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NDL-Net: A Hybrid Deep Learning Framework for Diagnosing Neonatal Respiratory Distress Syndrome from Chest X-rays

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ABSTRACT **Objective:** Neonatal Respiratory Distress Syndrome (NRDS) poses a significant threat to newborn health, necessitating timely and accurate diagnosis. This study introduces NDL-Net, an innovative hybrid deep learning framework designed to diagnose NRDS from chest X-rays (CXR). **Results:** The architecture combines MobileNetV3 Large for efficient image processing and ResNet50 for detecting complex patterns essential for NRDS identification. Additionally, a Long Short-Term Memory (LSTM) layer analyzes temporal variations in imaging data, enhancing predictive accuracy. Extensive evaluation on neonatal CXR datasets demonstrated NDL-Net's high diagnostic performance, achieving 98.09% accuracy, 97.45% precision, 98.73% sensitivity, 98.08% F1-score, and 98.73% specificity. The model's low false negative and false positive rates underscore its superior diagnostic capabilities. **Conclusion:** NDL-Net represents a significant advancement in medical diagnostics, improving neonatal care through early detection and management of NRDS.

INDEX TERMS AI-driven diagnosis, chest X-ray imaging, computational pediatric radiology, hybrid deep learning framework, neonatal respiratory distress syndrome.

IMPACT STATEMENT NDL-Net revolutionizes neonatal care by enhancing NRDS diagnosis from CXR, ensuring timely, accurate interventions, reducing errors, and significantly improving health outcomes in NICUs through advanced deep learning.

I. INTRODUCTION

THE NRDS presents as a neonates struggle to sustain breathing shortly after birth [1]. Rapid diagnosis and management are imperative due to its high mortality rate, particularly in countries with limited resources, where access to neonatal care is constrained [2]. Despite significant progress in high-income countries over the past decades, NRDS remains a major contributor to neonatal mortality in developing countries [3]. This challenge impedes the ability of developing nations to achieve the World Health Organization's Sustainable Development Goal 3, which targets reducing neonatal mortality rates to below twelve deaths per thousand live births by 2030 [4]. Therefore, healthcare professionals must attain proficiency in diagnosing and treating. NRDS to reduce the neonatal mortality rate and accomplish global health objectives.

This imperative is particularly crucial during the neonatal period, defined as the initial twenty-eight days after the birth of a newborn [5]. During this period, infants with conditions like premature birth, NRDS, infections, congenital anomalies, and cardiac issues may require treatment during the Neonatal Intensive Care Unit (NICU) [6]. NRDS is a critical condition frequently addressed in the NICU.[7]. Consequently, early detection of NRDS symptoms is essential [8]. The likelihood of NRDS in both full-term and premature infants was explored by analyzing the antenatal features using a predictive model [9]. Additionally, analyzing pulmonary function test data offers an alternative approach to identifying NRDS, complementing traditional predictive models [10]. As a case in point, Pederiva et al. (2023) employed data from pulmonary function tests to detect congenital respiratory abnormalities associated to NRDS [11].

Building on this research, recent advancements have introduced noncontact thermal imaging as an innovative method for diagnosing NRDS in neonates, effectively classifying newborns as healthy or ill. [12]. When neonates present with NRDS, CXR is often performed to determine the most appropriate diagnosis and possible treatment, ensuring timely and tailored medical interventions [13]. This underscores the importance of interpreting CXR images in the clinical evaluation of respiratory pathologies in neonates, guiding the development of effective management strategies [14]. Moreover, computer-assisted systems alleviate the

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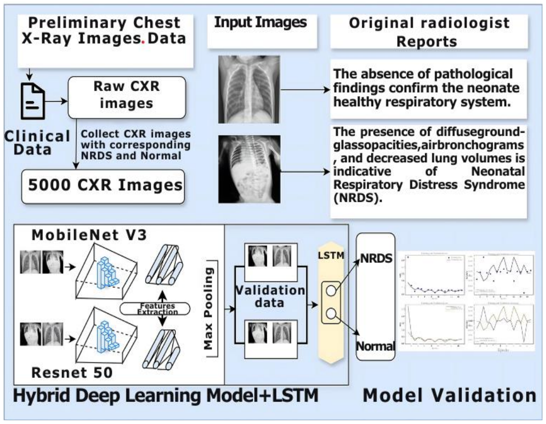

Fig. 1. Schematic representation of the hybrid deep learning framework for NRDS diagnosis

burden on specialists by performing complex tasks efficiently, allowing for increased patient throughput and improved healthcare delivery [15, 16].

