Diagnosis of NEC using a Multi-Feature Fusion Machine Learning Algorithm

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***Abstract*—Necrotizing enterocolitis (NEC) is a severe gastrointestinal emergency in neonates, marked by its complex etiology, ambiguous clinical manifestations, and significant morbidity and mortality, profoundly affecting long-term pediatric health outcomes. The prevailing diagnostic approaches for NEC, including traditional manual auscultation of bowel sounds, suffer from limited sensitivity and specificity, leading to potential misdiagnoses and delayed treatment. In this paper, we introduce a groundbreaking NEC diagnostic framework employing machine learning algorithms that utilize multi-feature fusion of bowel sounds, significantly improving the diagnostic accuracy. Bowel sounds from NEC patients and healthy newborns are meticulously captured using a specialized acquisition system, designed to overcome the inherent challenges associated with the low amplitude, substantial background noise, and high variability of neonatal bowel sounds. To enhance the diagnostic framework, we extract mel-frequency cepstral coefficient (MFCC), short-time energy (STE), and zero-crossing rate (ZCR) to capture comprehensive frequency and time domain features, ensuring a robust representation of bowel sound characteristics. These features are then integrated using a multi-feature fusion technique to form a singular feature vector, providing a rich, integrated dataset for the machine learning algorithm. Employing the support vector machine (SVM), the algorithm achieved an accuracy (ACC) of 88.00%, sensitivity (SEN) of 100.00%, and an area under the receiver operating characteristic (ROC) curve (AUC) of 97.62%, achieving high accuracy in diagnosing NEC. This innovative approach not only improves the accuracy and objectivity of NEC diagnosis but also shows promise in revolutionizing neonatal care through facilitating early and precise diagnosis. It significantly enhances clinical outcomes for affected neonates.**

Keywords*—Diagnosis of necrotizing enterocolitis (NEC); bowel sound; feature fusion; machine learning

I. Introduction

Neonatal necrotizing enterocolitis (NEC) constitutes a critical gastrointestinal pathology characterized by multifactorial etiologies leading to mucosal damage, ischemia, and hypoxia in the neonatal intestinal tract, culminating in diffuse or localized necrosis of the small intestine and colon [1]. This condition predominantly afflicts neonates, with a pronounced prevalence in preterm infants, positioning it as a significant concern in early neonatal critical care due to its high morbidity, mortality rates, and propensity for engendering numerous complications [2]. The Bell staging criteria for NEC delineate the progression of the disease into stages, where an advancement from stage I to stage II signifies a notable escalation in the complexity of required medical interventions, treatment durations, and therapeutic strategies [3]. This delineation underscores the imperative for prompt and accurate diagnosis, as well as the implementation of tailored therapeutic regimens to mitigate the progression and adverse outcomes associated with NEC.

The conventional diagnostic approach for NEC primarily hinges on clinical manifestations and radiographic examination through abdominal plain films. This methodology, however, is marred by limitations such as atypical presentations, low sensitivity, and a lack of specificity, rendering it insufficient for the timely and accurate diagnosis of NEC. Through an analytical examination of the Bell staging criteria for NEC, a pivotal distinction between stages I and II is identified as the cessation of bowel sounds. Bowel sounds, characterized as intermittent gurgling or gas-over-water noises produced by peristaltic and catabolic movements within the intestines, facilitate the movement of gases, liquids, and chyme through the intestinal tract [4]. These sounds are clinically acknowledged as vital physiological indicators reflective of the gastrointestinal tract's functional status. The diagnosis of NEC, predicated on the absence of bowel sounds, currently relies predominantly on manual auscultation conducted by medical practitioners [5]. This diagnostic practice is fraught with challenges, including a substantial reliance on the clinician's experience, a high degree of subjectivity inherent to manual auscultation, and the overall inefficiency of this method as a diagnostic tool [6]. These constraints underscore the necessity for the development of more objective, efficient, and less experientially dependent diagnostic modalities to enhance the accuracy and timeliness of NEC diagnosis.

By investigating related work, we found the application of machine learning algorithms in the monitoring of human physiological signals has witnessed a discernible surge in popularity [7]. A burgeoning body of research has been devoted to the utilization of machine learning algorithms for the analysis of bowel sounds. Yin et al. [8] notably employed support vector machine (SVM) for the purpose of recognizing bowel sounds within a wearable health monitoring device. In a parallel vein, Allwood et al. [9] innovatively amalgamated advanced acoustic signal processing techniques with a machine learning algorithm, adopting an AI-assisted paradigm to enhance the discernment of bowel sounds. Burne et al. [10] used an integrated approach for bowel sound detection on hand-crafted as well as features obtained from mel-frequency cepstral coefficient (MFCC).

