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A PROSPECTIVE STUDY ON APPLICATION OF ARTIFICIAL INTELLIGENCE IN DETECTION OF WHEEZE SOUNDS IN CHILDREN

Paediatrics

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ABSTRACT

Background: Wheeze is a common and clinically important adventitious lung sound in children that often signals airway obstruction and may indicate asthma exacerbations. Manual auscultation is subjective and can miss subtle adventitious sounds, particularly in young or uncooperative children. Recent advances in deep learning offer an opportunity to automate and standardize wheeze detection. **Methods:** We performed a prospective analytical study at the Department of Paediatrics, A.J. Institute of Medical Sciences, Mangalore (April 2023–October 2024). One hundred eight children (age 1–12 years) presenting with respiratory complaints were enrolled. Four chest auscultation recordings per child (anterior/posterior, left/right) were collected with an electronic stethoscope (432 recordings total). After preprocessing and mel-spectrogram extraction, we trained and compared multiple models (3-layer LSTM, 4-layer CNN, 4-layer CNN + tabular data, and a proposed ResNet34 with Convolutional Block Attention Module [CBAM] combined with tabular data). Model performance was evaluated on held-out test data using accuracy, AUC, precision, recall, and F1-score. Clinical performance of the AI algorithm was compared against general pediatricians' auscultation. **Results:** The proposed ResNet34+CBAM+tabular model achieved the highest performance: accuracy 91.2%, AUC 0.891, precision 94.4%, recall 81.0%, and F1-score 87.2%. Across 403 analyzable recordings (93.2% of total), the AI algorithm outperformed general pediatricians for wheeze detection (sensitivity 86.4% vs 82.2%; specificity 83.0% vs 72.1%) and markedly for crackles (sensitivity 81.1% vs 47.8%; specificity 94.1% vs 77.1%). Multivariable analysis identified male sex, family history of asthma (OR 2.20), household smoker (OR 1.43), and history of eczema (OR 3.85) as independent risk factors for current wheeze. **Conclusion:** A ResNet34-based deep learning model with attention and minimal tabular inputs accurately detects wheeze and other adventitious sounds and outperforms general pediatricians in this cohort. AI-assisted auscultation shows promise as an objective adjunct for pediatric respiratory assessment and could aid earlier diagnosis and monitoring of wheeze-associated conditions.

KEYWORDS

Artificial Intelligence; Wheeze; Children; asthma; breath sounds.

INTRODUCTION

Respiratory diseases in children are primary causes of illness and death worldwide, with conditions like asthma, bronchiolitis, and pneumonia being particularly prevalent (1)(2). A critical indicator of many respiratory conditions in children is the presence of wheezing, a high-pitched whistling sound produced during breathing.

Wheezing can indicate narrowing or obstruction of airways, frequently linked to conditions such as asthma or upper respiratory tract infections (3). Early detection of wheezing is essential for prompt intervention, which can greatly lower risk of complications and enhance treatment outcomes (4). However, detecting and accurately diagnosing wheezing in children presents number of challenges, particularly in early stages of illness when symptoms may be subtle.

Traditional diagnostic methods for identifying wheeze primarily rely on clinical auscultation using stethoscopes, where healthcare professionals listen to the patient's breath sounds. While experienced clinicians can recognize wheezing sounds, this process remains subjective, dependent on the clinician's expertise and ability to distinguish between normal and abnormal breath sounds (5). Moreover, children, particularly infants and young children, may find it difficult to cooperate during physical exams, making it harder for clinicians to perform accurate auscultation. The variability in wheeze sounds further complicates manual detection, as wheezing can range from mild to severe, and its frequency and intensity can fluctuate depending on the condition's progression (6).

