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An Intelligent Security for Preventing Infant Abduction and Ensemble Metaheuristics Optimization Algorithm for Data Regression

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Abstract- Newborn infant care is the most crucial and delicate area of biomedicine. Towards the goal of better infant care, a prototype is created that provides a dependable and efficient monitoring system. In this study, we explore the use of non-invasive sensors to construct a smart health monitoring system in an incubator. Health monitoring sensor system that simultaneously measures blood saturation levels (SpO2), heart rate, electrocardiogram (ECG), motion rate, JAUNDICE, weeping monitor system, and body temperature is designed and exhibited. This technology can identify the presence of harmful gases in the incubator in addition to monitoring the vital signs of the child. Because of its stability and simple plug-and-play functionality, the embedded system is built on the Arduino platform. With the help of a Wi-Fi module, the measured vitals are sent to the mobile application, where they can reassure worried parents and medical professionals. This method also verifies that the newborn is safe, which means that the infant's location can be required in the program by means of a GPS module, making it less likely that infants would be kidnapped or stolen. After the health monitoring sensor system has gathered the important parameters, the next step is to analyze the data than an ensemble metaheuristics optimization algorithm is used to do regression analysis, and statistical tests like ANOVA test have been done to show that the proposed algorithm is better and more powerful.

Keywords: *Health Monitoring, ECG , Metaheuristics, Ensemble Regression Analysis*

I. INTRODUCTION

Premature infant mortality has been reduced as a result of recent technological developments in the medical business. This is because premature newborn babies are often treated with the help of incubators. Premature infants rely on incubators, yet the atmosphere and operating conditions of these devices necessitate interactions between instruments and health care providers. The workload of the instrument-health carer are considerable, which leads to incorrect monitoring of the incubators [1], because the ratio of the number of carers to the number of newborns does not match, i.e., more infants and fewer carers. Premature newborns require oxygen and nutrients to survive. Additionally, the temperature should be just right. Premature infants placed inside conventional incubators have been observed to suffer from severe hypothermia. Premature babies are affected by temperature changes in the womb. The purpose of the incubator is to provide a stable environment for newborn infants born prematurely. This is due to the inability of premature infants to regulate their body temperature and immune systems. They are more susceptible to the effects of their surroundings. A minor shift in their environment might have a significant impact. Therefore, artificial gadgets are required to make these newborns viable in society. In 2010, there are reportedly 1.49 million low-birth-weight preterm babies born in the world. Additionally, even in underdeveloped nations, hospitals are often more than 8 kilometres away from the infant's residence [2]. Premature infants are the greatest challenge for professionals in the biomedical field.

Some premature infants face a higher risk of sickness or mortality than others due to their advanced gestational age or heart conditions. Physiological factors including heart rate, oxygen saturation, body temperature, blood pressure, etc., sometimes fluctuate in response to illness. The existence or absence of these disorders can be determined through a series of hospital-based examinations that involve comparing the results of various physiological parameters to reference norms. Recent developments in wireless sensor networks have led to numerous attempts in remotely transmitting newborn data to the mother. In this study, we suggest an intelligent control system for an infant incubator to aid in the treatment and observation of newborns. In the accompanying paper, we detail the hardware and software designs used to monitor a child's vital signs, transmit live video of the infant, and pinpoint the infant's position. This technology finds use in the intelligent infant incubator, where it provides streaming and tracking services for the purpose of infant care and health monitoring. The intelligent infant incubator system suggested in this research offers superior conditions and more consistent care for infants than the conventional incubator.

II. The proposed System

The proposed method centres on designing and implementing a closed-loop control system, as depicted in fig.1, that monitors and controls the neonatal incubator's temperature, humidity, and light intensity using Light Emitting Diodes (LEDs) to protect the infant from developing jaundice and ensure that he or she receives the right amount of oxygen. The system's implementation is split into three distinct sections: an android app on a mobile device, an Arduino board in the incubator with a Wi-Fi module, and a GPS module with a Wi-Fi module in the baby wristband. The incubator and the premature infant's body are monitored by a network of sensors, with the Arduino serving as the central control unit. The recorded or sensed data is wirelessly transmitted from the Mega via the Wi-Fi Module (ESP8266) to the Firebase platform.

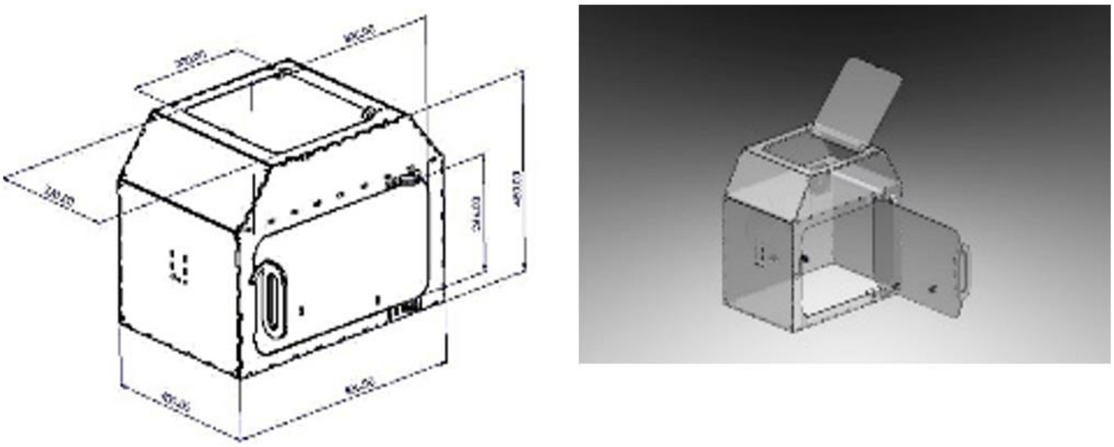


Fig.1 the proposed System

The proposed method centres on the development and implementation of a closed-loop control system to manage the neonatal incubator's environment, including the infant's temperature, humidity, and vital signs, the intensity of the light provided by Light Emitting Diodes (LEDs) to prevent jaundice, the ratio of carbon dioxide to oxygen, any noxious gases present, and the Infrared Thermometer's readings. The system's implementation is split into three distinct sections: an android app on a mobile device, an Arduino board in the incubator with a Wi-Fi module, and a GPS module with a Wi-Fi module in the baby wristband. The incubator and the premature infant's body are monitored by a network of sensors, with the Arduino serving as the central control unit. The recorded or sensed data is wirelessly transmitted from the Mega via the Wi-Fi Module (ESP8266) to the Firebase platform.