Nevertheless, it is noteworthy that the extant studies investigating machine learning algorithms for bowel sounds

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have predominantly relied on singular feature extraction methods. In the context of machine learning, the maximization of valuable information during model training is paramount [11]. In cognizance of this, our research adopts a comprehensive approach by considering both frequency domain features and time domain features inherent in neonatal bowel sounds. We have strategically extracted MFCC [12], Short Time Energy (STE) [13], and Zero Crossing Rate (ZCR) [14] as integral components of our feature extraction methodology. These features collectively encapsulate the nuanced characteristics of neonatal bowel sounds. Then, we employ the concatenate function for splicing features in the domain, creating a fused representation of the spectral and temporal attributes.

Subsequently, these fused features serve as input data for machine learning algorithms, including but not limited to adaboost [15], random forest [16], support vector machine (SVM) [17], k-Nearest Neighbors (KNN) [18], and stacking [19]. The rationale behind employing a diverse set of models lies in the pursuit of achieving a robust and accurate automatic diagnosis of NEC based on bowel sounds. This approach aligns with the overarching objective of harnessing the collective strengths of various machine learning paradigms to improve diagnostic precision and reliability. Our methodology, rooted in a meticulous fusion of medical and computational techniques, contributes to the burgeoning field of medical computing. By expanding the spectrum of features considered and leveraging a diverse ensemble of machine learning models, our research endeavors to advance the state-of-the-art in automatic diagnosis, particularly in the critical domain of neonatal healthcare.

In summary, our research undertakes a comprehensive exploration by employing multi-feature fusion, incorporating three distinct types of frequency and time domain features (MFCC&STE&ZCR) derived from neonatal bowel sounds. The primary objectives are to realize automatic diagnosis of NEC and contribute to the evolving landscape of medical computing. The key contributions of this paper are delineated as follows:

1) Based on Bell-NEC staging, neonatal NEC diagnosis is performed by the indication of weakened or absent bowel sounds.

2) Multi-feature fusion in the time-frequency domain (MFCC&STE&ZCR) is used to extract more valuable information of bowel sounds.

3) Adaboost [15], random forest [16], SVM [17], KNN [18], and stacking [19] machine learning algorithms are used to automatically perform bowel sounds classification.

The manuscript is structured as follows: Section II delineates the methodology for acquiring bowel sounds and provides a step-by-step exposition on constructing the model through the multi-feature fusion machine learning algorithm. This section encompasses the foundational research concept, details of feature extraction, and the process of feature fusion. In Section III, we expound upon the experimental intricacies, presenting a comprehensive analysis of the experimental details and results. This section serves to elucidate the empirical validation of the proposed model. Finally, Section IV succinctly encapsulates the study's outcomes, offering a cohesive summary of the research findings.

II. Methods

A. Collection of Bowel Sound

In this study, the Lobob stethoscope was used to collect neonatal bowel sounds. The Lobob stethoscope was realized by using muRata and TDK high-performance electronic devices, five-layer shielded wire design, GETTOP flagship electro-acoustic sensor and CSR8670, the world's top audio processing chip, to collect and preprocess bowel sounds. Through the above methods, the potential problems of low amplitude and large amount of background noise of newborn bowel sounds can be solved, and high-quality bowel sounds can be finally collected.

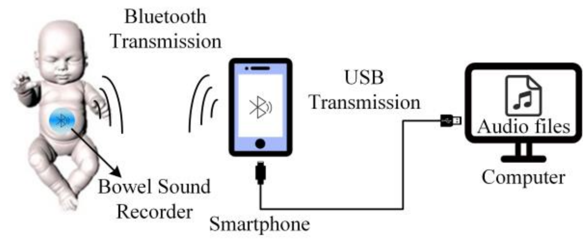


Fig. 1. Bowel sound collection system.

To achieve the objective of efficient and artifact-free neonatal bowel sound collection, the devised system, illustrated in Fig. 1, is meticulously outlined in this study. The collection protocol is systematically detailed as follows:

1) Verify power level. Initial verification involves checking the power status of both the bowel sound recorder and the utilized cellphone for data acquisition to ensure optimal functionality.

