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Bio-Remote Sensing in Predicting Infection in Neonates With Thermal Imaging and Machine Learning

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***Abstract*—Premature birth complications have different causes and vary in different parts of the world with sepsis as one of the leading causes of these complications. The body releases anti-inflammatory substances when an infection is detected and this, in turn, could damage healthy organs, especially when they are not fully developed. Preterm babies are susceptible to diseases due to their underdeveloped organs and immune systems. Hence, it is extremely important to treat sepsis as soon as the baby is diagnosed. Neonatal sepsis is a dangerous non-specific disease in babies, and it is a clinically very difficult and challenging task to diagnose. Late or incorrect treatment of infants' sepsis can lead to death which is one of the most causes of mortality rate in neonates. In the traditional treatment of sepsis, the needed time and accuracy for diagnosis are still very concerning, considering the number of involved risks in late diagnosis or mistreatment of sepsis cases. Thus, the need for having a fast and reliable algorithm with high accuracy to predict sepsis before clinical recognition would help the doctors to treat the neonates in time and to reduce the mortality rate related to sepsis.**

This paper presents a fast, accurate, and reliable thermographic Bio-Remote Sensing approach to predicting sepsis in neonates and discusses the significance of combining the Thermal Imaging technique with Machine Learning (ML). At the same time, it provides a more practical and desirable solution for physicians by minimising the traditional diagnosis time and maximizing the accuracy of the prediction needed to detect sepsis in neonates.

Keywords—Bio-Remote Sensing, Predicting Infection, Thermographic technology; Artificial Intelligence (AI), Machine Learning (ML), Premature babies, Incubator; Sepsis, Infrared thermal imaging; neonates; Body temperature measurement.

I. INTRODUCTION

Neonatal sepsis is a generalised systemic and whole-body infection occurring in neonates. To have a more generic definition, specific infections like meningitis and pneumonia, are included in the sepsis definition. Infection is caused by the invasion of viruses, bacteria, or other microorganisms. It causes a reaction from the body's immune system to fight the foreign organism, which usually involves inflammation [1]. Neonatal sepsis can be acquired in several ways [2]:

- Postpartum (external source after birth).
- In utero trans placentally (through ruptured membranes).
- Intrapartum (in the birth canal during delivery).

Neonatal sepsis can be classified into 2 categories, namely: 1- Early Onset Neonatal Sepsis (EONS), which means that the neonate shows sepsis symptoms within 3 days of birth. Usually, neonate with EONS acquires the infection from organisms intrapartum. 2- Late-Onset Neonatal Sepsis (LONS), which means that the neonate shows the sepsis symptoms 3 days after the birth, with the source of the pathogen from the environment or postpartum.

Thermographic technology provides a remote, non-invasive, and safe way to accurately measure a neonate's body temperature in an incubator [3]. Tracking and monitoring the body temperature and following the variations and trends of a Thermal Profile Region (TPR) provides physicians and nurses with valuable information about the health condition of the baby. The extracted features from the temperature variations and their patterns can be used in techniques like Artificial Intelligence, Machine Learning, or Deep Learning. It is important and a prerequisite to have a reliable and accurate real-time temperature measurement [3] and tracking system for the long term to measure and monitor the highest skin temperature of an Elastic Thermal Profile Region (ETPR). This means that the Region of Interest (ROI), which is part of the to be monitored skin of the neonate should be exposed and visible within 55^{o} angle in the Field of View (FOV) of the thermal camera lens. This guarantees a constant directional emittance and reflectance during the temperature measurement [4]. The pre-processed step before Sepsis Detection Algorithm (SDA) ensures that the temperature tracking system locks and follows the ETPR even during sudden rapid body movements of the neonate. The extracted features from the neonate's ETPR are used for the training and test datasets and are fed to a limited amount of ML models. In this paper, a novel and promising non-invasive method is being explored by combining thermographic technology with Machine Learning supported by a powerful embedded system to predict sepsis in neonates very fast and more reliable.

II. MEASUREMENT SETUP

For the Machine Learning training model and the measurement setup in general following hardware and software can be used:

- A Single Board Computer (SBC) with enough number-crunching power for signal and image processing.
- An infrared camera.
- A Linux operating system.