There has been growing interest in leveraging artificial intelligence (AI) to overcome these limitations during recent years. AI, particularly machine learning (ML) and deep learning (DL) techniques, has demonstrated the ability to analyze complex datasets with remarkable accuracy, and is increasingly being applied in healthcare to automate diagnostics (7). Regarding respiratory sounds, AI algorithms are trained using extensive datasets of recorded breath sounds to recognize subtle patterns that may be difficult for human ears to detect. Through advanced signal processing and feature extraction techniques, AI can classify sounds such as wheezes with high sensitivity and specificity, offering promising tool for early diagnosis and continuous monitoring of respiratory conditions in children (8).

The integration of AI into the detection of wheeze sounds could revolutionize pediatric respiratory care by providing faster, more objective, and more accessible diagnostic tools. This technology could enable healthcare providers to make quicker, more accurate diagnoses, even in remote or underserved areas where access to specialists may be limited (9). AI-powered systems could also allow for continuous, realtime monitoring of patients, especially those with chronic conditions like asthma, enabling more personalized treatment plans and reducing the frequency of hospital visits (10)

This study addresses challenges such as dataset limitations, variability in wheeze sound recordings, and integration of AI tools into clinical practice. The outcomes of this research could provide valuable insights into how AI can be effectively implemented in pediatric healthcare, offering a novel approach to diagnosis and management of respiratory conditions in children.

By improving ability to detect and monitor wheeze sounds, AI could play pivotal role in reducing burden of respiratory diseases and improving quality of care for children worldwide. Furthermore, the research will investigate the potential benefits of AI assisted diagnosis, including enhanced accuracy, early detection, and improved patient outcomes.

Therefore, this study aims to evaluate an artificial-intelligence system for accurate and early detection of wheeze sounds in children, thereby supporting timely diagnosis and management of pediatric obstructive airway disease. To achieve this, we performed a prospective analytical investigation in which recorded breath sounds were analyzed using multiple machine- and deep-learning approaches; specifically, our objectives were to distinguish wheezing from other auscultatory breath sounds and thereby aid identification of bronchial asthma; identify clinical and environmental risk factors associated with childhood wheeze; compare the diagnostic performance of existing machine- and deep-learning classifiers for pediatric asthma/wheeze detection; and determine whether combining spectrogram-based deep models with minimal tabular features (age, sex) yields an efficient classifier suitable for use in preschool populations.

METHODS

Study Design And Setting: This prospective analytical study was conducted at the Department of Pediatrics, A.J. Institute of Medical

Sciences, Mangalore, from April 2023 to October 2024. The research employed a comprehensive approach combining clinical evaluation with advanced artificial intelligence techniques for wheeze detection in pediatric patients. The study utilized both outpatient and inpatient settings to capture a diverse range of respiratory presentations, ensuring representative sampling of the target population

Participants And Eligibility: A total of 108 children aged 1-12 years presenting with respiratory complaints were enrolled using convenient sampling methodology. Inclusion criteria comprised children aged 1-12 years with history of wheezing, confirmed asthma diagnosis (>5 years), or at least two wheezing episodes (≤5 years). Exclusion criteria eliminated children with chronic conditions that could confound respiratory acoustics, including chronic sinusitis, whooping cough, immunodeficiency, laryngomalacia, infantile lung diseases, cardiac or neonatal pulmonary problems, and gastroesophageal reflux disease.

Sample size calculation utilized the single proportion formula based on Kim et al.'s study, with expected proportion of 7.63%, precision of 5%, and 95% confidence level (Z = 1.96), yielding a minimum requirement of 108 participants. This calculation ensured adequate statistical power for detecting meaningful differences in AI performance metrics.

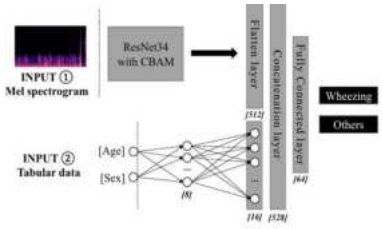
Data Collection And Clinical Assessment: Consecutive eligible children were recruited with IRB-approved informed consent from parents/guardians. A structured case record captured demographics, presenting complaints, vital signs, and focused respiratory examination with electronic stethoscope recordings at four chest sites per child (anterior/posterior, right/left). Standard-of-care investigations and management were provided at clinician discretion.