In the field of medical diagnostics, artificial intelligence (AI) and deep learning algorithms are deployed to detect and diagnose chest diseases [17]. Amidst the COVID-19 pandemic, these innovative approaches have proven essential in detecting COVID-19 and supporting healthcare practitioners [18, 19]. In this study, the routine examination of CT images and chest X-rays demonstrated the adaptability of AI and advanced computational techniques in medical imaging analysis [20, 21]. Research in the NICU has focused on using AI and advanced machine learning to predict 36 morbidity conditions, 12 mortality outcomes, and five lengths of hospital stays [22]. Furthermore, AI technologies have been instrumental in enhancing neonatal care by enabling the monitoring of vital signs, predicting diseases including congenital conditions, assessing risks, developing novel image recognition tools, and facilitating neurological diagnoses [23]. Recent studies underscore AI's growing role in neonatal healthcare by using it to estimate mortality rates in infants with neonatal sepsis, the third leading cause of neonatal death [24]. This highlights the growing interest in using AI for neonatal disease diagnosis, as evidenced by increased research efforts in this area [25].

Following this, they extended their methodology to pediatric CXR, attaining a ROC AUC score of 96.8%.In parallel, Mahomed *et al.*[26] developed CAD4Kids, software designed for analyzing the CXR of 858 children under five at Chris Hani Baragwanath Academic Hospital, South Africa. Their approach involved image segmentation, model training, feature extraction, and classification using Gaussian filters, yielding an AUC of 0.85 and corresponding sensitivity and specificity rates of 76% and 80%. In a related study, Jain *et al.*[27] trained six CNN models on pediatric CXR to distinguish between pneumonia and non-pneumonia cases, including VGG16, VGG19, Inception v3, ResNet50, and two and three-layer CNN, optimized with various parameters, attained an accuracy of 92.31%. Chouhan *et al.*[28] achieved a remarkable 96.4% accuracy in pneumonia diagnosis by employing a hybrid ensemble of top-performing models to analyze CXR data from the GWCMC. Utilizing the same dataset, Yue *et al.*[29] implemented an enhanced MobileNet model to diagnose pneumonia in 5,840 children aged 1–5 years. Their refined approach yielded an accuracy of 92.9%, building upon the insights gained from the previous study.

In a separate investigation, Chen *et al.*[30] explored three diagnostic approaches for common pediatric lung diseases: a YOLOv3-based model and both one-versus-one and one-versus-all schemes. Among these, the one-versus-one scheme emerged as the most effective, achieving an accuracy of 92.47%. Chagas *et al.*[31] developed an instantaneous IoT platform and evaluated various CNN models for diagnosing pneumonia from 6,000 pediatric CXR images. Their investigation revealed that the VGG19 architecture, coupled with an RBF kernel and SVM classifier, attained a peak classification accuracy of 96.47%. Similarly, researchers including [32] investigated the differentiation of sepsis and respiratory distress syndrome (RDS) in neonates using cry signals. Their research employed Multilayer Perceptron (MLP), SVM, and other machine learning methods, resulting in a top accuracy of 95.3%. Notably, the MLP method demonstrated superior performance across all metrics except the AUC. In a similar vein, Prakash et al.[33] employed feature extraction using Mobile Net and Dense Net models (121, 169, 201), and these features were incorporated with a stacked ensemble classifier to diagnose pediatric pneumonia. This methodology resulted in an impressive accuracy of 97.11%. Overall, the literature review dataset does not differentiate between adults and children, achieving the highest recorded accuracy of 97.58%. A hybrid deep learning framework is proposed to diagnose NRDS from neonatal CXR images, enhancing clinical decision-making at the edge. However, despite the increasing focus on AI in neonatal care, a notable gap exists in the literature. Specifically, there is a lack of studies that systematically assess CXR images of neonates for the diagnosis of NRDS, a common and potentially life-threatening respiratory condition. Additionally, the absence of publicly available neonatal CXR datasets further compounds the challenge of developing and validating AI-based diagnostic tools for NRDS. To address these issues, it is essential to employ more sophisticated and effective methods. Fig. 1. illustrates the overview of a hybrid deep-learning model designed for diagnosing NRDS in neonates using CXR images. The potential enhancements brought about by this model raise two critical questions:

1. How does a hybrid Convolutional Neural Network (CNN) with an LSTM layer, incorporating feature extraction from MobileNetV3 and ResNet50, enhance the performance of NRDS image classification compared to conventional CNN architectures?
2. How does integrating LSTM layers for handling temporal data influence the interpretability and predictive reliability of CNN-based NRDS classification models?

