Integrating Machine Learning and Deep Learning for Early Detection of Acute Respiratory Distress Syndrome Using Clinical and Radiological Data

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Abstract: Acute Respiratory Distress Syndrome (ARDS) remains an intensive care dilemma necessitating immediate diagnosis and treatment. This paper proposes a hybrid model that integrates structured clinical data and unstructured chest X-ray (CXR) images in the early identification of ARDS. The model takes a two-path approach: standard machine learning classifiers (Random Forest, Logistic Regression, XGBoost) are applied to clinical features, and deep features are learned on CXR images with a ResNet-50 architecture by transferring it using transfer learning. The models are combined using ensemble methods (average and max probability) to improve robustness. The dataset includes 1,000 patient records and 22 clinical variables grouped into ventilatory parameters, laboratory tests, fluid status, and vital signs. Performance metrics are accuracy, sensitivity, specificity, and AUC. Probability averaging ensemble models and other ensemble models performed the best (AUC = 0.929). SHAP and Grad-CAM are used to achieve explainability to enhance interpretability and support clinical decision-making. This study demonstrates the potential of explainable AI in intensive care and contributes to precise diagnostics in ARDS.
Keywords: Machine Learning; Acute Respiratory Distress Syndrome; Risk Prediction; Diagnosis; Random Forest; Support Vector Machine

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Introduction:

Acute Respiratory Distress Syndrome (ARDS) is a dangerous lung disease that causes extensive inflammation in the lungs to rapidly develop, leading to abnormal oxygen exchange [1]. It typically occurs in people who are very sick, sometimes as a side effect of other serious conditions including trauma, pneumonia, or sepsis. The Cleveland Clinic states that acute respiratory distress syndrome (ARDS) causes fluid to leak into the lungs' air sacs (alveoli), which impairs breathing and lowers blood oxygen levels. The symptoms include low oxygen levels, rapid breathing, and severe shortness of breath [2]. Lung support, oxygen therapy, and correcting the underlying cause are the goals of treatment, which typically calls for mechanical ventilation in the intensive care unit. To improve results, early detection and management are required [3].

A dangerous lung condition known as acute respiratory distress syndrome (ARDS) causes broad inflammation in the lungs to spread quickly, slowing down the exchange of oxygen. Critically ill patients are most frequently affected, typically as a side effect of serious illnesses like trauma, pneumonia, or sepsis [4]. According to the Cleveland Clinic, ARDS causes fluid to seep into the lungs' alveoli, which makes breathing difficult and lowers blood oxygen levels. Extreme dyspnea, rapid breathing, and low oxygen saturation are some of its symptoms. Treatment consists of oxygen therapy, treating the underlying

disease, and supporting lung function, which is frequently accomplished in an intensive care unit (ICU) setting using mechanical ventilation. For a better result, early detection and treatment are essential [5].