III. Hardware Implementation

Finding compatible components for the device was crucial. In order to compare "cost, handling, and convenience of use" among various control devices, a comprehensive study was conducted. Then, the controllers were chosen to enable tracking in the event of abduction, monitoring of the mother while the newborn was in the nursery, and the administration of numerous measurements of the newborn's fundamental vital rates. The Bi-Tracker app received the data from the IoT module.

1. Arduino Mega 2560 microcontroller Rev3

It was critical to locate components that worked with the gadget. A thorough analysis was performed to determine the relative "cost, handling, and convenience of use" of a number of different types of control devices. After that, the controllers were picked so that they could be used to keep tabs on the mother while the baby was in the nursery, take several readings of the newborn's vital signs, and locate the baby in the event of abduction. The information from the IoT module was sent to the Bi-Tracker app.

Fig. 2 Arduino Mega 2560 Microcontroller REV3

2. Arduino Uno

The ATmega328P forms the basis of the Arduino Uno microcontroller board.Fig.3 shows the board's physical components, including the USB port, power jack, ICSP header, reset button, and 14 digital I/O pins (6 of which might be utilised as PWM outputs).

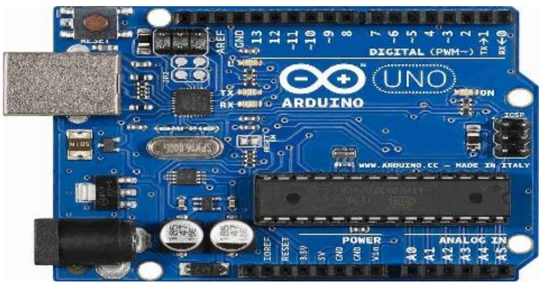


Fig. 3 Arduino Uno

3. Node MCU (ESP8266 Wi-Fi)

The Node MCU (ESP8266 Wi-Fi) has been used to bridge the gap between software and hardware. The ESP8266, a low-cost System-on-Chip (SoC), forms the basis for the Node MCU (Node Micro Controller Unit), which is based on open-source software. As seen in fig.4, it might either host the program itself or offload Wi-Fi networking tasks from another application processor.

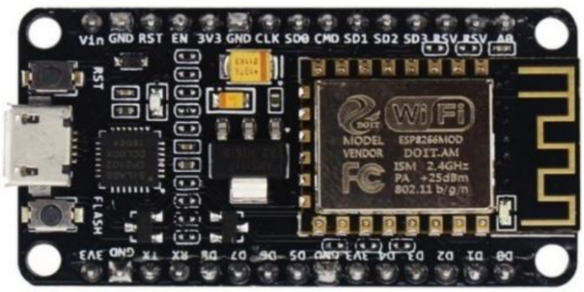


Fig. 4 Node MCU (ESP8266 Wi-Fi)

4. ECG Module AD8232

The AD8232 Single Lead Heart Rate Monitor served as an op-amp to help obtain a clean signal from the PR and QT Intervals, and the chip was developed to extract, amplify, and filter bio-potential signals for bio-potential measurement applications. Pins such as SDN, LO+, LO-, Output, 3.3V, and GND were present on heart rate monitoring sensors like the AD8232, as seen in fig.5.

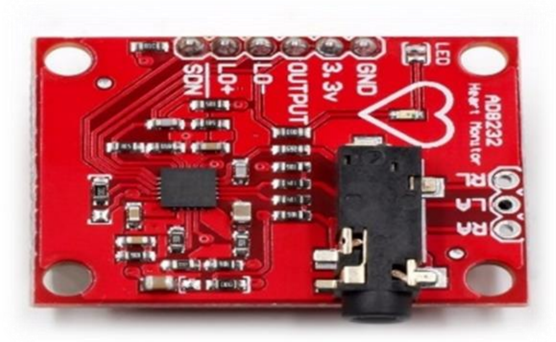


Fig. 5 ECG Module AD8232

5. Tcs3200 (Color Sensor)

There are four distinct filter configurations covering the diodes in this sensor. A total of 32 photodiodes—16 with red filters, 16 with blue filters, 16 with green filters, and the remaining 16 with no filters at all—make up the 8 × 8 array. The S2 and S3 inputs might be used to activate either variety. As can be seen in fig.6, each photodiode was covered with a unique set of filters, allowing it to pick up only the colours it was designed to detect.

Fig. 6 Tcs3200 (color sensor)

6. Max30102 (Pulse Oximeter SpO2)

The MAX30102 now features a built-in pulse oximeter and heart rate monitor. It had its own built-in LEDs, photodetectors, optical components, and low-noise, ambient-light-cancelling electronics. As shown in fig.7, the MAX30102 has supplied a whole system solution to simplify the design-in process for portable and wearable gadgets.