2) Sterilize and preheat. Measurement personnel engage in self-cleansing and disinfection procedures while simultaneously disinfecting and preheating the bowel sound collector.

3) Confirm newborn information. Relevant details of the newborn are confirmed. The Bluetooth stethoscope, sterilized and preheated, is positioned on the newborn's abdomen.

4) Configure and auscultate software. The software system, interfaced with the bowel sound recorder on the cellphone, is activated. Parameters are validated, and auscultation commences. Recording for a minimum of two minutes is initiated, followed by saving and software closure. The newborn's bowel sounds is then transmitted to the smartphone via the Bluetooth module.

5) Manage and sterilize file. Post-recording, file modification is performed, the Bluetooth stethoscope is removed from the child's abdomen, and subsequent sterilization is executed.

6) Transfer and compile data. The bowel sounds are transferred from the smartphone to the computer using the USB transmission protocol. The data is organized and synthesized into comprehensive bowel sounds tailored for experimentation.

It is imperative to note that all neonatal bowel sounds utilized in this experiment are meticulously collected by neonatologists from the Second West China Hospital of Sichuan University. Rigorous professional authentication procedures are adhered to, encompassing bowel sounds from both infants diagnosed with NEC and those from normal newborns.

B. Overview of NEC Diagnosis

Traditional manual auscultation of neonatal bowel sounds is hindered by the need for extensive medical expertise, time constraints, and subjective biases, leading to potential misjudgments [6]. This paper proposes an innovative approach leveraging machine learning algorithms for the automatic diagnosis of neonatal NEC through continuous monitoring and feature fusion of bowel sounds. The flow chart in Fig. 2 illustrates the application of a multi-feature fusion machine learning algorithm for NEC diagnosis based on neonatal bowel sounds, offering a systematic and automated framework to improve diagnostic accuracy and efficiency. This interdisciplinary research bridges medical and computational sciences, advancing diagnostic methodologies in neonatal healthcare.

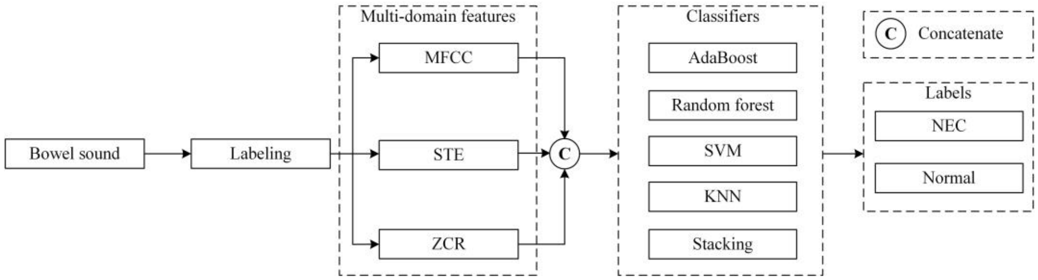


Fig. 2. NEC diagnosis framework.

Initially, the training of machine learning algorithms necessitates original labels. Therefore, we initially calibrated the bowel sounds using the statistical table of neonatal bowel sounds from the Second Hospital of West China of Sichuan University and Adobe Audition Audio Signal Processing Software. The calibration reveals 42 instances of NEC children's bowel sounds and 83 instances of normal newborn bowel sounds. Based on the characteristics of bowel sounds, including weak signals, strong background noise, large individual differences, and high randomness [20], and considering that bowel sounds of NEC patients may be weakened or even absent [21], we choose three types of bowel sounds—MFCC, STE, and ZCR—as frequency-domain and time-domain features for extraction. These features are employed for the classifier to learn and categorize the references. Then, to obtain richer information in neonatal bowel sounds signals to achieve more binary classification effect and better diagnosis of neonatal NEC disease, this paper adopts multi-feature fusion of bowel sounds time and frequency domain features, and performs direct multi-feature fusion through feature concatenating [22] to preserve the original data features of neonatal bowel sounds signals. Finally, since machine learning algorithms can automatically realize feature extraction and perform well in binary classification problems, this study adopts five popular machine learning algorithms with excellent mathematical logic and classification criteria, namely, adaboost [15], random forest [16], SVM [17], KNN [18], and stacking [19], to realize the automated diagnosis of neonatal NEC.

In the initial stages of this study, the training of machine learning algorithms necessitated the availability of accurately labeled data. We meticulously calibrate the neonatal bowel sounds utilizing statistical tables provided by the Second Hospital of West China, Sichuan University, and Adobe Audition Audio Signal Processing Software.