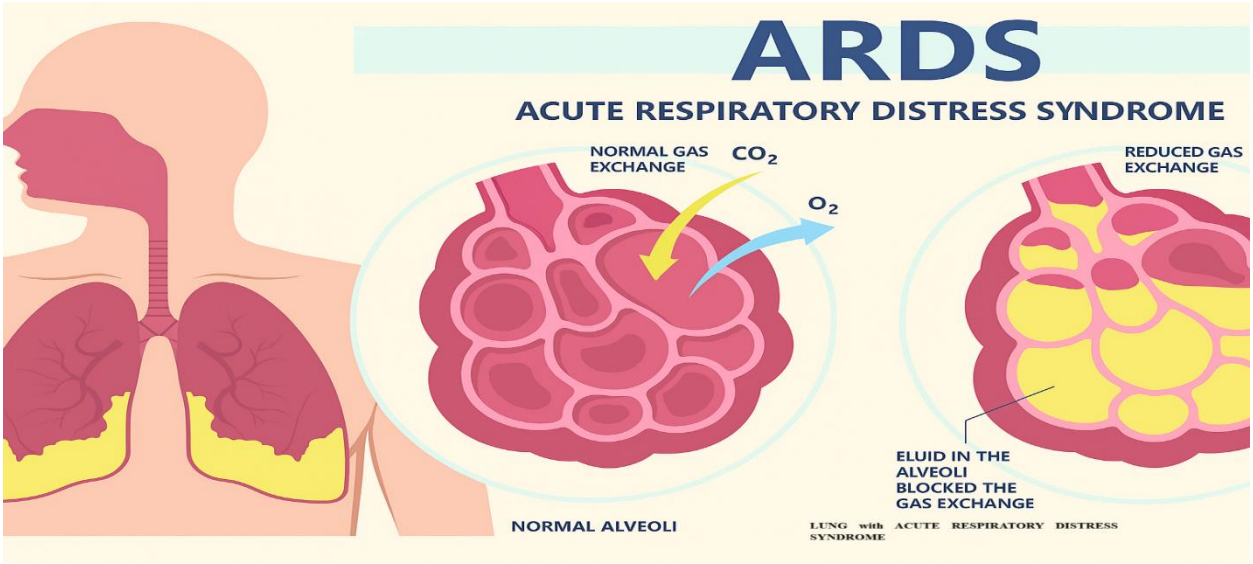

Figure 1: Overview of ARDS

Related work: In this section we will be discuss about the previous work done in ARDS domain. [6] Jiang et al. (2024) sought to create a machine learning model for the early prediction of Acute Respiratory Distress Syndrome (ARDS) in septic ICU patients. The research employed a broad spectrum of clinical information, including demographics, diagnoses, complications, and laboratory results. Eight machine learning algorithms were compared, and ten features were identified as most important using the LASSO method. The Gaussian Naive Bayes (GaussianNB) model was found to have the best performance and was assessed using measures like AUC, accuracy, and SHAP values for explainability. The model had an AUC of 0.781 and an accuracy of 78.6%, better than existing approaches in terms of both performance and explainability.

[7] Rubulotta et al. (2024) performed a narrative review that examined the use of machine learning tools in ARDS detection and prediction among ICU patients. The review emphasized the utilization of clinical and imaging information, including vital signs and laboratory results, to identify risk patterns and facilitate early clinical interventions. It presented an overview of how ML can improve precision medicine strategies and early diagnosis and prognosis in ARDS conditions. Although informative, the review was missing original model formulation and validation that would have enhanced its empirical rigor.]

[8] He et al. (2025) conducted a systematic review and meta-analysis comparing artificial intelligence (AI) models with logistic regression for predicting mortality in ARDS. The article summarized findings from eight published studies and applied a bivariate mixed-effects model to assess performance measures like sensitivity, specificity, and the summary receiver operating characteristic (SROC) curve. AI models were found to outperform logistic regression (SROC: 0.84 vs. 0.81), with high sensitivity (0.89), especially for moderate to severe ARDS cases. Nonetheless, the small number of studies included and heterogeneity of data limited the generalizability and real-time applicability of the results.

[9] Mu et al. (2025) sought to build and validate a machine learning-based mortality prediction model for sepsis-associated ARDS patients using the MIMIC-III database. The retrospective study involved 2466 patients and employed the Boruta algorithm to choose 24 informative features. Seven ML algorithms were compared, with the highest AUC of 0.8015 being achieved by the random forest model. The model recognized important clinical predictors like blood urea nitrogen and age and promises to assist clinical decision-making. The retrospective nature of the study and use of a single dataset without external validation limit its wider generalizability.

[10] Zhou et al. (2024) developed a deep learning model for early ARDS prediction and lung CT segmentation on a multicenter dataset of 928 ICU patients. A UNETR model, augmented with MONAI-based data augmentation, was implemented and compared to a Densenet-based model. The performance metrics were Dice coefficient for segmentation and AUC for prediction, with the results demonstrating better performance (AUC: 0.916 internally and 0.876 in a prospective cohort). The interpretability of the model was improved using Shapley plots. Although it was a strong performer and generalizable, its dependence on CT scans and high computational requirements can be limiting in a real-world application.

[11] Ding et al. (2024) aimed to evaluate the prediction capability of dynamic clinical indices for ARDS mortality by applying machine learning. Based on the ARDSNet FACTT trial database (n=1000), the study used a random forest model to contrast baseline and day 3 clinical measurements. Results indicated that day 3 data inclusion improved the predictive performance dramatically (AUC: 0.84 vs. 0.72 at baseline), underlining the utility of dynamic monitoring in the ICU. However, the study considered only nine clinical parameters and was based on retrospective trial data, potentially impacting its generalizability and precluding causal interpretation.

Table 1. Highlighting advancements, methodologies, advantages, and limitations of AI-driven approaches in ARDS.