Lung Sound Acquisition: Electronic stethoscope recordings were obtained at four chest locations across two respiratory cycles, targeting clear inspiratory/expiratory phases while minimizing ambient noise. From 432 total recordings, 403 met quality standards for AI analysis after excluding recordings with duration <9s, poor signal quality, or failure to meet gold-standard criteria.

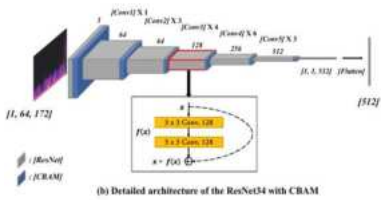
Reference Labeling And Ground Truth: Blinded validation established gold-standard classification of respiratory sounds (normal, wheeze, crackles, rhonchi, stridor) for training, validation, and comparative performance analyses against general pediatricians. These reference labels provided ground truth for supervised learning and algorithmic evaluation.

Audio Pre-processing: Audio signals were resized to uniform sample length, whitened to reduce bias, and converted into mel-spectrograms with repeat padding for standardized input dimensions. Training data underwent augmentation using six techniques (white noise addition, time shifting, stretching, reverse, minus, fit transform) followed by time/frequency masking to improve robustness and reduce overfitting.

Model Architecture: The primary model was a convolutional neural network based on ResNet34 with Convolutional Block Attention Module (CBAM) for channel and spatial attention on spectrogram inputs of size, producing 512 learned audio features. A parallel multilayer perceptron processed tabular metadata (normalized age, binary gender), with outputs fused before final classification, enabling multimodal discrimination.



(a) The overall architecture of the proposed model



(b) Detailed architecture of the ResNet34 with CBAM

Figure 1: Architecture of proposed model

Training And Validation: Cross-entropy loss was optimized using Adam with five-fold cross-validation and grid search for hyperparameter selection, plus stochastic weight averaging for improved generalization. Data were partitioned 70/10/20 for training/validation/testing, with models trained for up to 120 epochs using PyTorch framework compatible with torchaudio.

Comparators: Baseline architectures included 3-layer LSTM, 4-layer CNN, and 4-layer CNN with tabular data fusion. For broader context, ImageNet-pretrained backbones (VGG16/19, InceptionV3, ResNet50/101) adapted to spectrograms were benchmarked against the proposed model.

Endpoints And Performance Metrics: The primary endpoint was accurate wheeze classification versus other respiratory sounds. Secondary endpoints included multi-class accuracy across chest locations and comparative performance metrics (sensitivity, specificity, precision, F1-score, AUC) for AI versus general pediatricians using identical recordings. Performance evaluation used confusion matrices and derived metrics computed on held-out test sets.

Statistical Analysis: Descriptive statistics summarized categorical variables as frequencies/percentages and continuous variables as measures of central tendency/dispersion. Group comparisons used ANOVA where applicable with significance threshold $p<0.05$, performed in SPSS version 25.

Sample Size And Ethics: Sample size calculation using single-proportion formula yielded a minimum target of 108 participants via convenience sampling. The study was approved by Institutional Ethics Committee of AJ Institute of Medical Sciences & Research centre (AIEC /REV /102 /2023). Written informed consent was obtained using multilingual forms. All methods adhered to institutional/national ethical standards and Declaration of Helsinki principles with confidentiality safeguards.