Fig. 7 Pulse Oximeter

7. MLX90614 (Non-Contact IR Temperature Sensor)

The MLX90614 can be thought of as a digital temperature sensor that uses infrared (IR) technology to measure temperatures from -70 degrees Celsius to 382.2 degrees Celsius. As shown in fig.8, the sensor employed infrared (IR) rays to measure the object's temperature without touching it, and it sent this information to the microcontroller using the I2C protocol.

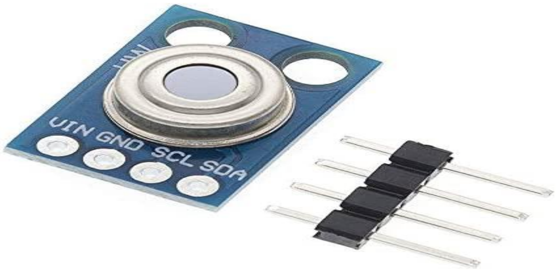


Fig. 8 MLX90614 Sensor

8. Gas Sensor MQ2

In the MQ sensor line, the MQ2 is one of the most used gas sensors. It is a Gas Sensor of the Metal Oxide Semiconductor (MOS) variety, often known as Chemi-resistors due to the fact that its detection relies on the sensing material's resistance changing as a result of contact with the Gas. A simple voltage divider network could be used to detect the gas concentration. As can be seen in fig.9, the MQ has a detection range of 200–10,000 ppm for gases.

Fig. 9 MQ2 Gas Sensor

9. KY-038 Sound Sensor Module

An amplifying circuit and a capacitance-sensitive microphone (50Hz-10kHz) make up the KY-038 sound sensor module. Sound waves have been converted into electrical signals using the module. It utilised a microphone for sound detection and sent that signal on to a processing circuit that included an LM393 operational amplifier. In addition, a potentiometer was included for adjusting the volume, allowing for simple control of the sound sensor module's output. The sensor's output can also be verified by attaching an LED or some other device to the output pins, as shown in fig.10.

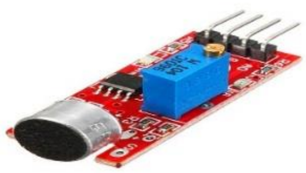


Fig. 10 Sound Sensor

10. Motion Circuit

The measurement of motion has been based on the use of both Laser and LDR modules as follows:

- **Laser Module 5mW, 650 nm**

This 5mW laser module emits a small intense focused beam of visible red light. The KY-008 Laser transmitter module consisted of a 650nm red laser diode head and a resistor as obtained in fig.11.

Fig. 11 Laser Module

- **LDR module**

This module has been able to detect ambient brightness, light intensity, adjustable sensitivity (via blue digital potentiometer adjustment), as well as it has been featured with wide-range voltage comparator LM393 with fixed bolt hole for easy installation as shown in fig.12.

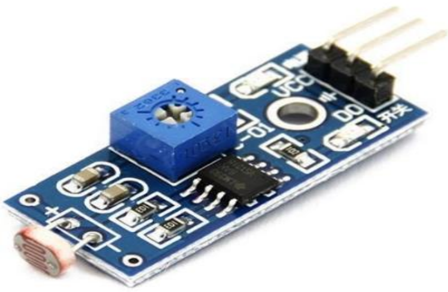


Fig. 12 LDR Module

11. ESP 32 CAM

The ESP32-CAM is a tiny, inexpensive development board that utilizes the ESP32 platform. It's proved great for Internet of Things use cases, prototype building, and do-it-yourself endeavors. Wi-Fi, regular Bluetooth, and low-power BLE were all built in to the board, which also had two powerful 32-bit LX6 processors. As can be seen in fig.13, its main frequency was adjustable from 80MHz to 240MHz, and it made use of a 7-stage pipeline architecture, an on-chip sensor, a Hall sensor, a temperature sensor, etc. Moreover, ESP32-CAM may find extensive deployment in numerous Internet of Things uses.

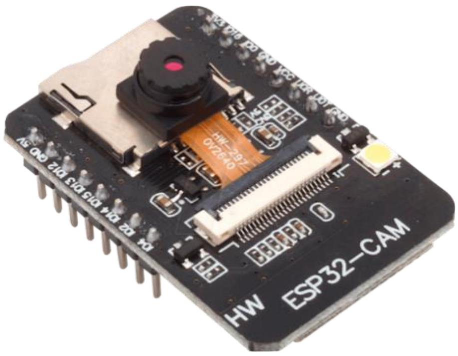


Fig. 13 ESP 32 CAM

12. NEO-6m GPS

The NEO-6 module series is a family of stand-alone GPS receivers featuring high-performance u-blox 6 positioning engines. These flexible and cost-effective receivers offered numerous connectivity options in a miniature 16 x 12.2 x 2.4 mm package as demonstrated in fig.14.

Fig. 14 NEO-6m GPS

IV.Software Application

The suggested mobile app is unusual in that it provides a communication protocol for real-time interchange of data on the patient's primary vital signs, allowing administrators, moms, and doctors to monitor the infant's health anytime, anywhere. The system's technical specs state that five variables can be measured with it: heart rate, SPO2, motion, temperature, and jaundice. The software not only tracks the baby's location but also provides a streaming service and a map. In addition, it details moms and doctors to facilitate communication. There are three distinct user interfaces in the proposed system: an administrative interface, a medical interface, and a maternal interface.

On the infant's display, the doctor can view a roster of the mother's previous offspring. A baby's profile screen, accessible via a click on the child's name, provides the doctor with access to the child's location and vitals, as well as streaming service. When you select the option to view baby's location, a map screen will load, allowing you to see the areas the baby has visited via a marker. Camera live stream is initiated by selecting to view baby's live camera, which launches a page in the browser displaying a live video, as shown in fig.15.