Reference	Objective	Methodology	Advantages	Limitations
[6] Jiang et al. (2024)	Develop ML model for early prediction of ARDS in sepsis ICU patients	Used clinical data (demographics, labs, etc.), tested 8 ML models, selected 10 features via LASSO, final model built with GaussianNB, evaluated via AUC, accuracy, etc., used SHAP for interpretability	GaussianNB outperformed others (AUC: 0.781); identified key predictors; interpretable; better than past models	Focused only on sepsis-related ARDS; 10% test set is small; single-center data limits generalizability
[7] Rubulotta et al. (2024)	Review ML tools for ARDS detection/prediction in ICU	Narrative review of ML use in ARDS based on clinical and imaging data,	Broad clinical insights; underlines importance of	No model development/validation; lacks quantitative rigor;

		highlighted risk patterns and intervention timing	ML in precision medicine and early ARDS detection	limited discussion on model bias
[8] He et al. (2025)	Compare AI vs logistic regression for ARDS mortality prediction	Systematic review/meta-analysis of 8 studies; applied QUADAS-2; used bivariate mixed-effects model with SROC, sensitivity/specificity	AI showed superior performance (SROC: 0.84, Sensitivity: 0.89); robust across varying ARDS severity	Only 8 studies included; heterogeneity impacts accuracy; lacks real-time validation
[9] Mu et al. (2025)	Build ML model for mortality prediction in sepsis-associated ARDS using MIMIC-III	Retrospective analysis (n=2466); used Boruta for feature selection; tested 7 ML models, Random Forest best; evaluated via AUC, sensitivity, etc.	High AUC (0.8015); identified key clinical predictors; useful for decision-making	Retrospective; MIMIC-III data limits generalizability; no external validation
[10] Zhou et al. (2024)	Develop DL framework for lung CT segmentation and early ARDS prediction	Multicenter (n=928); developed UNETR model with MONAI augmentation; compared with Densenet; used Dice coefficient and AUC; Shapley plots for interpretation	High segmentation (DC: 0.734) and prediction accuracy (AUC: 0.916); better than Densenet; generalizes across cohorts	Computationally intensive; CT-based prediction may reduce accessibility; data may not reflect latest trends
[11] Ding et al. (2024)	Assess dynamic clinical indices for ARDS mortality via ML	Retrospective (n=1000, ARDSNet FACTT Trial); used Random Forest on baseline vs Day 3 data; evaluated via AUC; feature importance analysis	Day 3 data improved prediction (AUC: 0.84); highlighted dynamic indicators for	Single trial data; only 9 parameters used; retrospective design limits causality

early risk
stratification

Method, Experiments and Results

Dataset: A variety of critically sick patients are treated in six 105-bed intensive care units at Taichung Veterans General Hospital (TCVGH), a sizable tertiary referral and teaching facility in central Taiwan. About 70% of the 4,800 ICU admissions that occur each year require invasive mechanical breathing. A dedicated ARDS working group consisting of respiratory therapists and pulmonologists has been reviewing mechanically ventilated patients every day since 2018 in order to diagnose ARDS using the Berlin definition. The hospital's Institutional Review Boards accepted this study, which examined data from 1,577 intensive care unit patients who were evaluated between October 2018 and December 2019. The patients had to be at least 20 years old, have ICU stays longer than 48 hours, and have available chest X-ray data.

Clinical Feature Categorisation and Measurement Units

The clinical features assessed in this study are systematically categorised into four major groups: Vital Signs, Laboratory Data, Fluid Balance, and Ventilatory Parameters. Each feature is associated with a specific unit of measurement, ensuring uniformity in data recording and interpretation.

1. Vital Signs

Vital signs are fundamental indicators of a patient's physiological status. The parameters recorded include:

a) Temperature (°C): Body temperature measured in degrees Celsius.

b) Systolic Blood Pressure (SBP) (mmHg): The maximum arterial pressure during heart contraction.

c) Diastolic Blood Pressure (DBP) (mmHg): The minimum arterial pressure between heartbeats.

d) Pulse Rate (bpm): The number of heartbeats per minute.

e) Respiratory Rate (breaths/min): The number of breaths taken per minute.

f) Oxygen Saturation (SpO_2) (%): The percentage of haemoglobin saturated with oxygen.