Considering the distinctive features of bowel sounds, such as low amplitude signals, pervasive background noise, substantial inter-individual variations, and inherent randomness [20], coupled with the potential attenuation or absence of bowel sounds in NEC patients [21], we opt for three representative types of bowel sound features –MFCC, STE, and ZCR. These features, derived from the frequency and time domains, are employed for subsequent classifier training to facilitate reference-based learning and classification.

To enhance the discriminative capacity and diagnostic accuracy for neonatal NEC, this research embraces a multi-feature fusion strategy, consolidating both time and frequency domain features of bowel sounds. Direct concatenation of these features is achieved through a feature concatenating technique [22], preserving the inherent data characteristics of neonatal bowel sound signals.

Capitalizing on the intrinsic capability of machine learning algorithms for automated feature extraction and robust performance in binary classification scenarios, we employ five well-established algorithms renowned for their mathematical rigor and classification efficacy: adaboost [15], random forest [16], SVM [17], KNN [18], and stacking [19]. These algorithms collectively contribute to the realization of automated neonatal NEC diagnosis. This interdisciplinary study, situated at the intersection of medical and computational sciences, holds promise for advancing diagnostic methodologies in neonatal healthcare.

C. Feature Extraction

1) Mel-frequency Cepstral Coefficient (MFCC): For the analysis of neonatal bowel sounds in the frequency domain, the project used mel-frequency cepstrum coefficient (MFCC) analysis. The mel-frequency $M(f)$ was proposed by researchers based on the mechanism of human ear hearing [23], and it has a nonlinear correspondence with the Hertz (Hz) frequency f, which is as follows:

$$M(f) = 1125 \ln(1 + f/700) \tag{1}$$

The application of MFCC in our study capitalizes on the inherent nonlinear relationship between mel-frequency and hertz, facilitating the computation of spectral features in the

Hertzian domain. An illustrative instance of MFCC representation for neonatal bowel sound is depicted in Fig. 3.

MFCC plays a pivotal role by transforming the raw audio signal into a discerning set of feature vectors. This conversion enhances the separability and recognizability of the underlying acoustic characteristics, thereby facilitating diverse applications such as speech recognition, speaker identification, speech synthesis, and audio classification [12]. Notably, the versatility of MFCC is underscored by its robustness and commendable recognition accuracy when compared to alternative feature extraction methods [24]. This robustness positions MFCC as a methodologically sound and effective tool for extracting salient features from neonatal bowel sounds within the context of our interdisciplinary research at the intersection of medical and computer sciences.

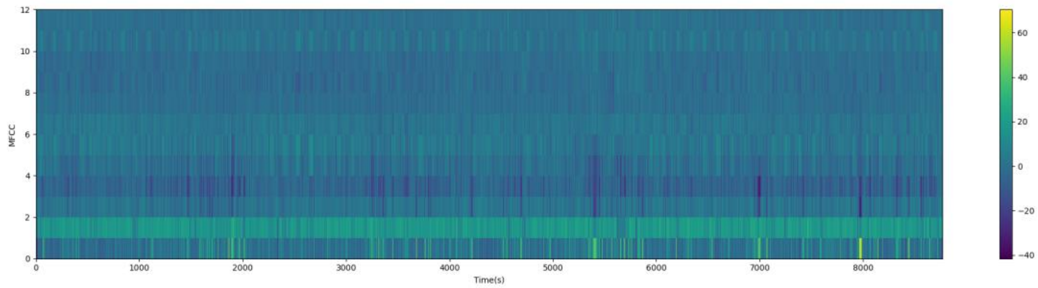


Fig. 3. Example of MFCC visualization of neonatal bowel sound.

2) Short Time Energy (STE): Short time energy (STE) is one of the common time-domain features in sound signals, which reflects the energy magnitude of the signal over a period of time [13]. After the above filtering and noise reduction process, compared with the background noise, the bowel sounds signal energy is obviously stronger, so the calculation of STE can effectively distinguish the bowel sounds. In this article, the neonatal bowel sounds signal is divided into frames, and the window is added to realize the "short-time", as shown in Fig. 4, which is an example of STE visualization of neonatal bowel sound. Let the *n*th frame of the speech signal obtained after the windowing process be $x(m)$, and the STE E_n of the *n*th frame of the speech signal be:

$$E_n = \sum_{m=0}^{N-1} x^2\,(\mathrm{m}) \quad (2)$$

where, N indicates the frame length.

