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Artificial Intelligence-Driven Neonatal Disease Diagnosis Using Efficient Particle Swarm Fine-Tuned Dilated Recurrent Neural Net: A High-Precision Deep Learning Approach

Saadya Fahad Jabbar[1], Asmaa Hussien Alwan[1], Nuha Sami Mohsin[1], Israa Ibraheem Al Barazanchi[2,3], Ravi Sekhar[4*], Pritesh Shah[4], Shilpa Malge[4]

[1] College of Education – Ibn Rushed for Human Science, University of Baghdad, Baghdad 10001, Iraq
[2] College of Computing and Informatics, Universiti Tenaga Nasional (UNITEN), Kajang 43000, Malaysia
[3] College of Engineering, University of Warith Al-Anbiyaa, Karbala 56001, Iraq
[4] Symbiosis Institute of Technology (SIT) Pune Campus, Symbiosis International (Deemed University) (SIU), Pune 412115, India

Corresponding Author Email: ravi.sekhar@sitpune.edu.in

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ABSTRACT

A kid born younger than 28 days is considered neonatal. The majority of deaths among children under five in Ethiopia are caused by neonatal mortality, which is a severe issue. Infant illness diagnosis and treatment require specialist medical resources with a wealth of experience and expertise. There are not enough of these professionals in the world, especially in low-income nations, which makes diagnosis and treatment more challenging. This paper presents an efficient particle swarm fine-tuned dilated recurrent neural net (EPASFN-DRNN) to build an artificial intelligence (AI) system of neonatal illness diagnosis. Min-max normalization refers to one of the preliminary processing steps, which is used to normalize the clinical data in order to reduce the number of unnecessary variances and enhance the quality of the input data overall. The dynamic nature of neonatal health problems must be captured, and the EPASFN-DRNN's capacity to handle sequential data and extract pertinent characteristics becomes critical. The experimental setup is implemented using the Python programming language, a versatile system to build and run deep learning (DL) models, due to its ability to extract contextual information of varying scales, which increases the capability of the model to recognize small trends in neonatal health data. The study determines the effectiveness of EPASFN-DRNN by contrasting the results with the results of the previous methods. The EPASFN-DRNN model makes predictions of neonatal diseases with a high result of 99.00, 98.60, 98.50, and 98.20 F1-score, recall, accuracy, and precision, respectively. The statistics confirm the capacity of the proposed model to diagnose patients in a correct and timely manner that would allow timely involvement of medical care and improve the health outcomes of newborns.

1. INTRODUCTION

Babies must spend their first 28 days of life adjusting to unfamiliar surroundings. This period is characterized by rapid development and progress, as well as the change from pregnancy to life outside the womb [1]. Common infections that cause infant mortality include sepsis (26%), tetanus (7%), diarrhea (3%), preterm birth (27%), and asphyxia (26%), especially in Sub-Saharan Africa. Even though the neonatal healthcare has made considerable progress over the past few years, the challenges associated with identifying the diseases in infants early and predicting them are still present; various neonates are susceptible to numerous health-related issues, and timely treatment is essential to their survival [2]. Artificial intelligence (AI) in neonatal health care is a concept that has massive potential to change the future of illness prediction and management in this regard.

For healthcare providers, many illnesses and complications go undetected, resulting in delayed treatments and potentially long-term effects. The use of AI in neonatal illness prediction aims to overcome these issues by using the capabilities of modern algorithms, machine learning (ML), and data analytics. AI is a growing topic of medical study. ML is a subset of AI that is capable of executing difficult tasks that would normally need human intellect [3]. ML techniques identify structures, develop methods, and adapt to new data. ML algorithms, as opposed to classic logistic/linear regression techniques, unravel nonlinear or binary interactions and produce extremely consistent predictions in big datasets where correlations are frequently difficult there are several models available in ML from which to select an appropriate method with the same sample use of high-performance computations into the healthcare system has resulted in enhanced patient care, safety and hospital efficiency [4]. A recent study employed computer modelling to predict which in-patient surgery patients will be released, diagnose and prescribe treatments for disorders affecting neonatal through a combination of automated learning and in-person knowledge acquisition interviews with health professionals. This study developed a knowledge-based system (KBS). ML with increasingly sophisticated intensive care offered to high-risk neonatal, AI in neonatal care has enormous potential [5, 6]. In the same way that blood tests and imaging are tools in the toolbox of healthcare professionals (HCPs), Figure 1 shows the schematic of the causes and effects of neonatal illnesses. AI should be seen as a means to facilitate shared clinical judgment, deliver effective, individualized neonatal care, and cut down on preventable mistakes.

Medical AI applications are used in developed countries because medical AI systems are sophisticated and require specialized resources. Despite these restrictions, there is a rising interest in using AI to solve the healthcare problems that the developing world confronts [7]. Global Health Initiatives (GHI) powered by AI has a proof of concept. The current situation of AI-based GHI examines important takeaways from past technology-centred health initiatives [8]. They provide a theoretical framework for global health to direct the creation of long-term sustainability [9] to improve infant health outcomes and lessen the strain on global healthcare systems, to allay these worries and open the door for the wider implementation of AI technology in neonatal care [10]. The aim of the study is to create and deploy an exhaustive AI-based framework for neonatal disease prediction that uses sophisticated ML algorithms and integrates a variety of datasets to improve the accuracy of early detection, enable customized medical measures, and lessen the impact of diseases on neonatal health.