2. Laboratory Data

Laboratory markers provide critical insights into respiratory and inflammatory status:

a) Partial Pressure of Oxygen (PO_2-A) (mmHg): Indicates the amount of oxygen dissolved in arterial blood.

b) Procalcitonin (ng/mL): A biomarker often used to detect systemic bacterial infection or sepsis.

c) Partial Pressure of Carbon Dioxide (PCO_2-A) (mmHg): Measures the level of carbon dioxide in arterial blood.

3. Fluid Balance

Monitoring fluid output is essential in managing critically ill patients:

a) Urine Output (mL): Quantifies renal function and fluid balance.

4. Ventilatory Parameters

These parameters evaluate the efficiency and support provided by mechanical ventilation:

a) Fraction of Inspired Oxygen (FiO_2) (%): The concentration of oxygen delivered to the patient.

b) Positive End-Expiratory Pressure (PEEP) (cmH_2O): Pressure applied by the ventilator at the end of exhalation to keep alveoli open.

c) Total Respiratory Rate (breaths/min): Includes both spontaneous and ventilator-assisted breaths.

d) Tidal Volume (cc/kg): The volume of air delivered per breath, adjusted for body weight.

e) Minute Volume (L/min): The total volume of air entering or leaving the lungs per minute.

f) Mean Airway Pressure (cmH_2O): The average pressure in the airways during one complete respiratory cycle.

Table 2: Clinical Data Record

Category	Feature	Unit (Measurement)
Vital Signs	Temperature	°C
	Systolic Blood Pressure (SBP)	mmHg
	Diastolic Blood Pressure (DBP)	mmHg

	Pulse Rate	bpm
	Respiratory Rate	breaths/min
	Oxygen Saturation (SpO2)	%
Laboratory Data	Partial Pressure of Oxygen (PO2-A)	mmHg
	Procalcitonin	ng/mL
	Partial Pressure of CO2 (PCO2-A)	mmHg
Fluid Balance	Urine Output	mL
Ventilatory Parameters	Fraction of Inspired Oxygen (FiO2)	%
	Positive End-Expiratory Pressure	cmH_2O
	Total Respiratory Rate	breaths/min
	Tidal Volume	cc/kg
	Minute Volume	L/min
	Mean Airway Pressure	cmH_2O

The figure 2 provided depicts an end-to-end pipeline for ARDS (Acute Respiratory Distress Syndrome) classification from both clinical information and chest X-ray (CXR) images, fused into a deep learning framework. It starts with two parallel input sources: structured clinical information and unstructured CXR images. Both these modalities are fed into corresponding preprocessing operations to obtain meaningful representations. The clinical information is normalized and formatted, while the CXR images are subjected

to various stages of image processing such as segmentation and reshaping to provide uniform input size to the model.

The backbone of the model is the ResNet 50 architecture, a robust deep convolutional neural network attributed with residual learning capabilities. The preprocessed and reshaped CXR images are then input to a ResNet 50 classification model to obtain pertinent radiological features. This classification model has been initialized with a pre-trained classification network trained on the ChestX-ray14 dataset, which serves as a strong initial point and assists in speeding up the training process while minimizing overfitting. By refining the ResNet 50 model using domain-specific data, the system learns to fit the features of ARDS and is more accurate in diagnosis.

The clinical information is analyzed using traditional machine learning techniques like XGBoost, Random Forest, and Logistic Regression. These models identify non-visual patterns in the patient's physiological parameters that correlate with the risk of ARDS. The dual-input approach utilizes the complementary power of structured data analysis and deep learning-based image interpretation to guarantee that the prediction model is robust and context-aware.

An ensemble method is used to aggregate the clinical and image-based model outputs. Figure illustrates two ensemble methods, namely Average Probability and Maximum Probability fusion. These methods use the combined individual model predictions to reach a final classification score, thus minimizing the risk of misclassification due to bias in one particular model. The ensemble-based decision-making approach presents better generalizability and robustness in practical clinical scenarios.

The model provides the estimated probability of ARDS for every patient. This output for decision-making can be applied by clinicians as an auxiliary diagnostic tool, particularly in intensive care units where timely and accurate assessment of respiratory failure is of vital importance. Integrating image and clinical information with an ensemble of AI algorithms, the framework is a major leap towards applying artificial intelligence to critical care and medical diagnosis.