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The main contributions of this article are:

1. Overcoming the limitations of conventional CNN architectures in NRDS image classification by integrating MobileNetV3 and ResNet50 for advanced feature extraction, such as depth wise separable convolutions, Edge detection features, fine-grained features, textures features, hierarchical features, and residual features with LSTM to process temporal dependency features, enhancing diagnostic accuracy and utility.
2. Development of a hybrid CNN-LSTM model leveraging the strengths of MobileNetV3 and ResNet50 for robust feature extraction integrating LSTM for dynamic temporal data analysis.
3. Extensive validation demonstrates the hybrid model's augmented performance over traditional CNNs, evidenced by marked improvements in classification accuracy, diagnostic sensitivity, and diagnostic specificity.
4. Evaluation results indicate that the hybrid approach surpasses traditional CNNs, demonstrating higher accuracy, increased sensitivity, and improved specificity.
5. Introduction of a novel integration technique for combining convolutional and LSTM networks, advancing the domain of medical imaging analysis.

II. Results

This section presents the performance metrics and model evaluation (see Supplementary Materials *Section I*.A.B).

A. Performance metrics/Evaluation

Performance metrics were used by the research community to assess the effectiveness of classification models, Key metrics include F1-score, recall, accuracy, specificity, and precision. To compute these metrics and validate the proposed model, four measures are needed: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

- **True Positive (TP):** This metric indicates the total number of cases correctly identified as having NRDS during the classification task.
- **True Negative (TN):** This metric represents the number of cases correctly identified as not having NRDS within the classification task.
- **False Positive (FP):** This metric denotes the number of cases incorrectly classified as having NRDS in the classification task.
- **False Negative (FN):** This metric represents the number of cases incorrectly classified as not having NRDS in the classification task. Based on the four measures above, the performance metrics were calculated as follows:
- **Accuracy**: Accuracy quantifies how often the classification model correctly identifies the condition across the entire dataset. It is calculated as the ratio of correctly predicted cases (both positive and negative) to the total number of predictions as described by equation 1:

$$Accuracy = \frac{TP+FN}{TP+FP+FN+TN} \tag{1}$$

- **Precision**: Precision represents the proportion of actual positive classifications out of all predicted positive classifications specified in equation 2:

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

- **Recall (Sensitivity)**: Recall measures the proportion of actual positive cases the model correctly identifies. It is the ratio of true positives to the total actual positive cases, calculated using this formula given by equation 3:

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

- **Specificity**: Specificity indicates the proportion of true negative classifications made by the model. It is calculated by equation 4:

$$Specificity = \frac{TN}{TN+FP} \tag{4}$$

- **F1-Score (Dice coefficient)**: The F1-score evaluates the balance between precision and recall, indicating how well the model handles false positives and false negatives. The score ranges from 0 to 1, with higher values indicating better performance, outlined by equation 5:

$$F1\ Score = \frac{TP}{TP+{}^{1}/_{2}(FP+FN)} \tag{5}$$

Table I summarizes the classification model's performance metrics, showcasing strong results. The plot depicting training and validation accuracy over epochs revealed a model that consistently improved with training, as evidenced by the gradual increase in accuracy from epoch 0 to 25. At the end of training, the model reached training and validation accuracies of 0.9912 and 0.9945, respectively, indicating excellent performance on both datasets and no significant overfitting. The most noticeable improvements occurred in the initial epochs, where validation accuracy steadily rises, surpassing training accuracy around epochs 0 to 5. There were slight fluctuations from epoch 5 to around 15, but the overall trend remained positive. After epoch 15, training and validation accuracies continue to increase consistently, showing similar high values and demonstrating the model's steady learning and effective convergence, as shown in Fig. 2. The loss curves for training and validation indicate that the model quickly converged to low error values. From this curve, during the initial 1-2 epochs, there was a sharp decrease in both training and validation losses, with the training loss dropping significantly from around 1.8511 to approximately 0.01. In contrast, the validation loss showed a similar trend, starting at 0.2381 and falling to about 0.01. After this initial sharp decline, both losses stabilized, suggesting that the model rapidly minimized error. From approximately the third epoch onwards, training and validation losses were maintained consistently, with low values and minimal fluctuation, reflecting effective training that ensured the model minimized error on both datasets. The close alignment of training and validation loss values throughout the epochs suggested the model generalized well to unseen data with minimal overfitting, as shown in Fig. 3.