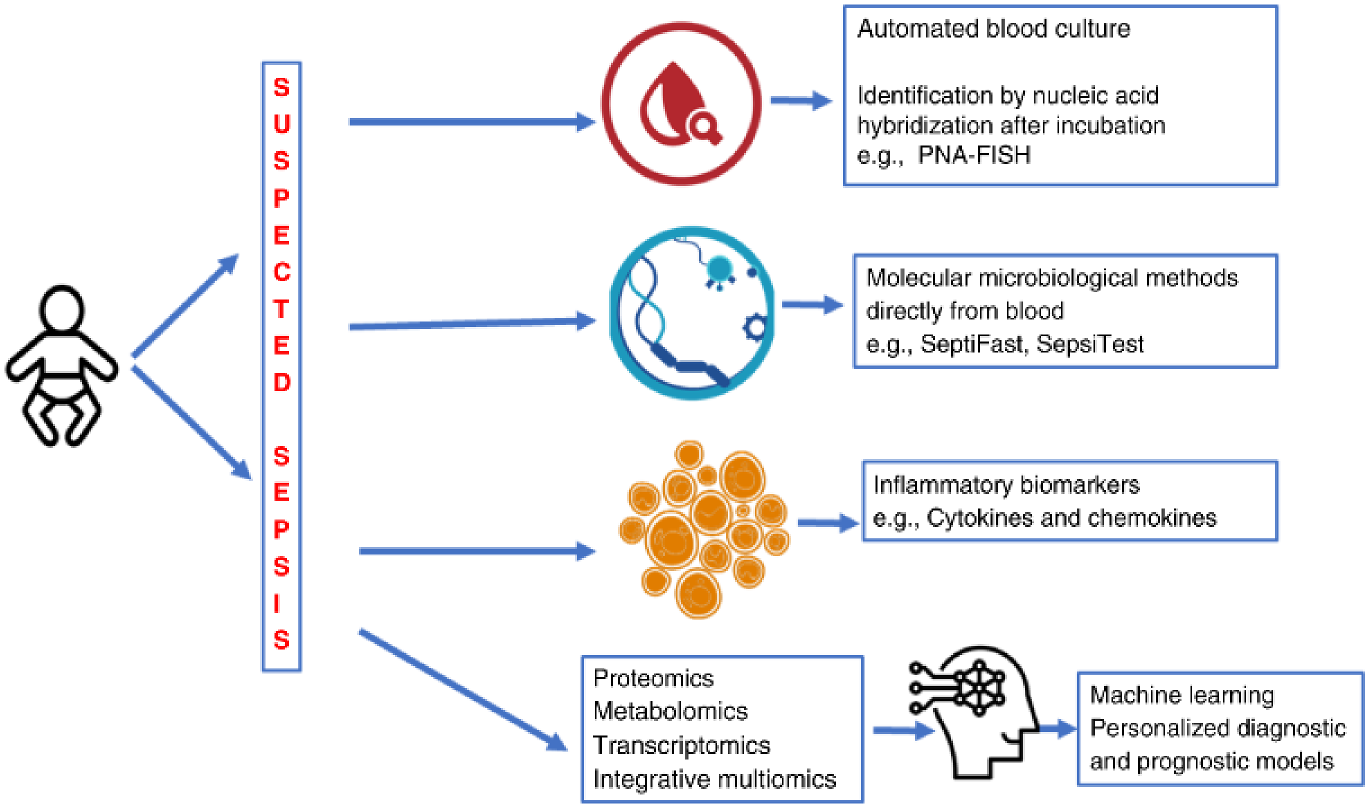

Figure 1. Causes and effects of neonatal illnesses interact

2. RELATED WORK

Kumar et al. [11] presented a summary of the research that has predicted or identified neonatal pathology by continuous examination of a single, their interactions, and the use of both clinical analytical techniques. They contend that big-data analytics holds a lot of potential and, with further work, can develop into an effective instrument to reduce neonatal illnesses in the twenty-first century. Ismail et al. [12] suggested that the given prophylactic antibiotics and the gut micro-biota included more anticipated genes linked to resistance to charged antimicrobial peptides and beta-lactamase. According to research using important microbial markers that differentiate between "beneficial" and "harmful" (diarrheic) gut micro-biota include Ruminococcus 2, Erysipelatoclostridium, uncultured Lachnospiraceae, Trueperella, and Streptococcus. These are found in the random forests ML technique.

Husada et al. [13] determined that healthy controls (154 cases) medical records provided the data. The sepsis category contained confirmed instances of bacterial neonatal sepsis. The neonatal in the non-sepsis group were free of infections. Risk variables, clinical circumstances, laboratory data, and treatment methods were considered potential predictors. Multiple logistic regression analysis served as the foundation for the model's development. Nadweh et al. [14] provided a secondary analysis of the multicenter, prospective, worldwide NeoPInS trial participants administered penicillin throughout the first 72 hours of life following 34 weeks of gestation because they were suspected of having early onset sepsis (EOS). The primary result was defined as the ability to predict proven by society EOS prior to beginning antibiotic treatment using established criteria. An RF was used to apply data mining to the system.

Table 1. Comparison of current methods and the contributions of EPASFN-DRNN

Current Method	Problems and Limitations	Importance of this Study and Solutions
SVM	Limited performance in handling high-dimensional, sequential data. Struggles with complex nonlinear relationships, leading to reduced accuracy in neonatal disease prediction.	The study introduces EPASFN-DRNN, which excels in managing sequential data and capturing intricate patterns in high-dimensional datasets, significantly improving diagnostic accuracy and addressing SVM's limitations.
RF	Susceptible to overfitting with noisy or imbalanced data. Limited scalability for large datasets with multiple features.	By leveraging particle swarm optimization and advanced neural network architectures, this study mitigates overfitting and enhances scalability, ensuring robust predictions even in diverse and imbalanced datasets.
XGB	Effective but computationally expensive, making it less practical for real-time applications. Requires extensive feature engineering.	EPASFN-DRNN reduces computational complexity through optimized processing techniques and handles feature extraction automatically, making it more efficient and suitable for real-time neonatal health monitoring.
Stacking	Complexity in model integration and interpretability. Requires significant effort in model selection and ensemble configuration.	The proposed model integrates multiple optimization techniques within a single framework, reducing complexity while maintaining high interpretability and providing a streamlined solution for neonatal disease prediction.

Note: EPASFN-DRNN = Efficient Particle Swarm Fine-Tuned Dilated Recurrent Neural Net; SVM = Support Vector Machine; RF = Random Forest; XGB = XGBoost.