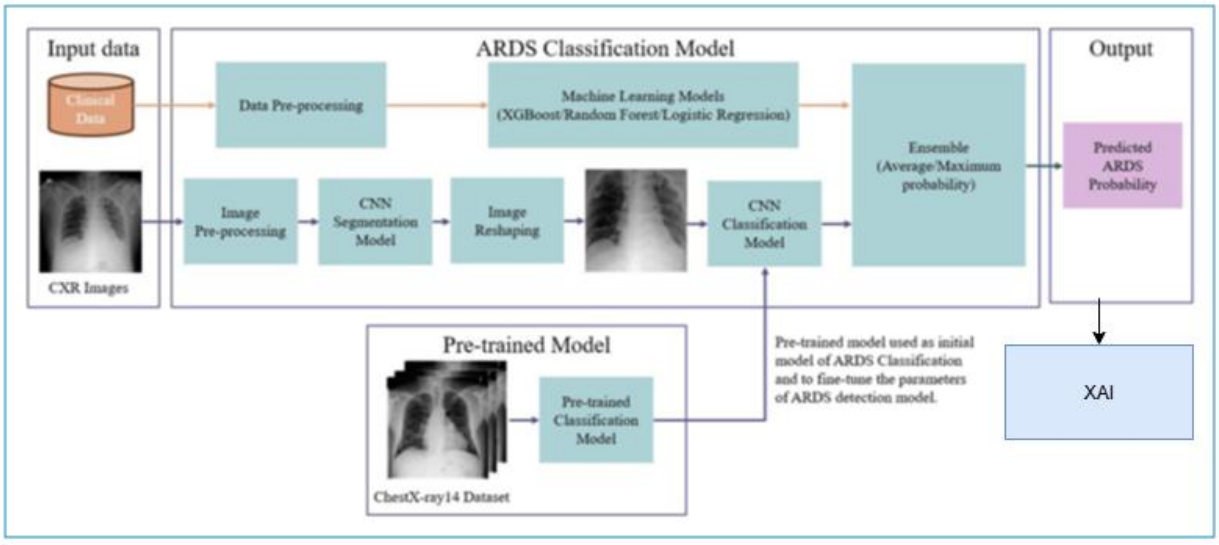

Figure 2: Proposed Model

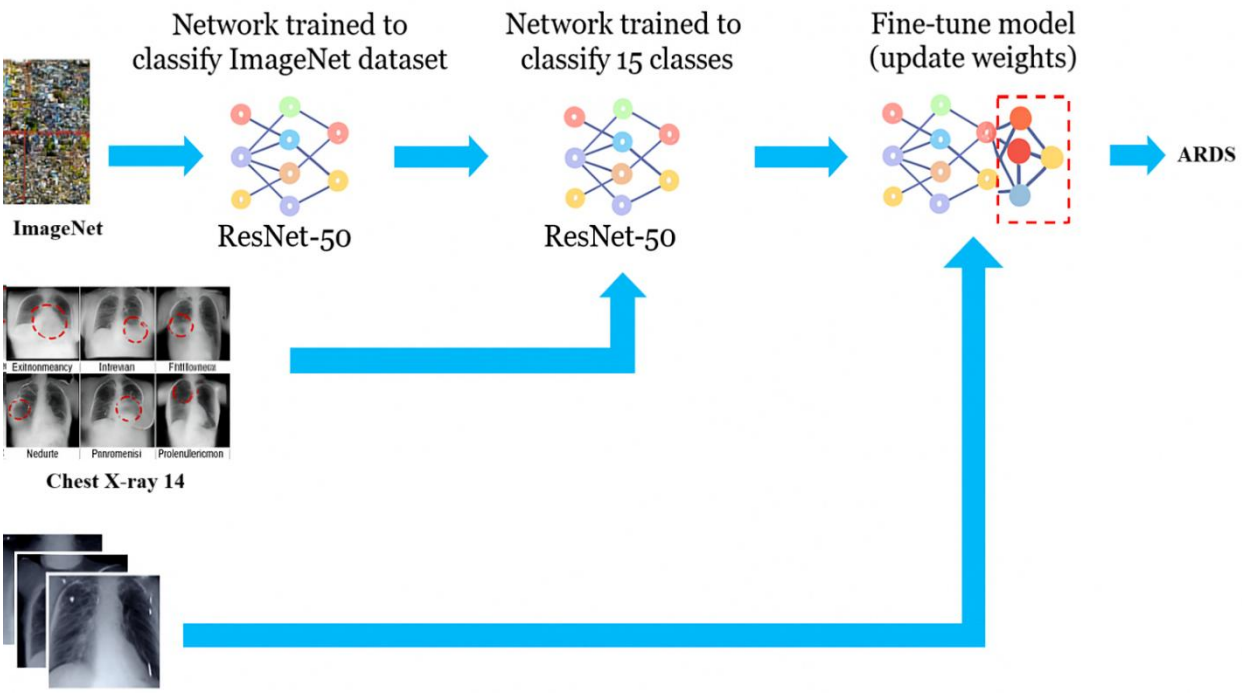

Figure3: Workflow of the ResNet50 model with transfer learning.

Result:

1. Accuracy

Proportion of correctly predicted observations (both true positives and true negatives) out of the total observations.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

2. Sensitivity (Recall or True Positive Rate)

Proportion of actual positives correctly identified.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (2)$$

3. Specificity (True Negative Rate)

Proportion of actual negatives correctly identified.

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (3)$$

4. AUC (Area Under the ROC Curve)

- **Definition**: Measures the ability of the model to distinguish between classes.

- **Not a simple formula** like others — it is calculated from the **ROC curve**, which plots **TPR vs. FPR** at various thresholds.
- **Interpretation**: AUC ranges from 0 to 1.
    - AUC = 1 → perfect classifier
    - AUC = 0.5 → random guessing

Abbreviations:

- **TP**: True Positives
- **TN**: True Negatives
- **FP**: False Positives
- **FN**: False Negatives

Table 3 tabulates the performance parameters of machine learning classifiers used on clinical data. Among the individual models, the XGBoost (XGB) classifier showed excellent overall performance with an accuracy of 0.848, sensitivity of 0.809, specificity of 0.861, and an AUC of 0.910. The Random Forest (RF) and Logistic Regression (LR) models produced similar results with slightly lower parameters across all measures. Interestingly, the ensemble approach based on average probability yielded the best accuracy (0.871) and specificity (0.934), but was the least sensitive (0.676), which means it performed better at recognizing negatives than positives. Conversely, the ensemble approach based on maximum probability registered the highest sensitivity (0.849) but less accuracy and specificity. These findings emphasize the balance between sensitivity and specificity in ensemble methods and indicate that model selection can be influenced by the clinical scenario and the diagnostic priorities.