RESULTS

A prospective analytical study was conducted on 108 children with respiratory issues at the Department of Pediatrics, AJ Institute of Medical Sciences, Mangalore. The following observations were made:

Table 1: Baseline Characteristics Of Study Participants (n=108)

Characteristics	Frequency(n)	Percentage (%)
Age group (in years)		
1-6	71	65.74
7-12	37	34.26
Gender		
Girl	42	38.89
Boy	66	61.11
Type of birth		
Term	64	59.25
Preterm	44	40.75
Family size		
≤3	63	58.34
>3	45	41.66
Family history of asthma		
Yes	58	53.71
No	50	46.29

All the children are aged between 1 and 12 years. Majority of children (65.74%) are in the 1–6 years age group and the mean age of study population is 5.78 ± 2.1 years. Out of them, 66(61.11%) are boys and 42 (38.89%) are girls. This distribution indicates slightly higher proportion of boys in study compared to girls. 59.25% were born at term, while 40.75% were preterm. 58.34% of children are from smaller families (≤3 members). 53.71% have a family history of asthma, while 46.29% do not. Over half of the children have a positive family history suggesting a potential genetic or familial predisposition.

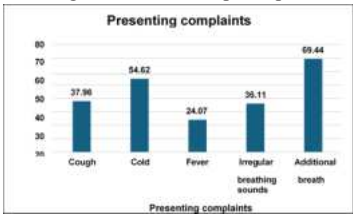


Figure 2: Presenting complaints of study population

Figure 2 shows presenting complaints of children when they attended the pediatric department. 75 (69.44%) children had additional breath sounds, followed by cold 59(54.62%) and cough 41(37.96%). Irregular breathing was present in 39 (36.11%) children and only 26 (24.07%) children had fever.

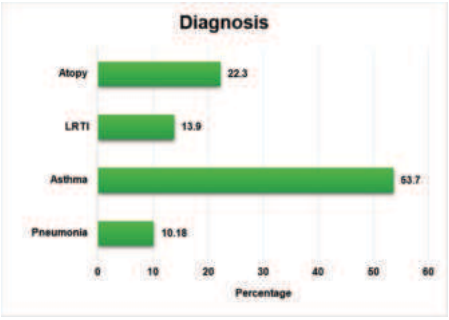


Figure 3: Diagnosis in study population

Figure 3 shows diagnosis of respiratory and other conditions in children. Acute exacerbation of asthma was diagnosed in 58(53.7%) children. 24 (22.3%) children had LRTI. Pneumonia and atopy were present in 11 (10.18%) and 15(13.9%) children respectively.

Table 2: Risk Factors For Wheeze / Asthma (Univariate Logistic Regression)

Characteristics	Without current wheeze	With current wheeze	Odds ratio	95%CI	P-Value
Gender					
Girl	27(64.2)	15(35.8)	-	-	**<0.05**
Boy	25(37.9)	41(62.1)	0.33	0.15-0.75	
Age group (in years)					
1-6	40(56.3)	31(43.7)	-	-	**<0.05**
7-12	12(32.4)	25(67.6)	0.37	0.17-0.9	
Type of birth					
Term	28(43.8)	36(56.2)		-	0.27
Preterm	24(54.6)	20(45.4)	0.64	0.29-1.4	
Family size					
≤3	31(49.2)	32(50.8)		-	0.79
>3	21(46.7)	24(53.3)	1.10	0.5-2.38	
Family history of asthma					
Yes	10(17.2)	48(82.8)	0.03	-	**<0.001**
No	42(84.0)	8(16.0)	-	0.01-0.10	
Smoker in household					
Yes	20(35.1)	37(64.9)	0.32	-	**<0.01**
No	32(62.8)	19(37.2)	-	-0.14-0.70	
Pet in house					
Yes	40(57.9)	29(42.1)	3.10	-	**<0.05**
No	12(30.8)	27(69.2)	-	1.3-7.12	
Eczema ever					
Yes	4(9.3)	39(90.7)	0.03	-	**<0.001**
No	48(73.8)	17(26.2)	-	0.01-0.11	

Above table presents risk factors for wheeze / asthma. The odds of having wheeze currently are significantly lower in girls than boys. Children aged 1-6 years have lower likelihood of wheeze currently compared to children aged 7-12 years Type of birth and family size were not significantly associated with likelihood of current wheeze. In contrast, factors such as family history of asthma, presence of smoker in household, having pets at home, and history of eczema were significantly associated with current wheeze.