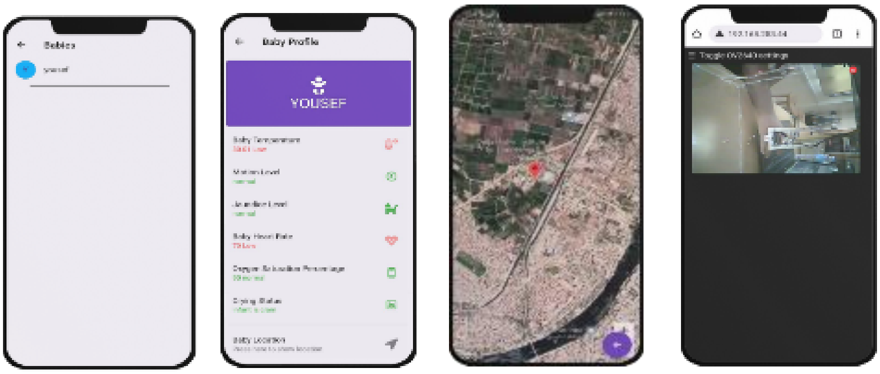


Fig.15 Babies Screen

V. Dataset

The design and presentation of a sensor system for continuous health monitoring allow for measuring many vital signs in real time. Sensors in this system record vital signs such as heart rate, EKG, mobility, temperature, jaundice, and tears. All these sensors work together for thorough, real-time health monitoring. It's helpful for medical professionals, careers, and patients alike to understand a patient's physiological condition better. Taking all these readings at once provides a complete picture of a patient's health and facilitates the early diagnosis and treatment of any problems that may arise [15-18]. This novel health monitoring sensor system exemplifies how cutting-edge technology may promote better medical outcomes and individualized wellness administration. The process of preprocessing data involves several stages that must be completed before the data can be correctly formatted and ready for analysis. The first thing that must be done is to handle any nulls or missing values in the dataset. This can be accomplished by locating the null values and selecting a suitable strategy for dealing with them after you have done so. The second step is to filter out the null values, which entails deleting any rows or columns that contain missing data. This is done because empty rows and columns can induce bias or influence the accuracy of the analysis. After the issue of null values has been resolved, the next step is to normalize the data via a technique such as min-max normalization or any other approach. This method frequently rescales the data to fit within a particular range. In this scenario, the values of each feature are altered such that the minimum value becomes 0, the highest value becomes 1, and all other values are changed proportionally to decimals between 0 and 1. The normalization method ensures that the many features are on a comparable scale, which prevents any feature from dominating the analysis due to its higher magnitude [19-21].

	SpO2	**Heart Rate**	**Motion Rate**	**JAUNDICE**	**Temperature**	**Weeping Monitor System**
1	0.005495	0.314214	0.219745	0.455882	0.081967	0.076647
2	0.008242	0.231920	0.149682	0.641711	0.081967	0.051497
3	0.010989	0.304239	0.159236	0.632353	0.049180	0.052695
4	0.013736	0.239401	0.219745	0.687166	0.049180	0.038323
...	...	...	...	...	...	...
3617	0.991758	0.364090	0.391720	0.784759	0.049180	0.049102
3618	0.994505	0.426434	0.372611	0.790107	0.065574	0.069461
3619	0.994505	0.416459	0.289809	0.754011	0.065574	0.076647
3620	0.997253	0.406484	0.289809	0.725936	0.016393	0.040719
3621	1.000000	0.407124	0.300753	0.776738	0.032987	0.048733

In addition, visualization methods are utilized to gain insights and comprehend the patterns within the dataset. Trends, outliers, and the relationships between variables are all easier to spot with the help of data visualization. Visual exploration of the data and the identification of recurring patterns are made possible through graphical representations such as scatter plots, histograms, and bar charts. The study of correlation is a further stage that is vital to the process. This requires analyzing how the different variables in the dataset are connected. Correlation analysis helps determine the intensity and direction of correlations between variables, which is useful information for comprehending dependencies and possible predicting factors. The degree of the linear relationship between variables can be evaluated by computing correlation coefficients like Pearson's, which can assist in selecting features and conducting more research [22-25]. In general, formatting nulls, filtering out null values, normalizing the data, visualizing the data, and performing correlation analysis all contribute to preparing the dataset for further analysis. This makes the dataset more appropriate for generating relevant insights and drawing correct conclusions [26-32].