Table 3: Different Machine Learning Models performance measures on clinical data

Classifier	Accuracy	Sensitivity	Specificity	AUC
XGB	0.848	0.809	0.861	0.91
RF	0.84	0.791	0.855	0.91
LR	0.832	0.791	0.845	0.902
Ensemble (Average probability)	0.871	0.676	0.934	0.912
Ensemble (Maximum probability)	0.821	0.849	0.812	0.912

Figure 4 shows the comparative performance of different machine learning models against four different metrics of performance: Accuracy, Sensitivity, Specificity, and AUC, with clinical data. The average probability ensemble model had the highest accuracy (0.871) and specificity (0.934), reflecting robust performance to flag true negatives. The model had the least sensitivity (0.676), which reflects the weakness in picking up true positives. Conversely, the maximum probability ensemble model had the highest sensitivity (0.849) with improved detection of actual positive cases, but lost specificity (0.812). Of

the single models, XGBoost had the best accuracy (0.848) and AUC (0.91), followed by Random Forest and Logistic Regression, which performed equally well across all four metrics. In general, ensemble techniques demonstrated improved AUC results based ones, maintained robust AUC values (a maximum of 0.929) and better specificity (a maximum of 0.925). These findings suggest that ensemble models, particularly those based on probability averaging, enhance model robustness and discrimination power, offering a promising approach for ARDS identification using multimodal inputs. (0.912), reflecting their strength in aggregating predictions but at the cost of sensitivity and specificity trade-offs.