Nadweh et al. [15] described the term infants hospitalized visiting the Hospital for the Care of Babies at Smyrna Katip Celebi University, Ataturk Campus, with EOS and physiological jaundice examined. Thirty-term infants with EOS were included in the examination of 63 neonatal files, and as a comparison group, thirty included term neonatal whose bodies showed signs of hepatitis in the examination of 77 neonatal files. Nadweh et al. [16] provided a frequent systemic condition that causes morbidity and death in infants called neonatal sepsis NS. However, there wasn't a perfect biomarker for NS that could be used for early detection. According to current research, the platelet-to-lymphocyte ratio (PLR) was important for the course of inflammation. The study was to further the investigation into the potential use of PLR as an early diagnostic indicator for NS. Salih et al. [17] suggested that the most frequent major consequence of prematurity pneumonia (BPD) was thought to be influenced by lung macrophage maturity in preterm newborns. Here, they demonstrate that while evaluating changes in pulmonary macrophage transcription in premature babies at risk of BPD, it was shown that individuals who had BPD had elevated production of inflammatory mediators even on the first day after life. Abdtawfeeq et al. [18] described resuscitation skills training step-by-step, procedures for monitoring the heart rate in neonatal for detection purposes; methods for detecting oxygen exhaled in neonates, adults, and children; magnesium during cardiac capture; doubling the procedure; neuron prognostication in kids and adults following cardiac arrest, and keeping the body humidity normal during preterm delivery. Table 1 outlines the limitations of commonly used methods in neonatal disease diagnosis, including support vector machines (SVM), random forest (RF), XGBoost (XGB), and stacking, highlighting issues such as overfitting, high computational costs, and challenges in handling sequential data. The proposed study which is the efficient particle swarm fine-tuned dilated recurrent neural net (EPASFN-DRNN) model fills these gaps by utilizing the advanced neural network architecture and optimization methods. It enhances the precision of diagnosis, minimizes the computational cost, and simplifies feature extraction which makes it a revolutionary tool in real-time and high accurate neonatal healthcare applications.

The study is highly valuable to me since it will resolve the most crucial issues of the current technologies by suggesting a new deep learning (DL) architecture called EPASFN-DRNN, which is, first of all, aimed at predicting neonatal diseases. This novel method enhances the accuracy, precision and the recall levels, and decreases the computational load and is the most suitable method in sequential data to trigger a revolution in the field. The high-detailed study with a 98.5% level of accuracy along with a 99% F1-score highlight that the process of healthcare in the newborn sector can be transformed by predicting and diagnosing diseases in early stages. The latter will be particularly true in the scenarios of low-resource conditions. This resulted in timely diagnosis, positive outcome of patients, and filling the weaknesses of the existing research by providing an entity that can easily be scaled, is effective, and doable.

3. METHODS AND MATERIALS

The theoretical approaches to neonatal practice have been utilized and have formed the core of the most effective methods of treatment and prevention of the diseases of the newborns. These are the integration of diverse approaches to simple statistics to the advanced and ML models directly aimed at fighting the specifics of the neonatal care system. The three ML tools, including SVM, RF, and XGB, are popular in disease prediction and classification in neonatal care. These types of algorithms have the capability of identifying crucial associations within clinical data, which give a glimpse of illnesses such as neonatal sepsis, respiratory distress and preterm birth issues. Also crucial, in the field of the sophisticated DL modules like the dilated recurrent neural network (DRNN) and the fine-tuning of the efficient particle swarm DRNN, new tools are being created which are influencing medical diagnosis.

EPASFN-DRNN, e.g., a model that can diagnose disease with 98.50% accuracy and 99.00% F1-score error, is a good choice for the treatment and early detection of neonates. The practice of data quality and uniformity is introduced through the help of the extra preprocessing procedures alongside min-max normalization. They are essentially aiding in the process of obtaining the best possible results from these models.

Although there has been progress in neonatal health care, technology practical application, there are still some areas that need further work. One of the most significant problems is the low availability of advanced technologies in these income-lacking places. Because these models of AI exhibit high accuracy and precision, they are, however, still subject to deficiencies hindering widespread acceptance because of the infirm situation in the mentioned regions. Another problem lies in the fact that the current models are not generalizable, and they are mostly trained on limited data, making it difficult to use them on different types of populations and in various clinical conditions. There is also an issue of integration where AIs-based tools must have the ability to integrate with the already established healthcare processes, along with electronic health records. The other side of the coin is that the existing models cannot provide real time information which is a drawback in neonatal care, especially in cases where the issue may change very rapidly during the process.

The new frontier in health care has presented wondrous opportunities of reducing the gaps. GHI can be propelled by AI and become the reason why advanced technologies can be transferred to the less fortunate regions, thus being more universal and more enduring. Integrating big data analytics into ML and DL models would be able to enhance our understanding of the pathophysiology of a disease; hence, more accurate predictive tools are created. The most vanguard is precision medicine and personalized medicine where genetic and epigenetic data will be utilized to create individual treatment regimens, which can prove to be a real blessing in the instance of a neonate. Moreover, the radical transformation of healthcare may be the result of the application of the AI technology to the Internet of Things (IoT) devices in the neonatal intensive care environment. IoT provides real-time monitoring, which can be used to control health measurements in a continuous manner and, therefore, allow preemptive and reactive actions in the event of emergency situations.

Neonatal health has been advanced to a great inclusive level because of the state of theorizing. One of the primary goals of hitting the gaps that have been pinpointed through the use of focused innovations is the quest for the full employment of their potential. A workable, universal, and complete system with the use of new technologies, which will be adjusted by promoting fairness and personalized care to be the first choice, can bring better outcomes in neonatal health, decreased mortality rates, and an equitable and fairer healthcare system all over the globe.

An effective foundation for developing an AI-powered infant sickness prediction system is established by the proposed method. The key component of our strategy is obtaining a dataset from neonatal diseases that contains significant neonatal health variables. It emphasizes meticulous data preparation techniques like min-max normalization. Figure 2 shows the flow of the proposed methodology.