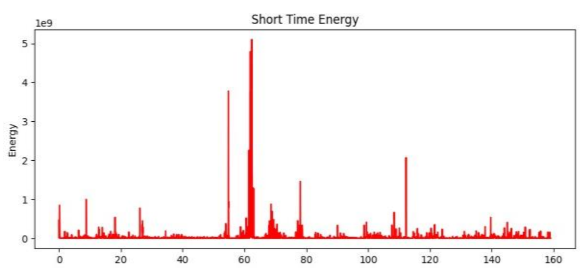


Fig. 4. Example of STE visualization of neonatal bowel sound.

3) Zero Crossing Rate (ZCR): The short-time average zero crossing rate refers to the number of times the signal crosses the zero value in each frame, which can reflect the frequency spectral characteristics to a certain extent, and is a kind of sound signal time-domain feature often used in speech endpoint detection [14]. As the bowel sounds signals vary in strength, it is difficult to see obvious changes in the STE only for the sudden and weaker bowel sounds, while their short-time average crossing zero rate is usually higher, which can be used as one of the features to analyze the bowel sounds. As shown in Fig. 5, an example graph of ZCR visualization of neonatal bowel sound is shown. The short-time average zero crossing rate Z_n is calculated as:

$$Z_n = \frac{1}{2}\sum_{m=0}^{N-1} |sgn[x_n(m)] - sgn[x_n(m-1)]| \quad (3)$$

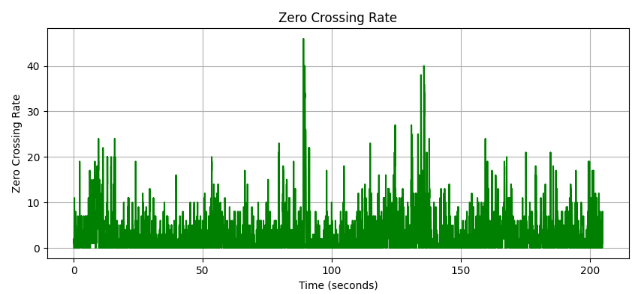


Fig. 5. Example of ZCR visualization of neonatal bowel sound.

D. Feature Fusion

The inherent challenges associated with bowel sounds acquisition includes signal weakness, randomness, individual variability, and background noise. What's more, the discriminative capability between bowel sounds from patients with NEC and normal bowel sounds in terms of signal characteristics such as amplitude, frequency of occurrence, and auditory perception [25] is superior. This study advocates for the fusion of three distinct features extracted from the frequency-domain and time-domain analyses of bowel sounds, namely MFCC, STE, and ZCR. By amalgamating these features, a more comprehensive understanding of bowel sounds can be attained, providing richer information for analysis.

The fusion of MFCC, STE, and ZCR features enables the extraction of a diverse set of features, enhancing the diagnostic capabilities of machine learning algorithms for discerning patterns indicative of neonatal NEC. This approach leverages the synergistic benefits of multiple feature types, thereby augmenting the classification performance of the model and bolstering its diagnostic accuracy for neonatal NEC diagnosis.

The multi-feature fusion approach chosen in this study is based on data-level concatenate [26]. This feature fusion method not only preserves the features of the original data and maintains the feature diversity of multi-features, but also is able to handle features of different dimensions and shapes. Whether it is one-dimensional, two-dimensional or higher dimensional features, they can be fused by the concatenate function, which has better robustness and flexibility, and is more intuitive and efficient [27]. In this study, by extracting multi-dimensional acoustic features of bowel sounds and splicing them into a feature vector in the feature space, more information of bowel sounds can be obtained, so as to better analyze them and further diagnose neonatal NEC.

III. Results and Discussions

A. Experimental Setup

The experiments are conducted on a system featuring an NVIDIA GeForce RTX 3060 Laptop GPU, 32 GB RAM, and Windows 11. All machine learning algorithms are implemented in Python 3.10 using the Scikit-learn library. The dataset is split into training and testing sets with an 8:2 ratio. After preprocessing, classifier parameters are set according to Table I. This standardized approach, leveraging Scikit-learn, ensures reproducibility and facilitates comparison. The chosen hardware and software configurations provide a robust foundation for exploring machine learning algorithms at the intersection of medical and computer sciences.