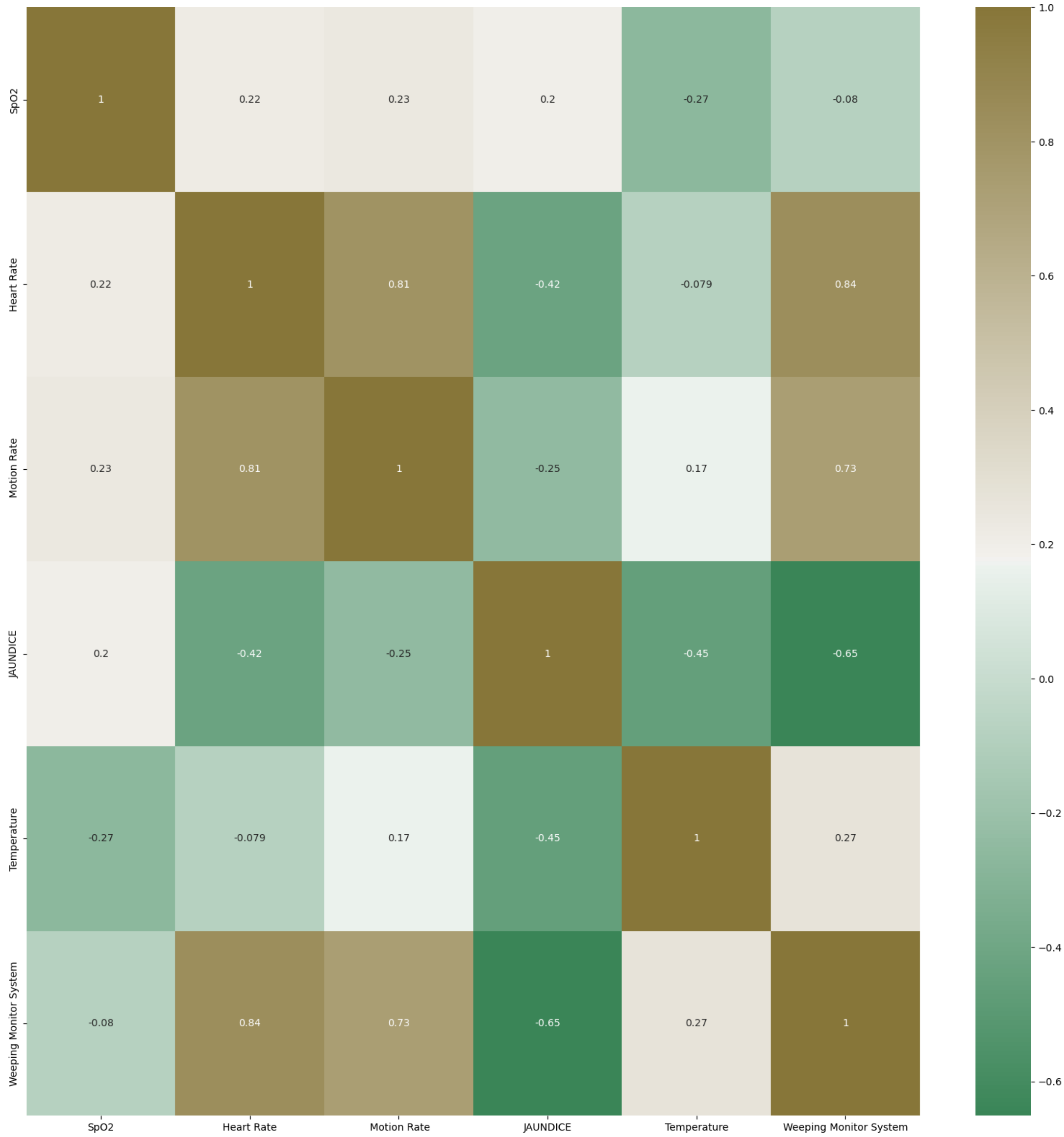


Fig 16: Correlation Matrix

VI.Proposed Metaheuristics Optimization Algorithm

Dipper Throated Optimization

The foraging behavior of birds, particularly flying and swimming birds, inspired the development of the Dipper Throated Optimization (DTO) algorithm. The following equations are used in DTO to determine how to update the positions and velocities of swimming birds:

$$BL_{nd}(t+1) = BL_{best}(t) - C_1 . | C_2 . BL_{best}(t) - BL_{nd}(t)| \quad (1)$$

Where $BL_{nd}(t)$ and $BL_{best}(t)$ are the normal location and best location of the bird at iteration t, and C_1 and C_2 are adaptive values whose values are changed during the optimization process based on the iteration number and random values. The update of the flying bird's location is performed using the following equation.

$$BS(t+1) = C_3 BS(t) + C_4 r_1 (BL_{best}(t) - BL_{nd}(t)) + C_5 r_1 (BL_{Gbest} - BL_{nd}(t)) \quad (2)$$

$$BL_{nd}(t+1) = BL_{nd}(t) + BS(t+1) \quad (3)$$

Where $BS(t+1)$ is the updated speed of each bird, r_1 is a random number in [0; 1], BL_{Gbest} is the global best location, and C_3 is a weight value, C_4 and C_5 are constants.

To simulate how birds, behave when they are naturally hunting for food, the DTO algorithm uses these equations to control the movement and updating of flying and swimming birds. DTO's goal is to speed up the process of finding the best solution to a given problem by adjusting the placements and speeds of the birds depending on these equations. This is done to optimize the search process.

Grey Wolf Optimization

When it comes to optimizing the Grey Wolf, a wolf that is an alpha, beta, or omega wolf is considered an inferior wolf (or delta, according to other references). The alphas and betas are considered lower in rank than the delta wolves, who dominate the omega. The members of this group include elders, hunters, and scouts. They depend on the hunters to assist them in their search for food, so the hunters provide the group with sustenance. The Sentinels are the ones that are responsible for ensuring the safety of the organization. The primary responsibility of a scout is to patrol the area around the group in search of potential threats and communicate those findings to the other unit members. The pack members that have previously held the positions of alpha or beta are referred to as the pack's Elders. How grey wolves hunt as a pack is an aspect of their social structure that is even more fascinating. The grey wolves surround their prey, as stated in the last report. The following equations can be used to represent the encircling behavior seen here and showing in Fig.16:

$$\vec{F}(t+1) = \vec{F}_p(t) - \vec{A} . \vec{D} \quad (4)$$

$$\vec{D} = |\vec{C} . \vec{F}_p(t) - \vec{F}(t)| \quad (5)$$

where $\vec{A}$ and $\vec{C}$ are vectors of coefficients, t represents the current iteration, $\vec{F}$ is the grey wolf's position vector, and $\vec{F}_p$ indicates the position vector of the prey. If there is a better solution in each iteration, $\vec{F}$ is updated to the best solution.