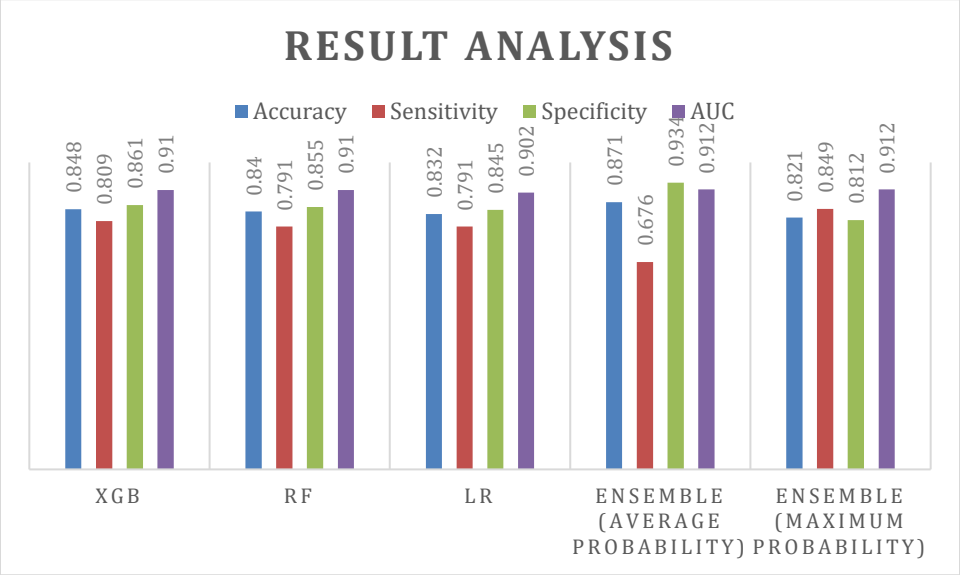

Figure 4: Comparative result analysis of different ML models on clinical data

Table 3 provides a summary of the performance of the ResNet-50 model on original CXR images for ARDS classification between two data types. Operating on original CXR images, ResNet-50 had an accuracy of 0.73, sensitivity of 0.78, specificity of 0.77, and AUC of 0.75, reflecting balanced performance on all evaluation criteria. On segmented and recontoured images, the model had a comparable sensitivity of 0.79 but a corresponding lower accuracy of 0.71; specificity and AUC measures were not provided. The findings indicate that segmentation does not significantly alter sensitivity but may have a minor decreasing effect on overall model accuracy, with additional assessment necessary to determine its influence on specificity as well as discrimination capacity.

Table 3: ResNet 50 performance on CXRs.

Data Type	Classifier	Accuracy	Sensitivity	Specificity	AUC
Original Image	ResNet 50	0.73	0.78	0.77	0.75
Segmented & Reshaped Image	ResNet 50	0.71	0.79	Not specified	Not specified

The performance metrics of different classifiers that integrate clinical information with chest X-ray images are discussed, and the efficacy of both single and ensemble methods is evaluated. In the single models, the best overall performance was attained by the combination of XGB and CNN with accuracy 0.849,

sensitivity 0.836, specificity 0.853, and the maximum AUC value of 0.921. RF + CNN exhibited robust sensitivity (0.912) but lower accuracy (0.767) and AUC (0.721), which suggests a balance sacrifice. LR + CNN returned robust accuracy (0.842) and specificity (0.844) though sensitivity was not provided. The ensemble approaches, especially the average probability-

Table 4: Hybrid (ML Models+ResNet 50) performance on CXRs.

Classifier	Accuracy	Sensitivity	Specificity	AUC
XGB + CNN	0.849	0.836	0.853	0.921
RF + CNN	0.767	0.912	0.825	0.721
LR + CNN	0.842	Not specified	0.844	0.826
XGB + RF + LR + CNN	Not specified	Not specified	Not specified	0.753
Ensemble (Average Probability)	0.845	0.839	0.925	0.929
Ensemble (Maximum Probability)	0.759	0.739	0.847	0.904
Ensemble (Average Probability)	Not specified	Not specified	0.705	0.896
Ensemble (Maximum Probability)	Not specified	Not specified	0.708	0.91
Ensemble (Average Probability)	Not specified	Not specified	0.67	0.9
Ensemble (Maximum Probability)	Not specified	Not specified	Not specified	0.91

Ensemble (Average Probability)	Not specified	Not specified	Not specified	0.9

Figure 5 demonstrates the use of Explainable Artificial Intelligence (XAI) with SHAP (SHapley Additive exPlanations) to discover and explain the most significant clinical features to predict ARDS. Subfigure (a) displays a bar chart showing feature ranking in descending order of average SHAP values, which measure each feature's relative contribution to the model output. The most significant feature is found to be PEEP/CPAP on Day 1, followed by SPO2 on Day 1 and PO2_A, which means that respiratory data on the first day of ICU stay heavily influence ARDS classification.