Table 3: Multiple Variate Logistic Regression Of Risk Factors

Characteristics	Odds ratio	95% CI	P- value
Gender			
Girl	**Ref**	-	**<0.05**
Boy	1.46	1.12-1.88	
Family H/O asthma			
No	**Ref**	-	**<0.001**
Yes	2.20	1.69-2.87	
Smoker in household			
No	**Ref**	-	**<0.05**
Yes	1.43	1.04-1.96	
Pet in house			
No	**Ref**	-	0.062
Yes	1.75	0.97-3.14	
Eczema ever			
No	**Ref**	-	**<0.001**
Yes	3.85	2.10-7.08	

Above table 3 shows the multivariate regression analysis of risk factors for wheeze/ asthma. Boys have 1.46 times higher odds of having the outcome compared to girls (p= 0.005). Having family H/O asthma increases the odds of the outcome by 2.20 times compared to those without a family H/O asthma ($p < 0.001$). The odds of having the outcome are 1.43 times higher if there is a smoker in the household compared to if there is no smoker in household ($p = 0.027$). Having H/O eczema increases odds of outcome by 3.85 times compared to those who never had eczema ($p < 0.001$). Having pet in house was not significantly associated with presence of current wheeze.

Breath Sounds Classification (Figure 4): Breath sounds recorded were from four chest locations of each child. Anterior Right, Anterior Left, Posterior Right and Posterior Left. A total of 432 respiratory sounds were recorded from study population. Among abnormal sounds, wheeze was the most frequent finding — 103 recordings (23.8%) — followed by rhonchi in 79 recordings (18.1%) and stridor in 64 recordings (14.8%). Crackles were the least common abnormality, appearing in 41 recordings (9.4%). A majority of the children exhibit normal breath sounds (33.5%).

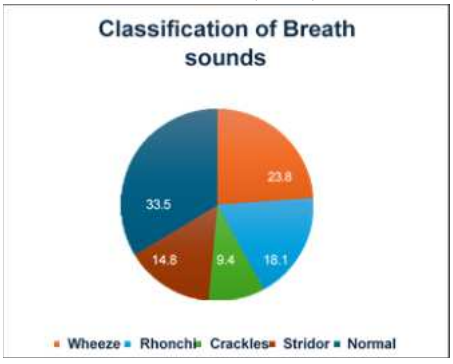


Figure 4: Classification of breath sounds

Characteristics Of The Recordings In Study: Among the 103 wheeze recordings, the distribution across chest sites was fairly even: 23 were from the anterior left site (22.3%), 29 from the anterior right (28.2%), 28 from the posterior left (27.2%), and 23 from the posterior right (24.4%). The 184 recordings classified as other breath sounds showed a similar site distribution—46 anterior left (25.0%), 49 anterior right (26.6%), 44 posterior left (23.9%) and 45 posterior right (24.5%)—and there was no statistically significant difference in recording location between wheeze and other-sound groups ($p = 0.883$).

However, the duration of sounds differed markedly: wheeze recordings had a mean duration of 89.36 ± 39.51 ms, compared with 63.09 ± 27.79 ms for other breath sounds, a difference that was highly significant ($p < 0.001$), indicating that wheeze events were substantially longer in duration than other adventitious sounds.

Performance Of AI Algorithm And General Pediatrician In Classifying The Recordings

A total of 432 auscultation recordings were collected and 403 (93.2%) were analyzed by AI algorithm. Recordings were rejected if the duration of the recording was < 9s, signal was of low quality, or the recording did not meet the gold standard requirements.