$$\vec{a} = 2 - t\left(\frac{2}{Max_{iter}}\right) \tag{6}$$

$$\vec{A} = 2\,\vec{a}.\vec{r}_1 - \vec{a} \tag{7}$$

$$\vec{C} = 2\,\vec{r}_2 \tag{8}$$

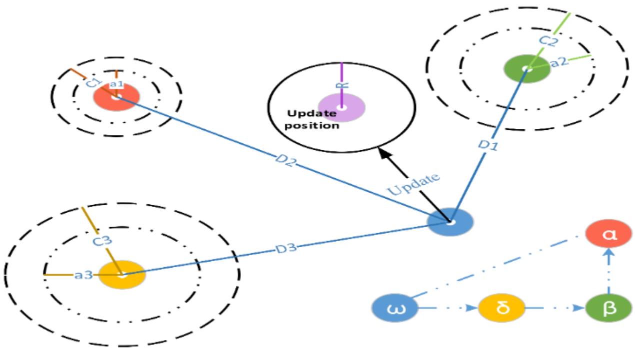


Fig 17: The hunting process of grey wolf optimization

The proposed algorithm GWDTO (Grey Wolf Dipper Throated Optimization)

Algorithm 1: The proposed GWDTO algorithm

Initialize birds locations BL_i $(i = 1, 2, 3, \ldots, n)$ with size n, BS_i $(i = 1, 2, 3, \ldots, n)$,
Fitness function Fn, f_n, r_1, r_2, r_3, R, C_1, C_2, C_3, C_4, C_5, $t=1$, and max iterations $iter\_max$
Evaluate fitness function Fn for each BL_i
Find best bird BL_{best}
While t < $iter\_max$ **do**
    for ($i = 1$; $i \leq n$) **do**
        If (R < 0.5) **then**
            Update Location of the gey wolf agents using:
            $\vec{D}_\alpha = |\vec{D}_1 * \vec{F}_\alpha - \vec{F}|$, $\vec{D}_\beta = |\vec{D}_2 * \vec{F}_\beta - \vec{F}|$, $\vec{D}_\delta = |\vec{D}_3 * \vec{F}_\delta - \vec{F}|$
        else
            Update Speed of the flying bird using:
            $BS(t+1) = C_3 BS(t) + C_4 r_1 \big(BL_{best}(t) - BL_{nd}(t)\big)$
            $+ C_5 r_1 (BL_{Gbest} - BL_{nd}(t))$
            Update Location of the swimming bird using:
            $BL_{nd}(t+1) = r_1 + z * r_2 + (1 - z) * r_3 + BS(t+1)$
        end for
    end for
    Evaluate fitness function Fn for each $\overrightarrow{BL_i}$
    Update R, r_1, r_2, r_3, c, C_1, C_2
    Find best bird BL_{best}
    Set $BL_{Gbest} = BL_{best}$
    Set t = t + 1
end while
return BL_{Gbest}

VII. Evaluation Results

Outlines the measures that were utilized in the evaluation of the suggested technique, along with the formulas that corresponded to each statistic. These measures are the root mean square error (RMSE), the normalized root mean square error (NRMSE), the Nash–Sutcliffe model efficiency (NSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the R2 metrics.
The key performance indicators used in assessing the proposed methodology

Key	Formula
NSE	$1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(y_i - mean\ of\ y)^2}$
RMSE	$\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2\right)}$
MAPE	$\frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{A_i - F_i}{A_i}\right\rvert$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert x_i - x\rvert$
NRMSE	$\frac{RMSE}{mean}$
R^2	$1 - \frac{unexpected\ variation}{Total\ variation}$

Table 1: Evaluation Results Machin Learning Models

Models	mse	rmse	mae	R2	RRMSE	MBE	SD	r	NSE
NearestNeighbors	0.0017	0.0418	0.0300	0.9667	0.0468	0.0008	0.0418	0.9832	0.9667
RandomForestRegressor	0.0037	0.0610	0.0462	0.9291	0.0683	0.0047	0.0609	0.9639	0.9291
SVR	0.0060	0.0773	0.0637	0.8863	0.0865	0.0064	0.0770	0.9415	0.8863
LinearRegression	0.0071	0.0842	0.0690	0.8650	0.0943	0.0102	0.0836	0.9300	0.8650
MLPRegressor	0.0072	0.0851	0.0700	0.8622	0.0952	0.0095	0.0845	0.9285	0.8622
DecisionTreeRegressor	0.0074	0.0861	0.0648	0.8588	0.0964	0.0072	0.0858	0.9267	0.8588

Ensemble regression models are used a lot in machine learning to improve the accuracy and reliability of predictions. In this situation, putting together the best three machine learning models—NearestNeighbors, RandomForestRegressor, and SVR—can improve the ensemble's performance even more. The GWDTO (Genuine Water Dipper Throated Optimization) Metaheuristics Optimization Algorithm is used to find the best way to optimize the ensemble regression model.

The nearest neighbors’ model is an algorithm that doesn't use parameters and makes predictions based on how close data points are. It finds the data points that are closest to a given place and uses the values of those points to make predictions. On the other hand, RandomForestRegressor is an ensemble model that makes predictions by putting together several decision trees. Each tree is trained on a random subset of the data and makes its prediction, which is then averaged to make the final forecast. SVR, which stands for "Support Vector Regression," is a powerful regression algorithm that uses support vectors to predict a function that doesn't change in a straight line.

The GWDTO Metaheuristics Optimization Algorithm is used to improve the ensemble regression model. The algorithm tracks the locations and speeds of the ensemble models to mimic the search for the best combination of models. It was based on how water dippers look for food. During the optimization process, the models' weights and values are changed so that the ensemble can make the best predictions possible. By using the GWDTO method to update the positions and speeds of the models over and over again, the ensemble regression model gets closer and closer to the best answer.