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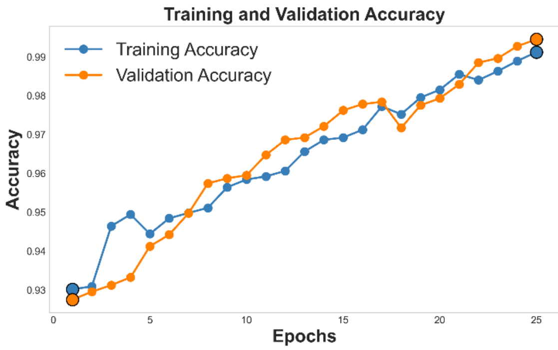

Fig. 2. Accuracy Variation Across Epochs

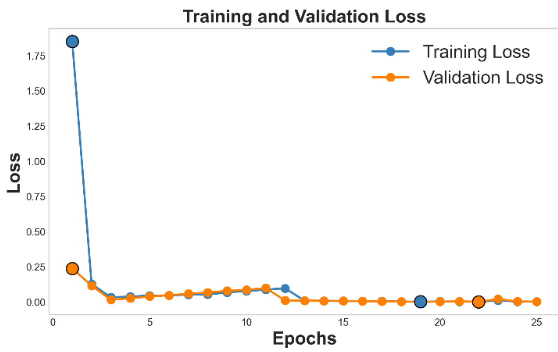

Fig. 3. Learning curve

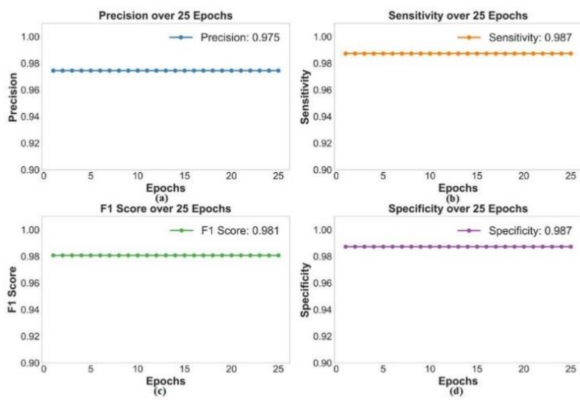

Fig.4. Evaluation of performance metrics includes: (a) precision, (b) sensitivity, (a) F1 Score, and (d) Specificity.

Fig. 4. presents the performance metrics of the proposed approach, including precision, sensitivity, and F1-Score, specificity. In the evaluation of the proposed NDL-Net network architecture, ten advanced deep learning models were selected for comparative analysis. The models chosen for this analysis included RetinaNet and Mask R-CNN[34], Ensemble (AlexNet, GoogleNet and ResNet) [35], AlexNet [36], VGG-19 [37], SqueezeNet [38], DenseNet-121 [39], InceptionV3 [40], GoogleNet [41], Xception [42] and EfficientNet [43].

Each of these models was implemented and tested using the same experimental conditions and the identical CXR dataset employed for the proposed model, ensuring a consistent and fair comparison across all models.

TABLE I

Performance Metrics of the NDL-Net Model

Accuracy	Precision	Sensitivity	F1 Scores	Specificity
98.09	**97.45**	**98.73**	**98.08**	**98.73**

III. Discussion

This section discusses the convergence of Backbone and Branch Network, evaluation of Loss Function and comparative analysis with state-of-the-art methodologies (see Supplementary Materials *Section II*.A.B).

A. *Convergence of Backbone and Branch Network*

The proposed model primary innovation is in the choice of backbone and branch networks, which significantly influenced its classification performance. Drawing from extensive prior research, MobileNetV3 and ResNet-50 were selected as backbone network and LSTM for the branch networks. These two networks were paired to create three configurations: MR and RD and NDL-Net where M represents MobileNetV3 and R denotes ResNet-50. As shown in Table II, using ResNet-50 for both the backbone and branch networks yielded best results, which is our final choice. The results indicate that the NDL-Net configuration significantly outperformed the two configurations, this confirms the efficacy of using ResNet-50 as both the backbone networks in achieving high-performance metrics for the classification tasks. These findings underscore the robustness of our model in delivering accurate and reliable diagnoses, thereby supporting improved neonatal care.