TABLE I. Parameters of the Classifier

Classifier	Parameters
Adaboost	Number of estimators:50
Random forest	Number of estimators:100
SVM	Kernel:’linear’
KNN	Number of neighbors k = 3
Stacking	Estimators:SVM (kernel:’linear’), KNN (k = 3); final_estimator:KNN (k = 3)

B. Evaluation Indexes

In this investigation, we adopt a comprehensive set of assessment metrics to evaluate the classification performance of machine learning models. These metrics include accuracy (ACC), precision (PRE), sensitivity (SEN), F1 score (F1), specificity (SPE), and area under the ROC curve (AUC). Accuracy (ACC) reflects the ratio of correctly predicted samples to the total number of samples, serving as a fundamental indicator of overall model correctness [28]. Precision (PRE) measures the proportion of correctly predicted positive samples to the total predicted positive samples, offering insight into the model’s accuracy specifically within positive categories [10]. Sensitivity (SEN) assesses the model’s ability to correctly predict positive samples relative to the total true positive samples, quantifying its sensitivity to positive category samples [29]. F1 Score (F1) represents the harmonic mean of precision and recall, providing a balanced evaluation metric suitable for imbalanced class distributions [30]. Specificity (SPE) quantifies the accuracy of the model in predicting negative category samples relative to the total true negative samples [29]. Area under the ROC Curve (AUC) characterizes the performance of the model across various classification thresholds, with higher values indicating superior performance, particularly in binary classification scenarios [31]. These metrics collectively offer a robust framework for comprehensively evaluating the efficacy of machine learning models in the context of medical and computer science integration.

C. NEC Diagnosis Results of Single Feature

In the context of neonatal NEC, the manifestation of weakened or absent bowel sounds serves as a crucial diagnostic indicator. These bowel sounds are characterized by attenuated signals, substantial background noise, considerable inter-individual variability, and stochastic elements. Leveraging machine learning for diagnosis, we explore the utility of three distinct features in the frequency and time domains of neonatal bowel sounds: MFCC, STE, and ZCR.

MFCC is employed to transform the original neonatal bowel sounds into feature vectors, enhancing recognizability and separability for robust audio classification. STE captures audio amplitude, while ZCR reflects the frequency spectrum of bowel sounds to a certain extent. Incorporating these features into a machine learning algorithm facilitates the accurate diagnosis of neonatal NEC. The experimental results, presented in Tables II, III, and IV for individual use of MFCC, STE, and ZCR as machine learning inputs, respectively, highlight their efficacy in single-feature machine learning classification tasks.

Given the primary objective of diagnosing neonatal NEC with utmost precision, emphasizing the classification of all positive samples as positive is imperative. In this binary classification scenario, the model’s performance is gauged through metrics such as SEN, ACC, and AUC. Analyzing the results, we observe that for MFCC, a feature demonstrating robustness and separability in the frequency domain, classifiers including adaboost [15], random forest [16], SVM [17], KNN [18], and stacking [19] yield superior classification results. Among these, SVM achieves an ACC of 80.00%, SEN of 85.71%, and AUC of 88.89%.

Examining Table III reveals that STE, a time domain feature, performs well in the Random Forest classifier, an integrated voting algorithm, achieving 71.00% SEN, 76.00% ACC, and 76.59% AUC. Notably, the decision tree, a weak learner within the Random Forest classifier, effectively captures detailed aspects of STE in bowel sound signals, optimizing classification results. Turning to Table IV, ZCR, commonly used in speech endpoint detection, exhibits strong performance in bowel sound classification. Despite a lower SEN in the SVM, an ACC of 84.00% and an AUC of 80.16% underscore ZCR’s significance as a vital feature in bowel sound classification.

TABLE II. COMPARISON RESULTS OF MACHINE LEARNING ALGORITHMS BASED ON MFCC ONLY

MFCC						
Models	**ACC (%)**	**PRE (%)**	**SEN (%)**	**F1 (%)**	**SPE (%)**	**AUC (%)**
Adaboost	72.00	50.00	71.43	58.82	72.22	77.78
Random forest	72.00	50.00	71.43	58.82	72.22	88.89
SVM	80.00	60.00	85.71	70.59	77.78	88.89
KNN	80.00	66.67	57.14	66.57	88.89	81.75
Stacking	80.00	62.50	71.43	66.67	83.33	78.17