A. Hardware and Software

In this research, the following hardware is used, see Fig. 1:

- A Pine Rockpool 64 (SBC) with a Rock chip RK3399 Hexa-core System on Chip (SOC) as well as a quad-core Mali-T860MP4 with 4GB of dual-channel LPDDR4 system memory.
- A FLIR SC305 infrared camera with 320x240 pixels resolution with a 9 Hz frame rate is connected to the SBC.
- Linux Labantu version 20.04 with necessary software (packages) running on both SBC and a Virtual Machine for the pre- and post-processing of the data.

Fig. 1. FLIR SC305 infrared camera (left picture), Pine RockPro 64 (SBC) (right picture).

The SBC is connected via an ethernet cable to the FLIR infrared camera. The produced data stream from the infrared camera is being pre-processed to create the thermal images. After some processing, these thermal images are being converted into a real-time live thermal video stream. In parallel, all pixels in each frame are number crunched individually through dedicated software to calculate the parameter settings such as temperature, humidity, emissivity, etc. Thereafter, the radiant energy emitted from the object in the form of the infrared wave is being calculated. By compensating for the environmental variables and capturing infrared waves from the object a very accurate temperature is measured per pixel in each frame [3].

B. *Measurement Setup*

There are 2 possible scenarios to model the environmental measurement, see Fig. 2. The possible scenarios are:

- The baby is outside the incubator (left picture).
- The baby is inside the incubator.

In the second scenario, the thermal camera lens is directed toward an open porthole (right picture).

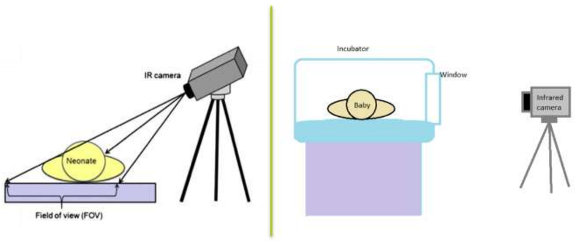

Fig. 2. Thermographic measurement model: The baby is out of the incubator (left picture), The baby is inside the incubator (right picture).

C. *Temperature Measurement*

For measuring the baby's body temperature in both thermographic models as depicted in Fig. 2, the thermal camera is positioned at a safe distance with its lens directed toward the neonate. It is very important and practical the thermal camera does not get in the way or interfere with carer providers' activities or daily work. Moreover, the FOV of the camera covering the ROI to measure the neonate's body temperature must be within a 55° angle to guarantee a constant directional emittance and reflectance [4]. Note, that directing the camera lens toward the relatively small size of the porthole opening of the incubator satisfies this requirement. It is obvious that the FOV path of the infrared camera must be clear in both thermographic measurement models depicted in Fig. 2.

Important: In both models, the radiation sources and thermal noise can and will affect the temperature measurements [3]. Without compensation for these sources, the temperature readings would not be correct, and the collected data for training and test datasets would have an effect Machine Learning algorithm.

III. Sepsis in Neonates

Neonate's body releases anti-inflammatory substances that can damage healthy organs when infection occurs. Because of underdeveloped organs, it is very dangerous and harmful to preterm infants. Therefore, it is of utmost importance to treat sepsis as soon as the baby is diagnosed.

A. *Golden Standard in Diagnosing Sepsis*

The very first step to sepsis treatment in the preterm infant is detecting and diagnosing it accurately. Once diagnosed, the infection can be prevented or counteracted by the administrated antibiotics to the baby. However, it is proven that sepsis diagnosis is a difficult task because the clinical characteristics of neonatal sepsis are non-specific and difficult to differentiate from other conditions [5],[6]. The golden standard for diagnosing sepsis is blood culture. A blood sample from the baby is cultured and tested to identify the presence of bacteria, but this method is time-consuming, for timely treatment. Note that, antibiotic usage during pregnancy delivery, blood volume, and laboratory capabilities could also affect the result of the diagnosis [6]-[8]. Unfortunately, other blood features, such as proteins, white blood cell count, and other biomarkers are not sensitive enough to be in routine clinical use [9]. In general, clinical symptoms like distress in breathing, poor feeding, fever, hypothermia, etc. [9],[10], are considered by physicians as the first signs in diagnosing disease. However, due to the complexity of neonatal sepsis, it has non-specific and varying symptoms. In other words, the symptoms may indicate diseases other than sepsis, which in turn lead to different conclusions and treatments. Anyhow, when the diagnosis process has reached its last step, antibiotic treatment is administrated.

