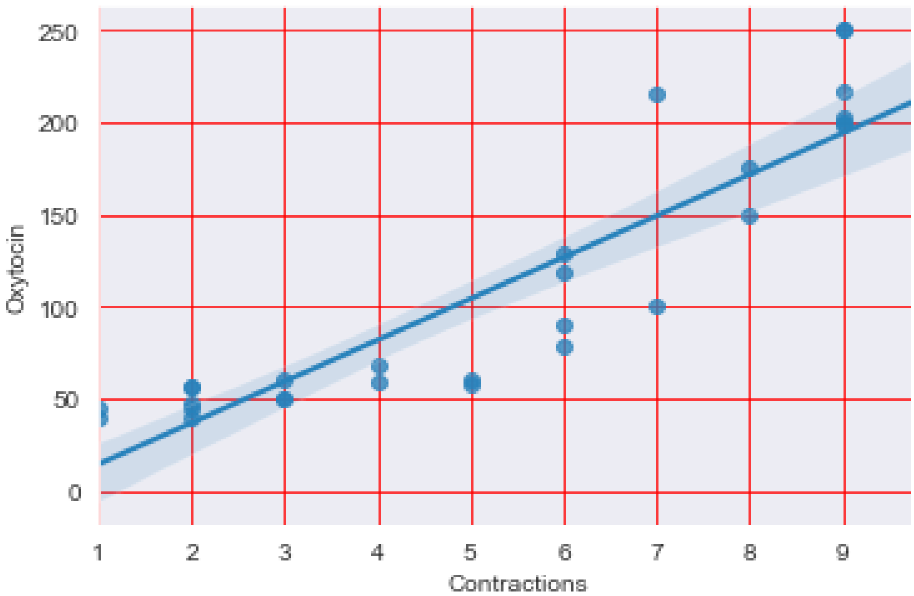
	Age	Weight	Glucose	Contractions	Oxytocin	Outcome	conditions
0	25	60	109	7	100	1	Labour
1	30	70	158	2	45	0	Not Pregnant
2	34	75	88	8	150	1	Labour
3	23	62	92	8	175	1	Labour
4	37	78	121	3	50	0	Not Pregnant
5	38	75	103	1	40	0	Not Pregnant
6	29	68	137	9	200	1	Labour
7	32	73	102	5	60	0	No Labour
8	22	67	90	6	90	1	No Labour
9	29	70	111	9	250	1	Labour
10	33	75	180	2	40	0	Not Pregnant
11	31	73	143	6	118	1	No Labour
12	25	67	106	9	250	1	Labour
13	30	74	171	3	50	0	Not Pregnant
14	35	80	169	1	45	0	Not Pregnant
15	24	79	180	3	60	0	No Labour
16	40	80	159	2	57	0	No Labour
17	31	75	71	6	129	1	No Labour
18	27	64	103	9	217	1	Labour
19	32	76	105	10	246	1	Labour
20	35	81	103	4	68	0	No Labour
21	28	62	101	7	216	1	Labour
22	30	65	98	2	56	0	No Labour
23	24	61	176	9	198	1	Labour
24	37	78	150	4	59	0	No Labour
25	34	74	103	5	58	0	No Labour
26	30	68	187	9	203	1	Labour
27	22	63	100	2	47	0	Not Pregnant
28	29	66	149	6	78	1	No Labour
29	26	71	105	10	153	1	Labour

In this output we could see the addition of a new column named as conditions, which state the status of the women which was done using the Oxytocin and Contractions parameters for computing.