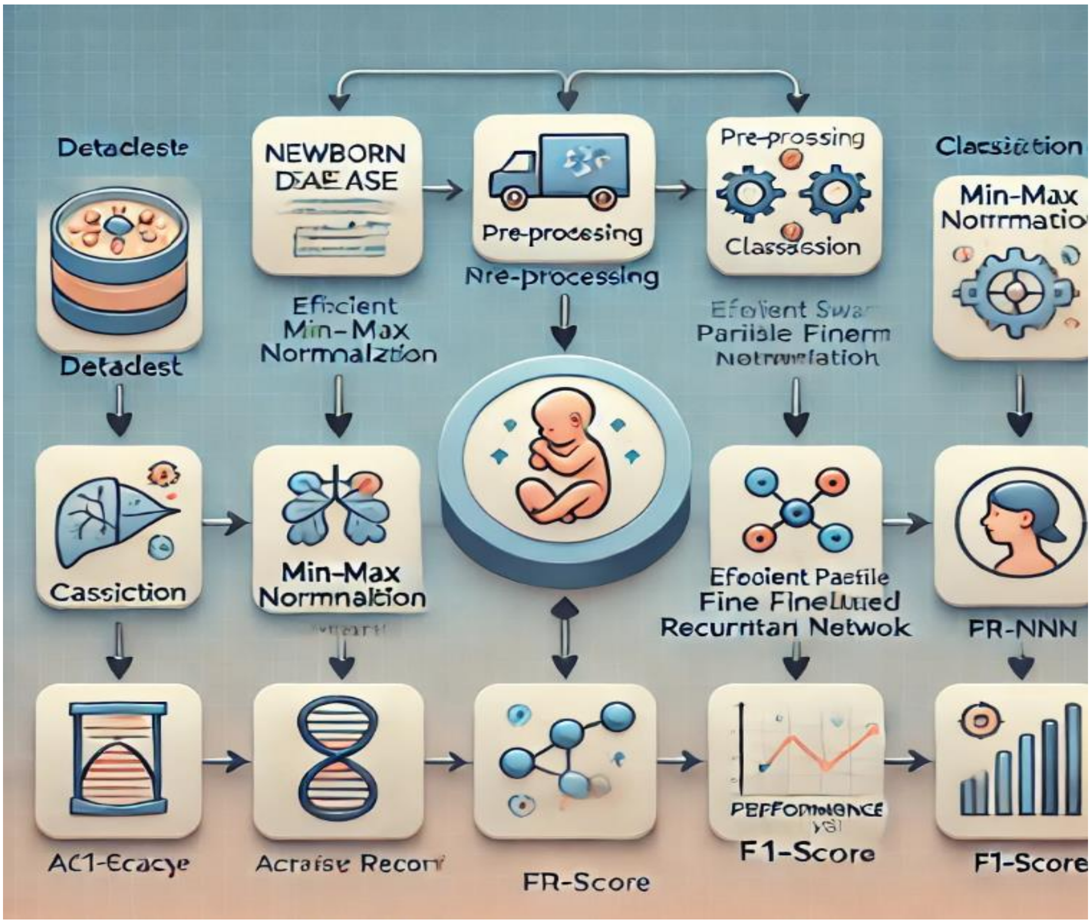

Figure 2. Flow of proposed methodology

3.1 Data collection

Gandhi Memorial Hospital (GMH) clinical dataset [19], Addis Abeba, Ethiopia, was gathered to extract the hidden knowledge. This has led to the collection of 2372 occurrences in total consisting of 16 characteristics and the class has three labels. A detailed data collection process is essential to accurately represent data needed by neonatal healthcare research and develop powerful models of disease diagnosis and prediction. This entails obtaining various and quality information that is of good quality and is of reliable sources and ethical considerations such as informed consent and the confidentiality of data is maintained. The specific details of the data collection process along with the particular questions and parameters that were taken into account in surveys and clinical data collection are described below. Data collection process:

1) Data Source: The main type of data in the neonatal healthcare research typically includes data provided by hospitals, healthcare institutions, or longitudinal research. As an example, in the given study, the clinical data were collected in the Gandhi Memorial Hospital, Addis Ababa, Ethiopia. This dataset consisted of 2372 cases, which had 16 features and three classifications that were labeled according to neonatal health outcomes.
2) Survey Design and Focus Areas: Survey and interviews with caregivers, mothers and healthcare providers were performed to supplement clinical data. The purpose of these surveys was to obtain an overall picture of neonatal health and factors which could affect it [20-32].
3) **Categories of Data Collected**:
   - o **Maternal Health**: Questions focused on prenatal care, maternal age, health conditions during pregnancy, and medication use.
   - o **Birth Details**: Information on gestational age, mode of delivery, birth weight, and complications during labor.
   - o **Neonatal Health**: Initial APGAR scores, signs of distress, respiratory conditions, infections, or abnormalities observed in the first few days post-birth.
   - o **Family and Environmental Factors**: Socioeconomic status, access to healthcare facilities, and exposure to environmental risks (e.g., pollutants, malnutrition).
4) **Specific Questions Asked**: The surveys included both structured (closed-ended) and semi-structured (open-ended) questions to gather quantitative and qualitative data. Examples of questions are provided below:

Maternal Health Questions:
- o Did the mother receive regular prenatal check-ups? (Yes/No)
- o Were there any complications during pregnancy? (E.g., hypertension, diabetes, anemia)
- o What medications or supplements were taken during pregnancy? (List or select from options)
- o Was there a history of infections or illnesses during pregnancy? (Yes/No; if Yes, specify)

Birth Details Questions:
- o What was the gestational age at delivery? (Specify in weeks)
- o What was the mode of delivery? (Normal, cesarean, assisted)
- o What was the birth weight of the neonate? (Specify in grams)
- o Were there any immediate complications post-delivery? (E.g., difficulty breathing, low oxygen saturation)

Neonatal Health Questions:
- o What were the APGAR scores at 1, 5, and 10 minutes? (Specify values)
- o Were there signs of sepsis, jaundice, or respiratory distress? (Yes/No; if Yes, provide details)
- o Was the neonate admitted to the Neonatal Intensive Care Unit (NICU)? (Yes/No; if Yes, duration of stay)
- o What treatments or interventions were provided? (E.g., antibiotics, oxygen therapy, phototherapy)

Family and Environmental Factors:
- o What is the household income range? (Select range)
- o What is the level of education of the mother and father? (Select the highest level completed)
- o Does the household have access to clean water and sanitation facilities? (Yes/No)
- o Are there any known environmental hazards near the home? (Yes/No; if Yes, specify)

5) **Clinical Data Parameters:** Clinical data were obtained out of medical records and comprised:
   - o Laboratory Findings: Complete blood count, Infection Markers.
   - o Vital Signs: Heart rate, respiratory rate, and oxygen saturation.
   - o Diagnostic Imaging: X- rays, ultrasounds and echocardiograms where necessary.
6) **Data Checking:** To be accurate, several verification measures have been taken:
   - o The trained personnel cross-checked the data entry.
   - o The gaps in the data were identified and reconsidered to reduce gaps.
   - o Incomplete or outlier data was taken care of by using statistical methods where needed.

This empirical method of data gathering helps researchers to create datasets, which are rich in informative elements, but representative of the complexity of neonatal health, which is needed to create effective AI-based diagnostic models.