TABLE III. COMPARISON RESULTS OF MACHINE LEARNING ALGORITHMS BASED ON STE ONLY

STE						
Models	**ACC (%)**	**PRE (%)**	**SEN (%)**	**F1 (%)**	**SPE (%)**	**AUC (%)**
Adaboost	72.00	50.00	57.14	53.33	77.78	75.79
Random forest	76.00	56.00	71.00	63.00	78.00	76.59
SVM	56.00	0.00	0.00	0.00	77.78	53.17
KNN	72.00	50.00	42.86	46.15	83.33	68.25
Stacking	72.00	50.00	28.57	36.36	88.89	65.87

TABLE IV. COMPARISON RESULTS OF MACHINE LEARNING ALGORITHMS BASED ON ZCR ONLY

ZCR						
Models	**ACC (%)**	**PRE (%)**	**SEN (%)**	**F1 (%)**	**SPE (%)**	**AUC (%)**
Adaboost	60.00	33.33	42.86	37.50	66.67	64.68
Random forest	64.00	40.00	57.14	47.06	66.67	60.71
SVM	84.00	100.00	42.86	60.00	100.00	80.16
KNN	56.00	30.00	42.86	35.29	61.11	52.78
Stacking	60.00	33.33	42.86	37.50	66.67	56.35

D. NEC Diagnosis Results of Fused Feature

Utilizing the individual neonatal bowel sound features, namely MFCC, STE, and ZCR, in isolation for machine learning classification tasks demonstrates proficient outcomes. However, recognizing the potential for enhanced classification performance through comprehensive information integration, we explore the impact of employing a concatenate function to amalgamate the original data of MFCC, STE, and ZCR across the frequency and time domains. Subsequently, five distinct machine learning algorithms, adaboost [15], random forest [16], SVM [17], KNN [18], and stacking [19], are applied to evaluate the classification performance.

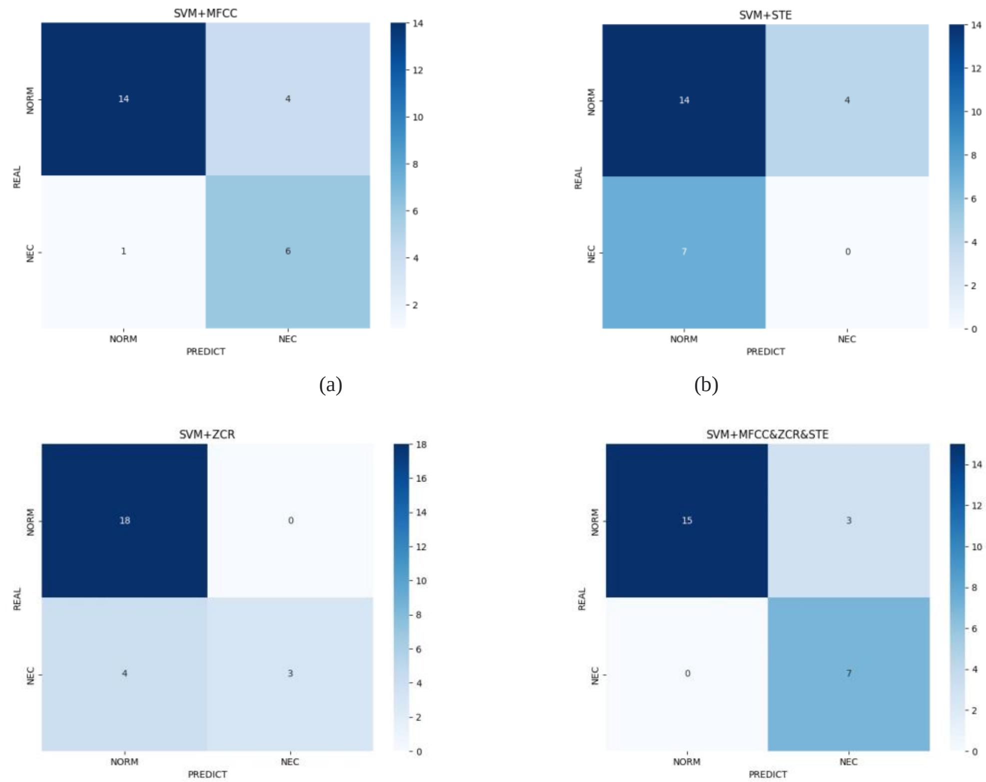
Analysis of the experimental results presented in Table V reveals the superior performance of the SVM classifier with a linear kernel function in neonatal NEC diagnosis following the multi-feature fusion of MFCC, STE, and ZCR. The achieved metrics include an ACC of 88.00%, PRE of 70.00%, SEN of 100.00%, F1 of 82.35%, SPE of 83.33%, and an area under the receiver operating characteristic curve (AUC) of 97.62%. Notably, the SVM classifier surpasses the capabilities of single-feature machine learning in bowel sound classification.