Table 4: Performance Of AI Algorithm And General Pediatrician

	General pediatrician	AI	P Value
Sensitivity (%)			
Wheeze	82.2	86.4	>0.05

Crackles	47.8	81.1	**<0.001**
Precision (%)			
Wheeze	64.9	76.0	**<0.001**
Crackles	38.6	80.6	**<0.001**
Specificity (%)			
Wheeze	72.1	83.0	**<0.001**
Crackles	77.1	94.1	**<0.001**
F1-score (%)			
Wheeze	72.5	80.9	**<0.001**
Crackles	42.7	80.9	**<0.001**

Table 4 summarizes the performance of the AI algorithm and the general pediatricians in classifying the recordings. Analysis of the performance of the AI algorithm showed that the sensitivity and specificity in the detection of crackles were 81.3 and 94.1%, respectively, with an F1-score of 80.9%. However, when marked by the general pediatricians, the sensitivity and specificity decreased to 47.8 and 77.1%, respectively, while the F1-score was 42.7%.

The sensitivity, specificity and F1-score of the AI algorithm in stratifying wheeze were, respectively, 86.4, 83.0, and 80.9%, which was higher than those of general pediatricians (82.2, 72.1, and 72.5%).

Table 5: Performance Of AI Algorithm In Breath Sounds Recognition Based On Location.

	Anterior		Posterior	
	Right	**Left**	**Right**	**Left**
Recordings	107	106	110	104
Accuracy	79.8	78.4	77.8	74.7
Sensitivity (%)				
Wheeze	85.7	82.6	85.7	83.3
Crackles	77.3	73.7	77.3	92.9
Precision (%)				
Wheeze	77.4	73.1	72.7	62.5
Crackles	85.0	83.4	81.0	76.5
Specificity (%)				
Wheeze	86.3	86.3	83.0	76.5
Crackles	94.7	94.5	93.2	93.4
F1-score (%)				
Wheeze	81.4	77.6	78.7	71.4
Crackles	81.0	77.8	79.1	83.9

Four sounds recorded in each child were collected and sent to AI algorithm for recognition.

When collection points on chest were compared, significant difference was not found in accuracy of AI algorithm in recognition of breath sounds collected from different locations ($\chi 2 = 1.178$, $P = 0.947$), and overall accuracy was approximately 75%.

Table 6: Performance Of Proposed Model And Comparison With Other Models

Models	Selected hyper-Parameters with grid search	Accuracy	AUC	Precision	Recall	F1-score
3-layers LSTM	Epoch: 40/batch size: 32/ Learning rate: 1e−3/dropout rate: 0.2	0.824	0.841	0.703	0.904	0.791
4-layers CNN	Epoch: 60/batch size: 16/ Learning rate: 1e−2/dropout rate: 0.4	0.887	0.855	0.874	0.756	0.813
4-layers CNN +Tabular data	Epoch: 60/batch size: 16/ Learning rate: 1e−3/dropout rate: 0.4	0.895	0.877	0.898	0.805	0.850
34-layers ResNet with CBAM + Tabular data	Epoch: 120/batch size: 32/learning RATE: 1e−3	0.912	0.891	0.944	0.810	0.872

Table 6 presents the performance comparison between the proposed model i.e 34- layers ResNet with CBAM + Tabular data and other experimental models such as the 3- layer LSTM model, 4-layer CNN model, and 4-layer CNN model with tabular data.

The 3-layer LSTM model for CNN and recursive neural networks (RNN) comparison showed an accuracy of 82.4%, AUC of 84.1%, precision of 70.3%, recall of 90.4%, and F1-score of 79.1%.

The 4-layer CNN model was set as the basic model that detected wheeze sounds with an accuracy of 88.7%, AUC of 85.5%, precision of 87.4%, recall of 75.6%, and F1- score of 81.3%.

When tabular data, including age and sex, were added to the basic model, the performance improved compared to that of the basic model. It had an accuracy of 89.5%, AUC of 87.7%, precision of 89.8%, recall of 80.5%, and F1-score of 85%.

The proposed model, a CNN-based 34-layer ResNet with a CBAM, and tabular data exhibited the highest performance among the experiments based on the CNN model. The model had an accuracy of 91.2%, AUC of 89.1%, precision of 94.4%, recall of 81% and F1-score of 87.2%.