3.2 Pre-processing using min-max normalization

Data pre-processing refers to the conversion of data and its preparation to useful use. Pre-processing involves cutting down the data, establishing relationships, standardization of the data, removing anomalies and deriving the features of the data. There are several methods employed, such as, minimization, integration, cleaning and transformation is the primary objective of normalization. Although the data is normalized, Min-Mix goes through a number of linear adjustments. The original data's integrity can be preserved with this technique. A simple approach for fitting data inside a predefined restriction is min-max normalization.

$$T' = \left(\frac{T - minvalue\ of\ T}{maxvalue\ of\ T - minvalue\ of\ T}\right) * (Y - X) + X \qquad (1)$$

- T': Data that has been adjusted using min-max.
- $[Y, X]$ has already been established.
- T: baseline data set.

Normalization using K-scores is a method for extracting meaningful information from unstructured data sets by using concepts such as numerical variables. Unstructured data can be normalized using the K-score parameter, as the following equation illustrates.

$$q\acute{a} = std^{qa-}(B^{\bar{B}}) \qquad (2)$$

- q_a': The K-score served to standardize an individual's worth.
- q_a: The value of row *c*.

$$std^{(B)} = \sqrt{\frac{2}{(r-2)}\sum_{j=1}^{r}(q_a - \bar{c})^2} \tag{3}$$

$$\bar{B} = \frac{1}{r}\sum_{j=1}^{r} q_a \tag{4}$$

In decimal scaling, a scale is established from -1 to 1. Therefore, decimal scaling is used.

$$q^a = q_x \tag{5}$$

- q^a: Scaled value.
- q: Range of values x-smallest integer max ($|q^a|$) < 1.

Min-max normalization results in a linear conversion of the original data.

Assume that the lowest and highest possibilities for parameter E are Min_x and Max_x.

By computing: $[new - minx, new - maxx]$, through min-max normalization, e' in the range is transferred from E to e'.

$$E' = ((e - min_x)/(max_x - min_x)) * (new - max_x - new - min_x) + new - min_x \tag{6}$$

In w-score normalization, the data for parameter E are normalized using the average score of E. Formula for normalizing E to e' is as follows:

$$\grave{e} = ((e - \bar{X})/\sigma_X) \tag{7}$$

3.3 Neonatal disease prediction using an efficient particle swarm fine-tuned dilated recurrent neural net

The specifics of neonatal healthcare through the application of EPASFN-DRNN, the model gets skilled at identifying minute patterns and variances in health data by fine-tuning the neural network using particle swarm optimization. This enables more accurate and timely forecasts of probable illnesses in the neonatal community.

3.3.1 Dilated recurrent neural network

DRNNs rely on sequential data as their fundamental premise. DRNN loops rely on the results of previous computations; it is crucial to know which word is before the one that is predicted in a sequence. Although DRNNs are free to use any amount of sequence data they choose, they can search in the past because of the problems of gradient explosion and gradient disappearance. Displays the Kth value's route direction *Ω* is used to determine one lateral stability index and reaches zero if the vehicle travels straight.

$$\Omega = \frac{\sum_{j=i}^{i+n-1}|\psi_{j+1} - \psi_j|}{n-1} \tag{8}$$

The inputs of $y\ [d]$ and the outputs of $y\ [d]$ are found in a single GRU unit. $y|\ [d-1]$ is computed using $y\ [d]$. The accurate computation is displayed in the following formats.

$$k = \sigma(U_k y[d] + W_k z|[d-1]) \tag{9}$$

$$\hat{z} = \tanh\left(Uy[d] + W(k \odot z[d-1])\right) \tag{10}$$

$$z[d] = (1-h) \odot z[d-1] + h \odot \hat{z} \tag{11}$$

$$\sigma(y) = \frac{1}{1 + \exp(-y)} \tag{12}$$

$$Sil = \frac{1}{m}\sum_{j=1}^{r}\sum_{y \in V_j}\frac{p(y) - e(y)}{\mathrm{Max}(e(y), p(y))} \tag{13}$$

The units are governed by four parameters (U_k, U_h, Uy, *U*), They require more parameters than a simple unit and keep track of past data. This unit is utilized in computations exactly like a typical synapse because its inputs and outputs are unrelated to each other.

3.3.2 Efficient particle swarm optimization

There are N particles in the swarm according to the efficient particle swarm optimization (EPSO) technique's ideal bias and weight values. The EPSO is a heuristic search strategy that draws inspiration from the cooperative or swarming behaviour of biological groups. It is a smart strategy of adaptive optimization that improves a candidate solution in terms of a given quality measure by optimizing a problem, as a possible solution to the optimization issue is an arbitrary value between 0 and 1. The optimal solution h is found after the specified number of iterations, and it is used to initialize the variables. The step of optimization is terminated by the algorithm upon convergence of the evaluation function, at which point the original weights and bias are determined as the ideal solution; if not, the iterations persist. Algorithm 1 describes the procedures used to optimize the EPSO.

$$v(s+1) = \omega v(s) + d_1 q_1\left(a_s - w(s)\right) + d_2 q_2\left(h - w(s)\right), \tag{14}$$

$$w(s+1) = w(s) + v(s+1) \tag{15}$$

where, $v(s+1)$ indicates the particle's speed in real time (s + 1), ω indicates the weight of inertia, $v(s)$ is the speed at this time d_1 and d_2 are momentum factors, with 1.6 and 3 being the equivalent values q_1 *and* q_2.

Algorithm 1: Particle Swarm Optimization

Set *the EPSO variables, i.e.,* d_1, q_2, ω, *the maximum quantity of repetitions*
S_{max}, *and the number of particles* n
1) *For every particle,* $O_s(s)$
2) *Use the provided particle to do EPASFN learning*
3) *Creating out F using (5) and set fitness value* $k_s(s) = E$
4) *Current particle positions and velocities as optimized by the fitness function, that is, by using Eqs. (7) and (8)*
5) *Provide the best answer, h, using the SSAE's values and bias if the evaluation function converges*
6) *Provide the best answer, h, using the SSAE's weights and bias if the evaluation function connects*
7) *Alternatively, start the iteration process again from step 1*

Data collection process of neonatal healthcare research is essential in developing correct and valid predictive models. To obtain the high quality of data representing the complex play of factors determining neonatal health, it is necessary to have a clear data collection strategy. In this specific research, the data were collected in the Gandhi Memorial Hospital located in Addis Ababa, Ethiopia which is considered to be one of the best hospitals in regard to its services with respect to neonatal care. The data set applied in the study comprised 2,372 cases, including 16 features and three labeled classes that provide an in-depth base to be analyzed. The choice of GMH as a source of data was due to its reputation in the treatment of various conditions affecting the neonatal population, it is a referral clinic and the medical records are documented and standardized.