By combining the strengths of the NearestNeighbors, RandomForestRegressor, and SVR models within the ensemble framework and optimizing them with the GWDTO Metaheuristics Optimization Algorithm, the ensemble regression model can handle complex relationships and improve the accuracy of predictions. This method takes advantage of the differences between the models and uses an optimization algorithm to find the best mix. This leads to better performance and more accurate predictions in many regression tasks.

Table 2: Evaluation Results GWDTO Metaheuristics Optimization Algorithm Ensemble Regression

Models	mse	rmse	mae	R2	RRMSE	MBE	SD	r	NSE
GWDTO	0.0005	0.0002	0.0003	0.9987	0.0015	0.0000	0.0001	0.9998	0.9897

Statistical Results Analysis

The evaluation of the performance and efficiency of the GWDTO Metaheuristics Optimization Algorithm Ensemble Regression is made possible, in large part, by the statistical results analysis that is performed. The power and dependability of this ensemble methodology can be evaluated using several different statistical methods, such as the ANOVA test and the boxplot.

The analysis of variance, or ANOVA, is a statistical test that analyses the means of different groups to see whether significant differences exist between them. The test comes from the scientific term "analysis of variance." The analysis of variance (ANOVA) test can be utilized in analyzing the GWDTO Metaheuristics Optimization Algorithm Ensemble Regression to compare the ensemble's performance with that of alternative regression techniques or individual models. If we examine the variances and p-values, we will be able to establish whether or not the ensemble regression model performs noticeably better than other methods.

Table 3: Results of the one-way analysis of variance (ANOVA) tes

ANOVA	SS	DF	MS	F (DFn, DFd)	P value
Between columns	111.3	6	44.88	F (6, 77) = 78.51	P<0.0001
Within columns	40.89	57	0.6109		
Total	262.2	77			

Boxplots can also be used to visualize the distribution of prediction errors or performance metrics, which can be done when comparing the GWDTO Metaheuristics Optimization Algorithm Ensemble Regression against other regression models. Boxplots can also be used to compare the different regression models. The boxplot offers insightful information regarding the forecasts' variability, central tendency, and outliers. Regarding its prediction accuracy and robustness, the ensemble technique may be evaluated by comparing the boxplots of its many models. This allows us to determine the strategy's strengths and limitations.

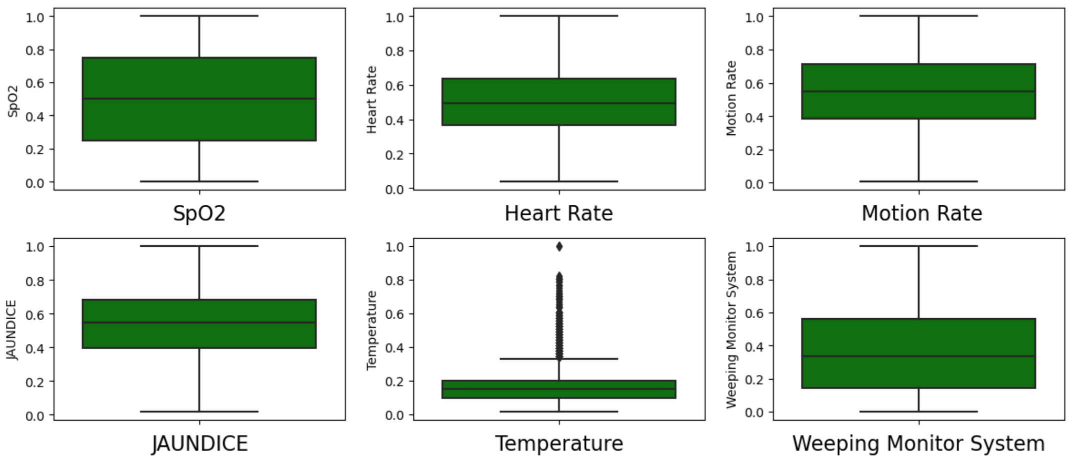
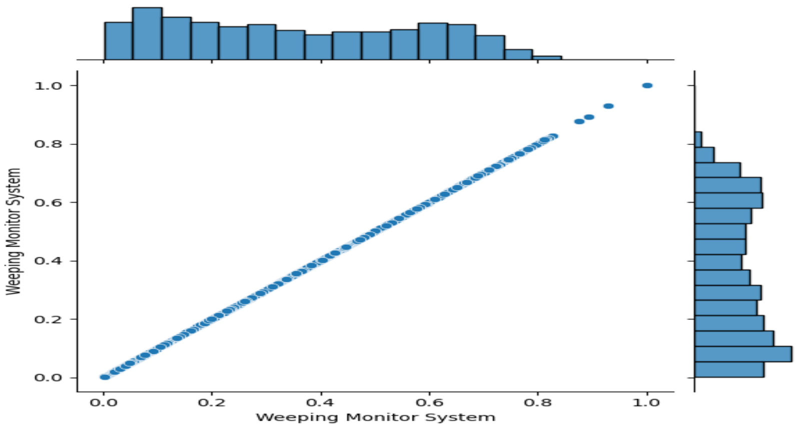


Fig 18: Boxplot Data

In addition, statistical results analysis can include metrics to assess the performance of the GWDTO Metaheuristics Optimization Algorithm Ensemble Regression, such as mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R-squared). These metrics offer objective measurements of prediction accuracy, making it possible to evaluate how well the ensemble can capture and describe the underlying relationships in the data.