IV. Machine Learning, Used Sepsis Prediction Model and Dataset

Machine learning is one of many subset applications of AI providing a statistical model which can learn and improve itself from learning processes without any prior and explicit programming steps. For the learning process, it is important to feed the model with a training dataset so it can update itself based on the pattern in the data. Once trained, the model can be fed with new input data and the outcome would be based on the prior statistical learning process of the trained model. ML models can be categorized into three groups, namely: 1- Supervised Learning (SL), 2- Unsupervised Learning (UL), and 3- Reinforcement Learning (RL). In SL, each training data set has input data with known outcomes or output. This is called Labelled Training data. SL is usually used for classification and regression problems. However, UL would have only input data as the training data. This model is able to group similar input data or find structures from the input data. RL as the final category can deal with known system environment and goals, without knowing the perfect outcome.

In the literature studies for sepsis prediction, the research subjects were mainly adults [11] and different types of ML models have been explored like; Logistic Regression (LR), Naive Bayes (NB), K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Decision Tree (DT) or Random Forest (RF), Gadabouts, Gradient Boosting (GB) that were cable of recognizing sepsis based on electronic health record data [12],[13].

For this study, the number of involved neonates was very limited, because of Covid-19 pandemic restrictions at the hospitals. Thus, achieved results are based on the vital signs of 26 subjects with a total of 57 thermal measurements and tracking the highest skin temperature. The dataset was labelled as (none) sepsis and fed and utilized to the ML model as input data to train and test several machine learning models for predicting and classifying sepsis cases on neonates.

A. Machine Learning Training Model for Predicting the Sepsis

To predict sepsis in neonates, the ML algorithm is used to analyze the infrared live stream of the preterm babies. For this purpose, the ML algorithm needs to be trained and evaluated prior to real measurements. The training algorithm filter chain is depicted in Fig. 3 and described in the following steps:

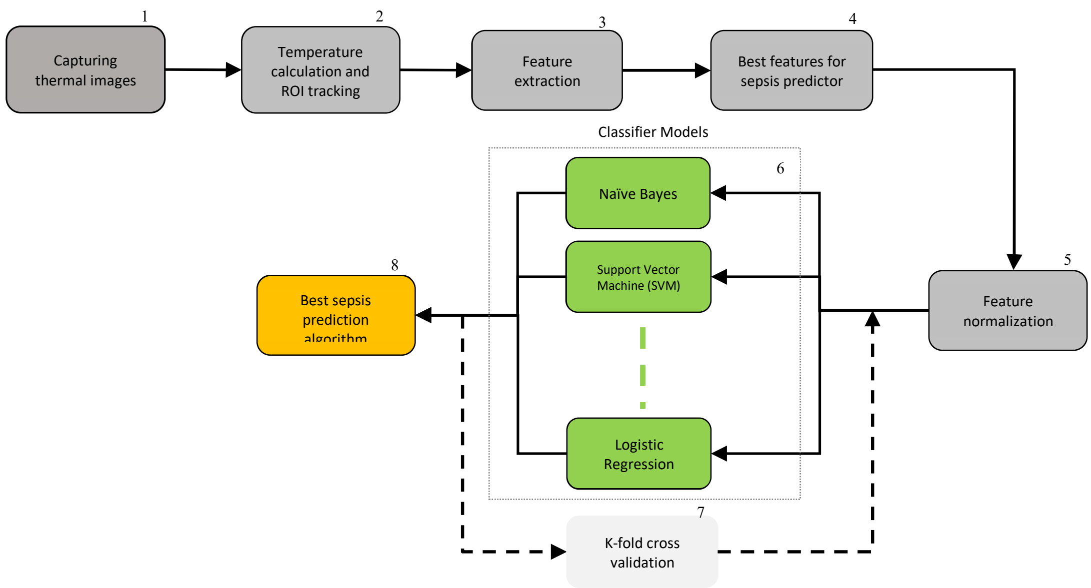

Fig. 3. Filter chain for Machine Learning training model.