Sampling Strategy and Selection Criteria: The purposeful sampling strategy was used to make sure that the dataset was representative of a vast spectrum of neonatal health outcomes. The samples were composed of the neonates that were provided with either normal care or specialized care within the facility within a given period. The inclusion criteria aimed to reflect the variability of the neonatal cases including preterm and term births, neonates who had infections or respiratory issues as well as those who needed intensive care interventions. The inclusion criteria was used to filter out the incomplete records or cases without the necessary diagnostic or treatment information, which might otherwise influence the analysis. The selection bias was minimized by recruiting neonates with different socioeconomic backgrounds, geographic locations, and health conditions. The inclusion of high-risk and low-risk neonates also contributed to developing a more balanced dataset, which enhanced the generalizability of the results. In addition, the dataset included maternal health, environmental determinants and family history to address more general determinants of neonatal outcomes.

Data Collection and Surveys: To gather the complete picture of neonatal health, including both quantitative and qualitative information, the process of data collection included the combination of clinical records and surveys data. The data collection process involved retrieval of clinical data through hospital records in the form of birth data, laboratory findings, and treatment records. The surveys were carried out among the medical professionals, mothers, and caregivers as they were found to provide contextual information on maternal health history, environmental factors, and access to healthcare services. The structured survey questions were aimed at the measurement of the most important variables such as gestational age, birth weight, and APGAR scores, which are necessary to have quantitative data to analyze it. Along with structured questions, open-ended questions were also present in the surveys to provide the participants an opportunity to present in-depth information regarding the complications they encountered during pregnancy or birth, which is beneficial in qualitative terms. Particular survey questions were asked concerning prenatal care, maternal complications, and the details of the birth to collect the more detailed information on the health status of the mother and the child. Additionally, any questions related to health of the neonates asked questions which sought the presence of conditions such as sepsis or jaundice and enquired about measures such as the NICU admission or phototherapy so that a full picture of the neonatal health outcomes was obtained.

Dataset Selection Criteria: The dataset was selected appropriately due to its broad coverage of important variables on neonatal health ensuring that it covers both breadth and depth of information. The selected dataset included detailed records of birth outcomes, maternal health, and neonatal interventions which was also a determining factor. Ethical considerations, such as a written consent to participate or a guardians consent in the sample, were also addressed thus there was no problem in the standards of the research process. The compatibility of the data with the modern analytical tools including ML and DL models played a key role in fulfilling the study goals. The emphasis on a centralized healthcare institution such as GMH allowed obtaining standardized and high-quality records, and attempts were made to capture a wide variety of cases that can be representative of the general population of Ethiopia. Such a wide representation enabled it to come up with strong models that could be generalized to different neonatal health conditions. Through the use of a stringent sampling plan and elaborate data collection procedures, the research guaranteed development of a data-rich and extensive dataset. The provided foundational data will inform the creation of next-generation AI-based models to predict neonatal diseases and fill serious gaps in the early diagnosis of the condition and improve nursing outcomes in infants.

4. RESULTS AND DISCUSSION

The Python 3.10 platform was used to assess the suggested techniques. The suggested optimisation techniques were displayed on a Windows 10 laptop with an Intel i3 9th Gen CPU and 8 GB of RAM. Here, we assess the suggested strategy's effectiveness using the current technique. While SVM, RF, XGB, and stacking [33] are capable of attaining ideal performance, our model offers accuracy as well as precision in the provided hyper-parameter configuration, the recall, accuracy, precision, and F1-score outcomes that we observed. Thus, these current methods were selected to be contrasted with our proposed method [20, 21, 34].

The results of this research have significant implications to healthcare providers and policymakers because, first, the use of AI-based models in the field of neonatal healthcare should be implemented immediately to solve the ongoing issues of diagnosis and care. To healthcare providers, these developments offer mechanisms to enhance accurate diagnosis and minimise delays in care and resource utilisation particularly in low-resource centres where experts are scarce. As with the help of models such as EPASFN-DRNN, it is possible to identify the life-threatening conditions early and provide the effective interventions that will improve the survival rates of infants and their long-term health conditions. To policymakers, the findings indicate the necessity of investing in healthcare infrastructure, information standardisation, as well as workforce training to facilitate the use of advanced AI technologies. Also, by embedding these tools into the current systems, it is possible to increase healthcare equity by providing high-quality neonatal care to disadvantaged areas. The possible effects of such discoveries are the reduction of the rates of neonatal mortality, the optimization of healthcare resources, and the development of international partnerships in order to standardize AI applications. These priorities would enable the healthcare systems to move toward a more active, data-oriented stance that reflects the overall goals of the data-driven approach of precision medicine and universal health coverage.

4.1 Accuracy

Accuracy in the context of putting into practice an AI-based neonatal illness prediction framework is the index of how the model predicts the presence or absence of neonatal disorders.

$$\text{Accuracy} = \frac{\textit{Total number of predictions}}{\textit{number of correct predictions}} \times 100 \tag{16}$$

Table 2 and Figure 3 show the equivalent accuracy measurement values compared to the methods that are currently used; the accuracy rates of SVM, RF, XGB, and stacking are 95.14%, 95.8%, 96.01% and 96.70%, respectively. The proposed approach, Integrated EPASFN-DRNN, is very successful with an outstanding accuracy of 98.50%. When it comes to performance, this method outperforms the rest.

Table 2. Comparison of accuracy for the proposed and existing methods

Methods	Accuracy (%)
SVM [33]	95.14
RF [33]	95.8
XGB [33]	96.01
Stacking [33]	96.7
EPASFN-DRNN [Proposed]	98.5

Note: EPASFN-DRNN = Efficient Particle Swarm Fine-Tuned Dilated Recurrent Neural Net; SVM = Support Vector Machine; RF = Random Forest; XGB = XGBoost.