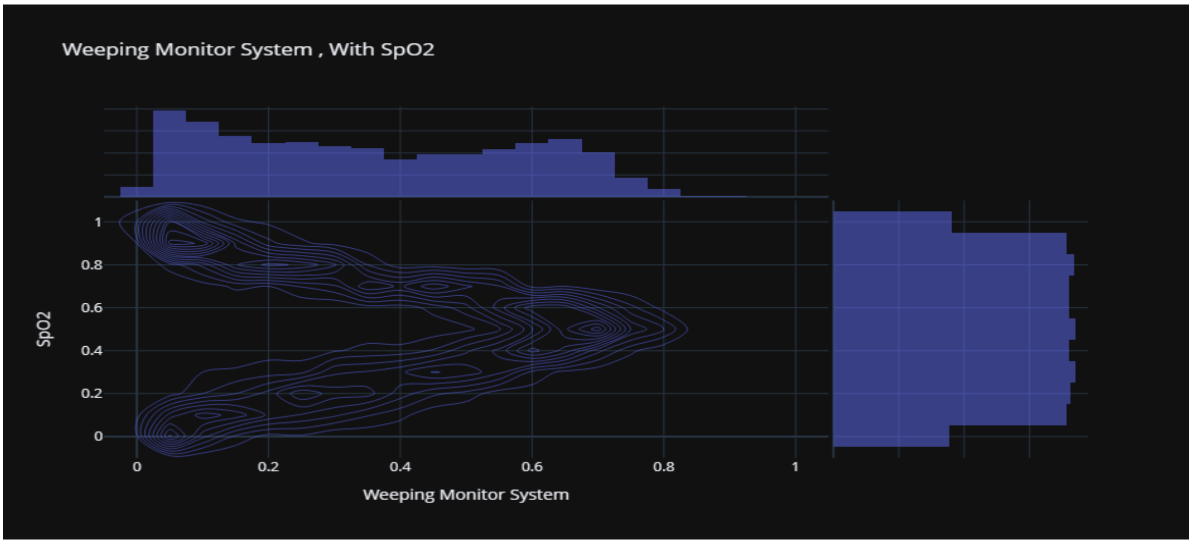
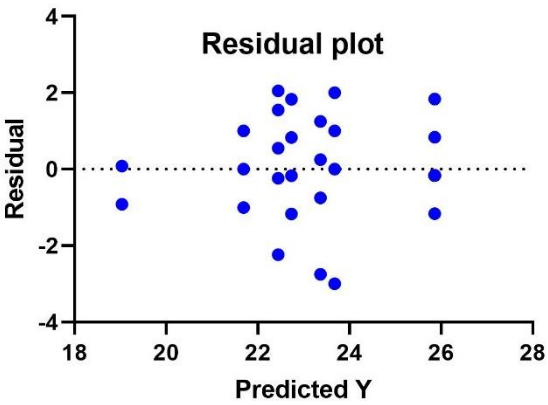
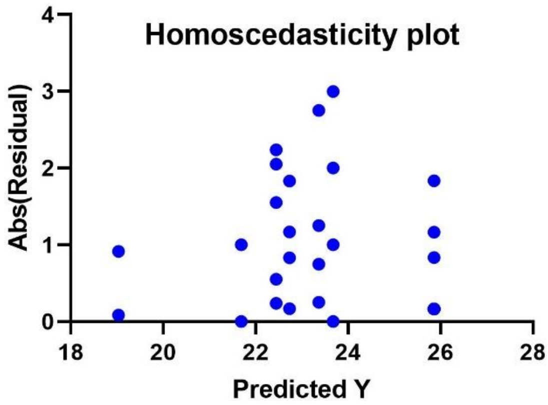


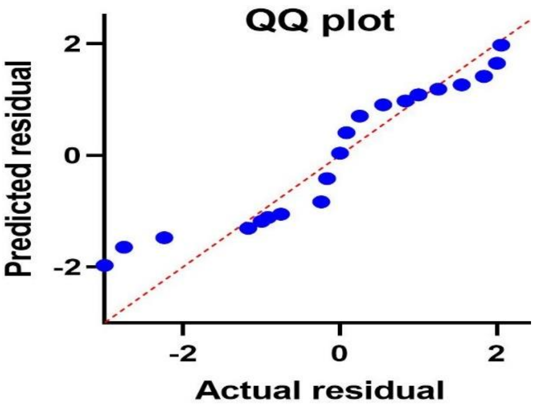
Fig 19: Statistical Results Analysis

Researchers and practitioners can acquire a more in-depth comprehension of the power and performance of the GWDTO Metaheuristics Optimization Algorithm Ensemble Regression by utilizing statistical methods such as the ANOVA test, boxplots, and performance metrics. These analyses provide quantitative evidence to support the claims that the ensemble approach provides improved accuracy, robustness, and reliability compared to other regression methods. As a result, they highlight the potential and advantages of utilizing the GWDTO Metaheuristics Optimization Algorithm in ensemble regression tasks.

More plots are shown in Fig. 20 that present the behavior of the residual, homoscedasticity, and QQ of the achieved results. In these plots, the proposed approach shows a promising performance







VIII. Conclusion

The health monitoring system is an important tool for diagnosing health problems before they become serious. The suggested technology would be able to track the baby's vital signs on a regular basis and evaluate them in relation to a set of typical values. If the current data deviates from the expected values, an alert will be sent to the doctor and the mother's smartphone so that they may both rest easy. In the event of an emergency, the doctor or career can utilize this data to better assess the baby's condition. The mother's presence serves as a constant signal of her baby's safety and whereabouts. The mother's worry over her baby's health in motion could be alleviated with the help of a smart camera that streams live footage to her device. The GWDTO has outperformed individual machine learning models and produced impressive statistical analysis findings. GWDTO uses Ensemble Regression to integrate NearestNeighbors, RandomForestRegressor, and SVR models to improve predictive accuracy. The ANOVA test, boxplots, and performance indicators show that the algorithm captures complicated relationships and improves prediction outcomes. The GWDTO method has proved its potential as a robust and dependable approach for Ensemble Regression, providing a viable solution for numerous regression applications and opening the way for metaheuristics optimization algorithm developments.

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