DISCUSSION

The present study aimed to analyze respiratory issues in children, focusing on breath sounds, AI detection of lung sounds and compare with traditional diagnostic methods used by pediatricians. A total of 108 children, aged 1 to 12 years, participated in study, with mean age of 5.78 ± 3.1 years. A majority of children were boys (61.11%) compared to girls (38.89%). The study outcomes reveal common respiratory conditions and additional breath sounds such as wheezing, crackles, rhonchi, and stridor, as well as use of AI algorithms to identify specific breath sounds like crackles and wheezes.

Age And Gender Distribution

The study population's mean age (5.78 ± 3.1 years) falls within the typical age range for pediatric respiratory illnesses, which are most prevalent between ages of 1 to 5 years. This aligns with findings from other studies on pediatric respiratory issues, which have demonstrated that young children are particularly vulnerable to respiratory conditions due to underdeveloped immune systems and smaller airways (11)(12). The slightly higher proportion of boys (61.11%) compared to girls (38.89%) aligns with prior studies, which frequently reports higher incidence of respiratory issues in male children, potentially due to genetic and hormonal differences (13)(14)(15).

Respiratory Symptoms And Conditions

Respiratory symptoms were commonly observed among the study population. Additional breath sounds were the most frequently reported (69.44%), followed by cold (54.62%), and cough (37.96%).

This is in agreement with previous studies in children where wheezing, cough, and cold are primary indicators of respiratory distress, especially in conditions like asthma (6)

The high frequency of wheezing (53.7%) and the association with conditions like asthma (58 children) highlights the prevalent nature of asthma in pediatric respiratory issues. Asthma is one of the leading causes of chronic respiratory illness in children, and its exacerbation often leads to wheezing, which can be heard through auscultation (12).

Risk Factors For Wheeze/Asthma:

The present study's finding that family history of asthma, presence of smokers, and history of eczema exhibited strong association with wheezing. This aligns with previous research on role of genetic and environmental factors in respiratory illnesses (12)(16)(17).

This study found relatively low percentage of pneumonia (10.18%) and lower respiratory tract infections (22.3%), suggesting that these conditions were not as prevalent in this cohort of children. Similarly, study conducted in District Bannu of Khyber Pakhtunkhwa, Pakistan, revealed that pneumonia was responsible for 21.2% of LRTI cases among children, with bronchiolitis being more prevalent (39%). This variation underscores the influence of regional factors on disease prevalence (18).

Additionally, a study from Thailand analyzing data from 2015 to 2019 found that pneumonia was most common LRTI, affecting 61.58% of hospitalized children. Children aged 1–5 years had highest incidence (19). This may reflect regional epidemiology or the selective nature of the study design.

Breath Sound Patterns And Auscultation Locations

Breath sounds were classified into different types such as normal sounds, wheeze, rhonchi, stridor, and crackles. Wheeze was most common breath sound (23.8%), followed by rhonchi (18.1%), stridor (14.8%), and crackles (9.4%).

These findings support known patterns of respiratory illnesses where wheezing is particularly associated with obstructive airway diseases like asthma (20). Rhonchi and stridor are often indicative of upper airway issues, while crackles are associated with pneumonia or fluid in lungs.

The study also observed no significant difference in breath sounds recorded from various chest locations (Anterior Right, Anterior Left, Posterior Right, And Posterior Left), which suggests that breath sounds are relatively uniform across these locations. This is inconsistent with some earlier research that found location-specific differences in sound frequencies and diagnostic accuracy, particularly in detecting wheezes and crackles (6).

Duration Of Breath Sounds

The study found that duration of wheeze sounds (89.36 ± 39.51 ms) was significantly longer than that of "other" group (63.09 ± 27.79 ms) with a p-value of <0.001. This observation is clinically significant, as breath sounds duration has been associated with severity of airway obstruction in conditions such as asthma (21). The longer duration of wheezing suggests more prolonged respiratory obstruction, which indicates more severe or poorly controlled asthma. This finding supports the clinical practice of using auscultation duration as a potential marker for evaluating asthma exacerbations (22).