1- **Capturing thermal images:** This step consists of capturing thermal images and converting them to a thermal video stream.

2- **Temperature calculation and ROI tracking:** This is considered a pre-processing step to do accurate temperature readings and track the ROI of the subject over a course of time.

3- **Feature extraction:** From all compiled measurements, several variables were selected as features and represented as 1 measurement, namely: ROI variables (median, IQ range, and standard deviation) with their time-series parameters; average, standard deviation, trend slope, and trend intercept.

4- **Best features for sepsis predictor:** In this step sepsis label (0 for no sepsis and 1 for sepsis) is added to each measurement. By calculating the features' correlation coefficient matrix, the best sepsis predictor features with high correlation can be selected and included in the training algorithm, see Fig. 4.

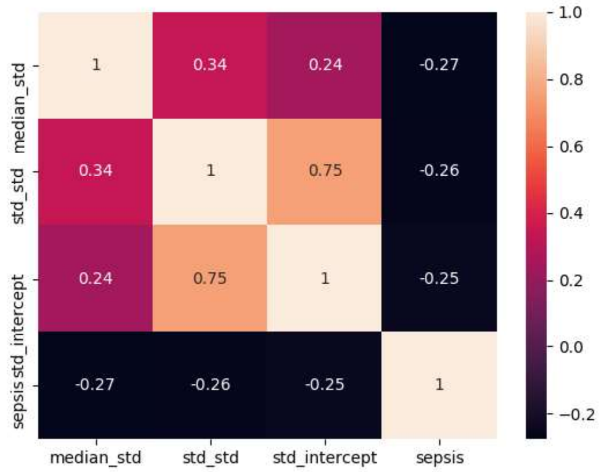

Fig. 4: Feature correlation coefficient matrix.

5- **Feature normalization:** Before training the model, it is important to normalize the features to avoid any bias in training the model.

6- **Classifier models:** There are many ML models available, but in this study, a set of models are explored that have been promising in training and validating sepsis detection [12],[13].

7- **K-fold cross-validation:** K-fold Cross-Validation (CV) is a validation method by dividing the dataset into k-number of sets and k-number of iterations. The set which has not been selected before is set aside to be the validation set while the rest are the training set. In the end, the model will be trained and validated for k-number of times and the result will be averaged to get the average accuracy of the model.

8- **Best sepsis prediction algorithm:** After evaluation of all models with their training outcome, the final training result of SVM shows that it is the best candidate model for predicting sepsis with an accuracy score of 80.5%, see below Table I.

Table I. Achieved accuracy by different models.

Models	Hyperparameter	Values	Accuracy (%)
LR	Solvers	liblinear	67.6
	Penalty	L2	
	C_values	0.1	
KNN	N_neighbors	17	70.2
	Weights	distance	
	Metric	manhattan	
SVM	Kernel	rbf	80.5
	C_values	1	
	Gamma	scale	
RF	N_estimator	100	79.0
	Max_features	log2	
	Criterion	entropy	
	Max_depth	2	
Adaboost	N_estimator	2	75.6
	Learning_rate	0.001	
Gradient boosting	N_estimator	1000	75.8
	Learning_rate	0.001	
	Subsample	1	
	Max_depth	3	
Decision Tree	Criterion	gini	78.0
	Splitter	best	
	Max_depth	2	
	Max_features	none	

V. Conclusions

Due to this research, the Support Vector Machine (SVM) is the best model for predicting sepsis using time-series temperature data variation as the feature. The sepsis prediction rate has an accuracy of 80.5% using 10 to 30 minutes thermal recordings of neonates as input data with 9 frames per second. The achieved results are more accurate, reliable, and less time-consuming compared to the golden standard as discussed in section III-A. However, there is still more room to improve the accuracy in the future.

The Doctors do not need to depend that much on their experience to diagnose neonatal sepsis because of its non-specific symptoms. Because the system is able to predict sepsis automatically and independent of the care providers and without any sensors attached to the neonate.

This novel, and state-of-the-art, algorithm has high accuracy with a very short time window for sepsis prediction, yet it is practical and simple to use. This method can help physicians and nurses in their decision-making to treat septic neonates in time or even during the course of sepsis development of the neonates. As result lives of the neonates could be safe and the mortality rate for sepsis cases hopefully will drop.

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