TABLE II

Analysis of Backbone and Branch Network Combinations in the NDL-Net

Performance	MR	RM	NDL-Net
Accuracy	95.95	96.02	98.09
Precision	96	96.0	97.45
Sensitivity	96	96.04	98.73
F1 Scores	96	96.07	98.08
Specificity	99	96.07	98.73

IV. Conclusions

NDL-Net, a hybrid deep learning framework, was introduced to diagnose NRDS from chest X-rays. By utilizing advanced neural network architectures, this approach achieves high diagnostic accuracy 98.09 %, demonstrating its potential as a valuable tool in neonatal healthcare. The findings show that NDL-Net performs better than traditional diagnostic methods and other existing models in accuracy and robustness. This improvement in diagnostic performance can be crucial for the early detection and timely treatment of NRDS, potentially reducing neonatal mortality and morbidity rates.

However, this study has some limitations. The dataset, although comprehensive, is not sufficient and could benefit from an additional inclusion of multiple cases, particularly with varying demographic and clinical backgrounds, to enhance the model's generalisation. Moreover, while the dataset size is sufficient for training, it may still constrain the model's ability to address rare instances, which could impact its robustness in real-world situations. The research presumes that images from chest X-rays alone provide for precise diagnosis, neglecting the incorporation of additional clinical aspects or patient data that could offer a more comprehensive understanding of NRDS.

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Multiple aspects must be taken into account while assessing the model validity. The primary concern is the dataset intrinsic biases, as it may not adequately represent the wide range of NRDS across diverse healthcare environments or patient demographics. Furthermore, although the model exhibits strong performance in a controlled research context, its real-time diagnostic capabilities may encounter difficulties when used in clinical settings characterised by diverse equipment, imaging techniques, or image quality.

Future work will integrate additional imaging modalities and patient data to enhance the diagnostic capabilities of NDL-Net further. Explainable AI techniques will also be explored to provide clinicians with more transparent and interpretable diagnostic insights. Based on current understanding, prior research has not explicitly addressed NRDS diagnosis using deep learning frameworks, making NDL-Net a groundbreaking effort in this area. Overall, NDL-Net signifies considerable progress in utilizing deep learning techniques in medical imaging for neonatal care. By improving diagnostic accuracy and providing reliable support to clinicians, this framework can significantly influence the identification and management of NRDS.

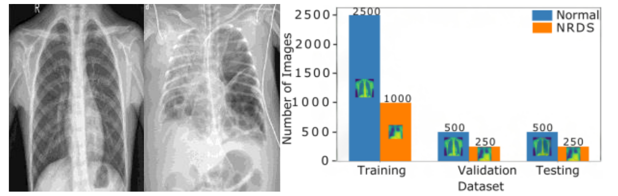
V. METHODS

In this section, the neonatal CXR dataset is discussed, while the detailed descriptions of the network architecture and the classification branch (see Supplementary Materials, Section III.A and B).

A. NEONATAL CXR DATASET

In this study, to demonstrate the implications of the proposed hybrid model, experimental analysis was performed on datasets of CXR images collected during neonatal care in the NICU at Sakina Child Care Hospital, Pakistan. The CXR images, which expert radiologists validated, were utilized following the acquisition of the required ethical approvals. The dataset comprises CXR images from 5,000 neonatal patients, with 3,500 of these cases labeled as normal. (not having NRDS) and 1,500 with NRDS were included in the dataset. The patients ranged from 0 to 4 days old, considering the susceptibility of neonates to NRDS within this early postnatal period.

In the dataset, represented in Fig. 5, the CXR images labelled as Normal and NRDS are distributed as follows:70% (3,500 images) are allocated for training, allowing the model to learn and adapt to specific classification features. Meanwhile, 15% (750 images) are employed in the validation set to optimize the model's parameters and mitigate overfitting. and the remaining 15% (750 images) are reserved for testing to ensure an impartial assessment of the model's performance on previously unseen data as shown in Table III.



(a) (b) (c)

Fig. 5. Sample Images (a)Normal (b)NRDS (c) Data distribution among dataset for binary classification

TABLE III

CLASS DISTRIBUTION AND PARTITIONING OF TRAINING, TESTING, AND VALIDATION DATASET

Class	No of CXR images	No of CXR images from NRDS Class	No of CXR images from Normal Class
Training data	3500	1000	2500
Validation data	750	250	500
Test data	750	250	500
Total	5000	1500	3500

Author Contributions: Conceptualization: X. Y.; Methodology: M. M. A.; Software: M. M. A.; Formal Analysis: M. M. A.; Investigation: N. Z., L. G., T. C., M. M. A., D. H.; Experimentation: M. M. A.; Writing—Original Draft Preparation: M. M.A.; Writing—Review and Editing: L. G. and N. Z., D. H.; Funding Acquisition: X. Y. All authors have reviewed and agreed to the published version of the manuscript.
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