AI Algorithm Performance

The performance of AI algorithm in detecting crackles and wheeze was a key focus of this study. For crackles, AI algorithm demonstrated high sensitivity (81.3%) and specificity (94.1%), which was significantly higher than sensitivity and specificity achieved by general pediatricians (47.8% and 77.1%, respectively).

These findings are similar to other studies demonstrating that AI models, especially those using deep learning techniques, can outperform clinicians in identifying subtle breath sounds (23). AI use in medical diagnostics has shown promise in improving diagnostic accuracy, mainly in areas where human error or fatigue may reduce performance (24).

For wheezing, the AI algorithm's sensitivity (86.4%) and specificity (83.0%) were also superior to those of general pediatricians (82.2% and 72.1%, respectively). The results suggest that AI can be a valuable tool for clinicians, especially in settings where auscultation may be challenging or time-consuming.

Comparison With Other Models

The study compared the proposed AI model, a CNN-based 34-layer ResNet with a CBAM, to other experimental models such as a 3-layer LSTM model, a 4-layer CNN model, and a 4-layer CNN model with tabular data. Among these, the proposed model showed the highest accuracy (91.2%), precision (94.4%), recall (81%), and F1-score (87.2%). These results highlight the effectiveness of more complex, deep learning models in medical sound classification.

The 4-layer CNN model with tabular data showed an accuracy of 89.5%, which is a strong performance, but it was surpassed by the proposed ResNet-CBAM model. The inclusion of tabular data (age, sex) in the CNN model improved its performance, which is in line with studies that suggest that combining audio data with demographic or clinical data can improve diagnostic outcomes (25)(26)(27).

Performance of existing models pre-trained on ImageNet proposed in a previous study using a respiratory sound dataset was compared with performance of ResNet model we adopted.

Below Table Shows The Comparison:

Table 7: Comparison Of Performance Of Existing Models Pre-trained On ImageNet Proposed In A Previous Study And Resnet Model We Adopted

Models	Accuracy	AUC	Precision	Recall	F-1 score
InceptionV3	0.841	0.838	0.772	0.809	0.794
VGG16	0.820	0.831	0.764	0.795	0.781
VGG19	0.852	0.844	0.806	0.812	0.810
ResNet50	0.859	0.849	0.809	0.810	0.809
ResNet101	0.877	0.863	0.850	0.809	0.829
ResNet34	0.877	0.873	0.818	0.857	0.837

#AUC - area under the curve; ResNet - residual network; VGG - visual geometry group network.

Above table shows that ResNet 34 performed best when compared to other models.

A recent study by Kim et al., revealed that VGG16 use pre-trained on ImageNet had the best performance in abnormal lung sounds detection, with an AUC 0.93 and an accuracy of 86.5% (28).

CONCLUSION

This prospective single-center study of 108 children (1–12 years) presenting with respiratory complaints characterized clinical risk factors and evaluated an AI-based auscultation pipeline for breath-sound classification. Wheeze was the most frequent abnormal sound and asthma and lower respiratory tract infections comprised a large share of diagnoses. Multivariable analysis identified male sex, younger age, household smoking, family history of asthma, and eczema as independent predictors of wheeze. Recordings from four chest sites showed no site-dependent differences in detection, but wheeze events had significantly longer duration than other sounds. We compared multiple architectures and found that a ResNet34 backbone augmented with a Convolutional Block Attention Module, combined with minimal tabular inputs, achieved the best diagnostic performance and exceeded general pediatricians in sensitivity and specificity for wheeze and crackle detection. Despite no significant differences in wheeze detection across various auscultation points, breath sound duration emerged as a distinguishing characteristic, especially in wheezing cases. The study's findings support the clinical utility of AI-enhanced auscultation as a reliable adjunct tool for respiratory assessment in children.

In conclusion, integrating AI into pediatric respiratory diagnostics holds promise for enhancing early detection and management of respiratory conditions. Future research with larger cohorts and longitudinal designs is warranted to validate these findings and facilitate the translation of AI models into routine clinical practice.

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