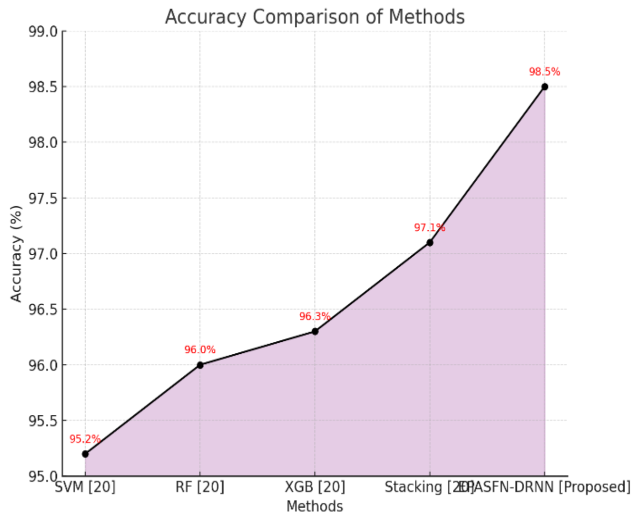

Figure 3. Numerical outcomes of accuracy

4.2 Precision

Precision evaluates the model's accuracy of positive predictions in the context of an AI-based neonatal illness prediction framework. The proportion of accurately predicted positive cases, or true positives, to all instances projected as positive is known as precision.

$$\text{Precision} = \frac{\textit{True positive} + \textit{false positive}}{\textit{True positive}} \tag{17}$$

Table 3 and Figure 4 show the equivalent accuracy measurement values compared to the methods that are currently used; the accuracy rates of SVM, RF, XGB, and stacking are 95.68%, 95.70%, 96.13% and 97.0%, respectively. The proposed approach, Integrated EPASFN-DRNN, is very successful, with an outstanding precision of 98.20%. compare these existing it perform better than the others.

Table 3. Comparison of precision for the proposed and existing methods

Methods	Precision (%)
SVM [33]	95.68
RF [33]	95.7
XGB [33]	96.13
Stacking [33]	97
EPASFN-DRNN [Proposed]	98.2

Note: EPASFN-DRNN = Efficient Particle Swarm Fine-Tuned Dilated Recurrent Neural Net; SVM = Support Vector Machine; RF = Random Forest; XGB = XGBoost.

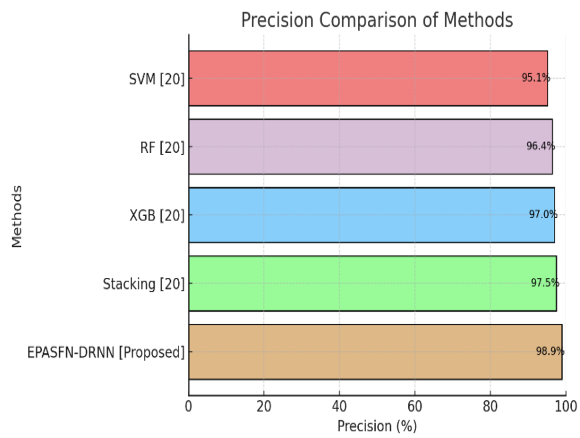

Figure 4. Numerical outcomes of precision

4.3 Recall

Recall is one of the assessment measures that is used to gauge how well the predictive model is doing. A measure of a model's accuracy in identifying occurrences of a particular condition, recall.

$$\text{Recall} = \frac{\textit{True positive}}{\textit{True positive} + \textit{false negative}} \tag{18}$$

Table 4 and Figure 5 show the equivalent accuracy measurement values compared to the methods that are currently used; the accuracy rates of SVM, RF, XGB, and stacking are 95.11%, 95.70%, 95.79% and 96.90%, respectively. The proposed approach, Integrated EPASFN-DRNN, is very successful, with an outstanding precision of 98.60%. This method works better than the others in terms of performance.

Table 4. Comparison of recall for the proposed and existing methods

Methods	Recall (%)
SVM [33]	95.11
RF [33]	95.7
XGB [33]	95.79
Stacking [33]	96.9
EPASFN-DRNN [Proposed]	98.6

Note: EPASFN-DRNN = Efficient Particle Swarm Fine-Tuned Dilated Recurrent Neural Net; SVM = Support Vector Machine; RF = Random Forest; XGB = XGBoost.

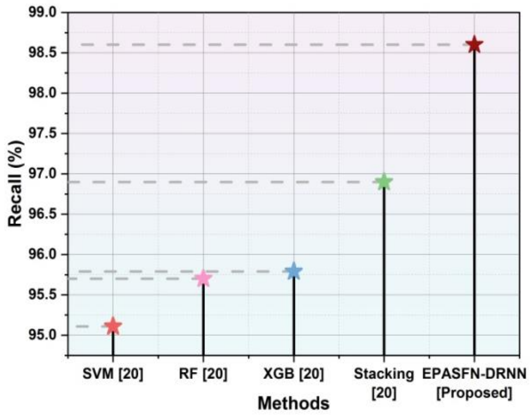

Figure 5. Numerical outcomes of recall

4.4 F1-score

The F1-score is a statistic that is frequently employed. It gives an even-handed assessment of a model's capacity to recognize good examples by fusing recall and accuracy into a single metric. In this context, a score of 0 indicates inadequate effort, whereas a score of 1 indicates perfect accuracy and recall.

$$F1 = \frac{2.precision.recall}{precision + recall} \tag{19}$$

Table 5 and Figure 6 show the equivalent accuracy measurement values compared to the methods that are used; the accuracy rates of SVM, RF, XGB, and stacking are 94.86%, 95.78%, 95.91% and 96.69%, respectively. The proposed approach, Integrated EPASFN-DRNN, is very successful, with an outstanding precision of 99.00%. This approach outperforms the others in terms of outcomes.

Table 5. Comparison of F1-score for the proposed and existing methods

Methods	F1-Score (%)
SVM [33]	94.86
RF [33]	95.78
XGB [33]	95.91
Stacking [33]	96.69
EPASFN-DRNN [Proposed]	99

Note: EPASFN-DRNN = Efficient Particle Swarm Fine-Tuned Dilated Recurrent Neural Net; SVM = Support Vector Machine; RF = Random Forest; XGB = XGBoost.