Input 4:

```
data.insert(6,"conditions","")
for i in range(0,len(data['Age']),1):
    if data['Oxytocin'][i]>=100 and data['Contractions'][i]>=7:
        data['conditions'][i]='Labour'
    elif data['Oxytocin'][i]<=50 and data['Contractions'][i]<=5:
        data['conditions'][i]='Not Pregnant'
    else:
        data['conditions'][i]='No Labour'
print(data)
```

Output 4:



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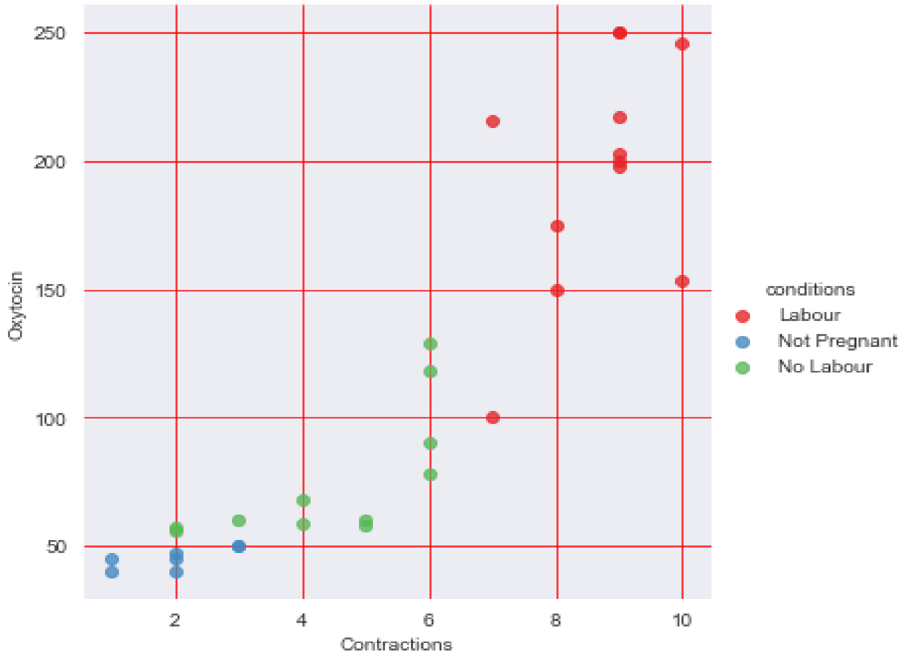
The above graph states a positive trend when analyzed through regplot() using seaborn library. With the analysis from Output 2 and Output 4 we can conclude that there is no deviation in trend when we go for a different analysis. So the two intended variables are having a strong association in terms of correlation.

Input 5:

```

sns.lmplot(x='Contractions', y='Oxytocin', data=data,
           hue='conditions', legend=True, palette='Set1',fit_reg=False)

```

Output5:



This graph states the type of conditions that exist using a lmplot(). All different category is illustrated in different color. Here the blue dots are at a position where Oxytocin and Contractions are at the minimal state. But the blue dot in Oxytocin(at exact50 in reading) is an exception case where a non pregnant women faces a maximal uterine contraction and oxytocin release.

The blue scatterplot denote the pregnant women with no labor pain. Here, the two green plot in Oxytocin(that exceeds 100 in reading). This states that the pregnant women has faced a false labor pain. This may occur due to minor stomach pain or any other health issue. So it is not considered to be parturition as muscle contraction has not exceeded the range.

The last red plot is the one that denote the labor pain.

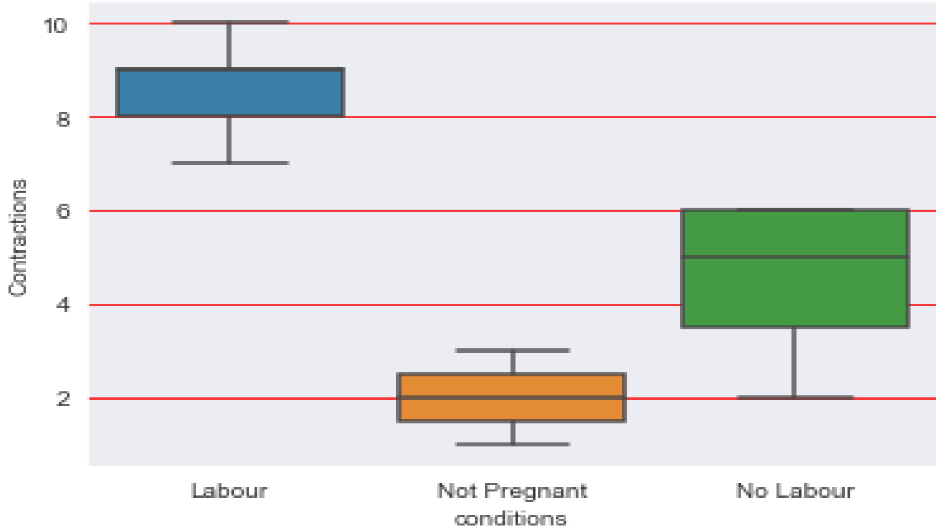
Input 6:

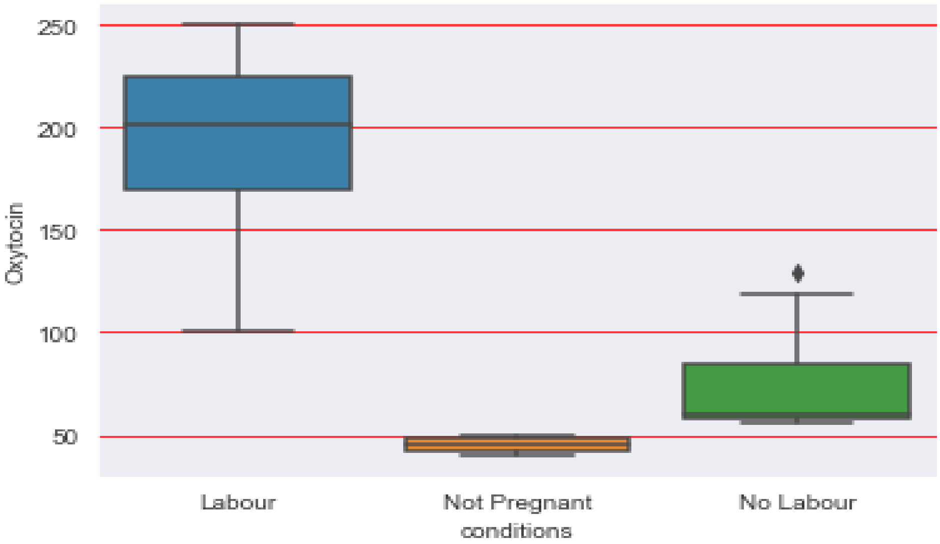
```

sns.boxplot(x=data['conditions'], y=data['Oxytocin'])

```

```

sns.boxplot(x=data['conditions'], y=data['Contractions'])

```

https://doi.org/10.56294/dm2023195

Output 6:





With the compared analysis between the two boxplots above states that the mean, median and mode of the analysis stands high for Labor, then for No Labor and least for Not Pregnant. With the comparison between the boxplots stating the action of Oxytocin and Contraction, states that with the extensive increase in oxytocin hormone the contraction of uterine muscle also increases drastically that may lead to labor pain. Most importantly after the comparison between the two boxplots if we notice the outlier on 'No Labor' in the fig, states that there can be excessive secretion of oxytocin without any hike in contraction that may lead to false prediction as labor pain. This should be rectified.

CONCLUSION

These analyzed data is pre-processed once again, visualized and correct outliers. This perfect data is incorporated into the sensor and is used for analyzing the pregnant women. A special band which is of a fine and wearable material is made, and the sensor is placed into it for wearing purpose.

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Research: Harshavardhan D, Saisree K, Ragavarshini S
Methodology: Harshavardhan D, Saisree K
Project management: Harshavardhan D, Saisree K, Ragavarshini S
Resources: Harshavardhan D, Saisree K, Ragavarshini S
Software: Harshavardhan D, Saisree K, Ragavarshini S
Supervision: Saisree K
Validation: Ragavarshini S
Display: Harshavardhan D, Saisree K, Ragavarshini S
Drafting- original draft: Harshavardhan D
Writing-proofreading and editing: Harshavardhan D