The exceptional AUC value of 97.62% attests to the model's outstanding performance, while a SEN of 100.00% signifies the SVM's accuracy in distinguishing bowel sounds of infants with NEC. As a robust supervised learning model, SVM stands out as a premier linear classifier, leveraging mathematical logic and model performance. Employing kernel functions and constrained optimization techniques, SVM constructs an optimal decision plane, maximizing classification spacing and effectively distinguishing between linearly separable sample classes. This intrinsic capability positions SVM as a promising tool for dichotomizing bowel sounds in neonates with NEC from those of normal neonates.

The experimental results are discussed below. Given SVM's prowess in high-dimensional feature spaces, particularly in scenarios involving multi-dimensional data such as the fusion of MFCC, STE, and ZCR features, SVM outperforms traditional and deep learning classifiers. The soft-margin and kernel techniques of SVM facilitate the establishment of a nonlinear decision boundary, addressing complex classification problems. The experiment, incorporating feature splicing through the concatenate function at the data level, fully preserves the original information of the three features. This allows the SVM machine learning algorithm model to glean more valuable insights into bowel sounds of infants with NEC and those of normal newborns, ultimately achieving superior classification and NEC diagnosis performance [32].

TABLE V. COMPARISON RESULTS OF MACHINE LEARNING ALGORITHMS BASED ON FUSION FEATURES OF MFCC AND ZCR AND STE

MFCC&ZCR&STE						
Models	**ACC (%)**	**PRE (%)**	**SEN (%)**	**F1 (%)**	**SPE (%)**	**AUC (%)**
Adaboost	76.00	54.55	85.71	66.67	72.22	89.68
Random forest	76.00	55.56	71.43	62.50	77.78	88.10
SVM	88.00	70.00	100.00	82.35	83.33	97.62
KNN	84.00	71.43	71.43	71.43	88.89	88.49
Stacking	80.00	60.00	85.71	70.59	77.78	86.90



(a) (b) (c) (d)

Fig. 6. Results of SVM confusion matrix after single-feature and multi-feature fusion. (a) SVM confusion matrix based on MFCC (b) SVM confusion matrix based on STE (c) SVM confusion matrix based on ZCR (d) SVM confusion matrix based on MFCC&ZCR&STE.

The comparative analysis of SVM confusion matrix results, as depicted in Fig. 6 (a)-(d), illustrates the pronounced improvement in the SVM machine learning algorithm model performance through multi-feature fusion. In conclusion, employing the SVM classifier with a multi-feature fusion algorithm for neonatal bowel sounds yields a more favorable diagnostic outcome for the automatic diagnosis of neonatal NEC.

IV. CONCLUSIONS

To achieve automated diagnosis of neonatal NEC using bowel sound signals, we conduct a study collecting data from newborns with NEC and healthy counterparts at the neonatal department of West China Second Hospital of Sichuan University. Employing a dedicated bowel sound acquisition system, we address the challenges posed by the random, weak, and variable nature of bowel sounds, including their attenuation or absence in NEC cases.

Three crucial frequency-domain and time-domain features—MFCC, STE, and ZCR—are selected for classifier learning. These features are strategically con—catenated in the feature space, utilizing a multi-feature fusion approach to preserve the entirety of original information. This process aims to enhance the effectiveness of the subsequent machine learning algorithm model for bowel sound signals of both NEC and healthy newborns.

Five distinct machine learning algorithms—adaboost, random forest, SVM, KNN, and stacking—are employed for model training and classification of neonatal bowel sound signals. Notably, the SVM classifier demonstrated superior performance in NEC diagnosis. Limitations of this study: The data volume needs to be further expanded, or the trained algorithm model can be applied to other data sets to verify robustness. This study outlines a potential development path for discriminating and diagnosing neonatal NEC through bowel sound signal features and machine learning algorithm modeling. The proposed approach holds promise for early detection, diagnosis, and treatment of neonatal NEC, contributing to the reduction of mortality and disability in affected newborns. In the future, while expanding the data set of intestinal sounds, the pathological features of other neonatal gastrointestinal diseases should be studied in combination with the acoustic features of intestinal sounds, and the multi-feature fusion theory of this study should be combined for model training and disease diagnosis.

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