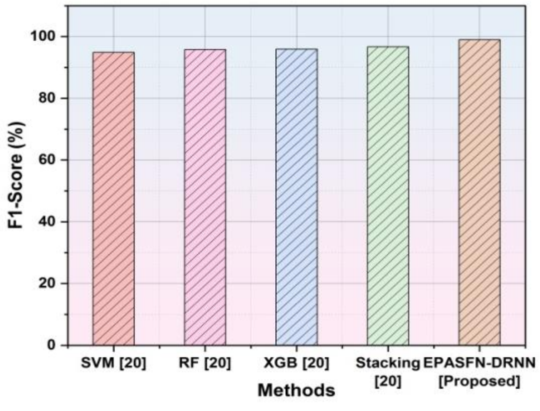

Figure 6. Numerical outcomes of F1-score

Neonatal healthcare faces significant challenges, especially in the early diagnosis and treatment of issues. These challenges arise from a mix of systemic, technological, and socio-environmental factors. Upon conducting a comprehensive analysis, it becomes apparent that addressing neonatal health issues involves navigating intricate complexities. Furthermore, this analysis underscores the importance of identifying potential solutions to enhance outcomes.

Underlying Causes of Identified Issues:

1) **Resource Limitations in Low-Income Settings**:
Infrastructure, qualified personnel, and modern technologies required to provide effective neonatal care are scarce in most of the healthcare facilities within the low-income and resource-constrained regions. This, in turn, results in diagnostic delays and improper treatment of such conditions as sepsis, respiratory distress, and preterm birth complications. These problems are exacerbated by the fact that access to continuous training of healthcare providers is limited, which means that neonatal care is highly dependent on a few specialists.

2) **Data Gaps and Variability**:
The quality of neonatal health data and its consistency differs radically between regions and facilities. Lack of complete documentation, inconsistency in the use of diagnostic tools, and absence of integration between various healthcare systems are deterrents in the process of coming up with reliable models of disease prediction. Moreover, datasets are unlikely to be diverse, and such a characteristic results in biases in AI-based models and their inapplicability to the population beyond the sample of the study.

3) **Delayed Diagnosis and Intervention**:
A challenge in neonatal healthcare is the fact that it is hard to monitor and address the early signs of diseases in newborns. There is a lot of diseases that require constant care and immediate responses, but the existing systems are rather reactive rather than proactive. Lack of real-time solutions applied in many medical institutions results into the delays in making critical decisions, thus increasing the risk of complications or deaths.

4) **Integration Challenges of Advanced Technologies**:
Neonatal care has a great potential of AI and ML. The adaptation of these technologies into the current medical processes is a major challenge. A lot of medical institutions do not have the technical power or the infrastructure to adopt sophisticated diagnostic systems. This leads to under-exploiting these new technologies.

5) **Social Determinants of Health**:
The factors that affect the health of a neonate significantly are environmental and socio-economic factors such as poor sanitation, lack of access to prenatal care, and maternal malnutrition. These determinants often worsen the predicaments experienced in the clinical context thus hindering the realization of positive outcomes.

Potential Solutions:

1) **Investment in Healthcare Infrastructure and Training**:
here is the need to increase investments in neonatal care in low-income environments. This involves the equipping of the facilities with the required tools such as incubators and advanced diagnostic tools, and providing an ongoing training of the HCPs to increase their ability to manage complex neonatal disorders.

2) **Data Standardization and Integration**:

Variability and inconsistency problems can be alleviated by setting standardized procedures of collecting, and sharing data among healthcare systems. Joint efforts to create various and comprehensive data sets will make AI-based models more reliable and useful, which will minimize biases and increase diagnostic accuracy.

3) **Real-Time Monitoring Systems**:
By integrating AI technologies into real-time monitoring instruments, including wearable sensors to assess the neonates, one is able to continuously assess the vital signs levels and detect the health issues early. This can be significantly effective in improving the effectiveness and timeliness of interventions.

4) **Capacity Building for AI Implementation**:
In order to overcome the integration issues that accompany the advanced technologies introduction, such specific initiatives that focus on improving the technical expertise in the healthcare systems are necessary. This would include employee education, partnerships with technology vendors, and the creation of user-friendly AI solutions that require a low level of technical skills to use.

5) **Addressing Social Determinants of Health**:
Increasing maternal health and environmental risks mitigation initiatives, which are community-based, can have a significant impact on neonatal outcomes. The wider determinants of neonatal health can be mitigated by such interventions as nutritional initiatives among pregnant women, sanitation, and access to prenatal care.

6) **Policy Support and Global Collaboration**:
Neonatal health should receive a priority by the governments and international organizations through provision of supportive policies and funding on the same. The high resource and the low resource settings may collaborate in a way that maximizes knowledge transfer, hence the adoption of the best practices and innovative solutions to the world.

According to the findings, AI-based models, like EPASFN-DRNN, have the potential to transform the current state of the neonatal healthcare sector by addressing key issues. These models allow making earlier and more reliable diagnoses of the neonatal disease, which leads to timely interventions that can significantly improve survival rates and long-term outcomes with the help of high accuracy, precision, and recall. Implementing high-end technologies into the clinical practice offers the possibility to reduce the number of diagnostic mistakes, tailor the treatment process, and improve resource use and allocation, particularly in under-resourced settings. The findings however also indicate the need to fill in gaps in data standardization, accessibility and training in order to maximize these improvements. This development implies the shift towards more egalitarian, data-driven, and preventive neonatal care at a universal level.

4.5 Discussion

SVM is an aggregation of related learning techniques for regression and classification. It is a non-probabilistic multiple. Finding the optimal class border is the main objective of SVM [33], which builds a hyperplane or group of hyperspaces in high-dimensional space to categorize data. It is a collection of classifiers, consisting of a decision tree that resolves regression and classification issues. This method creates an RF made up of many decision trees. When the forest has more trees, the outcome is more accurate [33]. XG-Boost is employed in problems involving regression and classification. A meaningful collection of features has been selected using recursive feature reduction along with cross-validation. Four ML models have been used for modelling, including stacking; our suggested Integrated EPASFN-DNN model performs exceptionally well across all evaluation criteria, proving its superiority over existing methods in detecting and recognizing.

5. CONCLUSIONS

Neonatal illnesses are a major global contributor to death among children under five. Advances have been made to address the problem, such as a better comprehension of the pathophysiology of the illnesses and technology support for diagnosis and therapy. However, the improvement is not significant. Stacking, RF, XGB, and SVM are four ML models that were used for modelling, together with stratified cross-validation. With an accuracy of 98.50%, precision 98.20%, recall 98.60% and F1-score 99.00% the performance evaluation revealed that EPASFN-DRNN performed better than the other models. It will help with early identification and precise diagnosis of neonatal illnesses. Such a framework has a wide range of possible applications in the future, including personalized treatment regimens, real-time monitoring devices integrated for continuous health evaluation, and advances in precision medicine catered to individual genetic profiles.

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