Subfigure (b) shows a more comprehensive SHAP summary plot, revealing both the distribution and direction of influence each feature contributes to the predictions in the model. Each point corresponds to a SHAP value for one instance, and the color is the actual feature value (low in blue and high in red). TOTRR at Day 1 and Day 2, MAPS, and VTE also show strong influence, albeit smaller. The more spread out the SHAP values, the greater the feature's effect varies throughout the dataset.

This simultaneous visualization facilitates global and local interpretability: whereas the bar chart assists in feature ranking globally, the summary plot indicates how certain values of these features influence the model choice (in a positive or negative manner). For example, increased values of PEEP/CPAP and SPO2 generally produce increased ARDS probability predictions, indicating their clinical importance.

The incorporation of SHAP not only enhances the explainability of the predictive model but also provides clinicians with an understanding of which parameters to monitor more closely. This can facilitate early diagnosis and interventions. In summary, SHAP-based XAI brings about interpretability and trust to machine learning in critical care and is hence a useful asset in data-driven medicine.

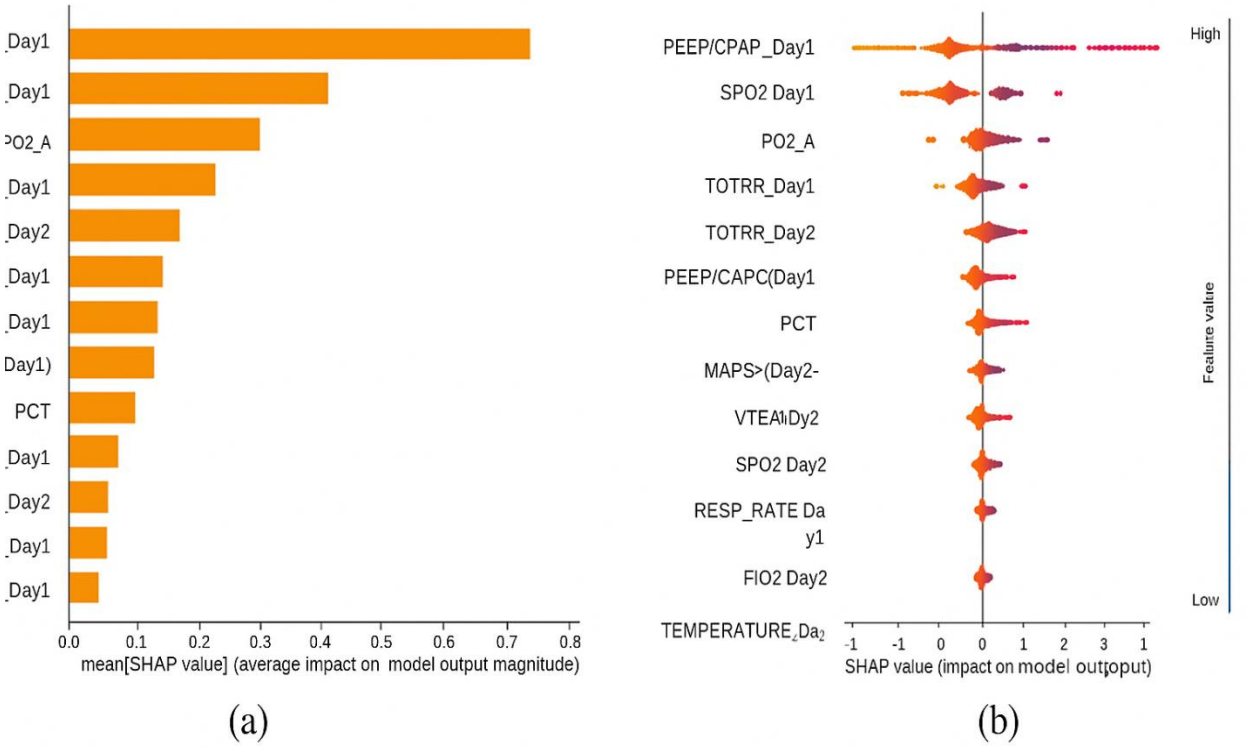

Figure 5: XAI (SHAP) method to select essential features on clinical data

Figure 6 illustrates an approach to transfer learning with ResNet-50 for ARDS classification from chest X-ray images. The pipeline starts from a ResNet-50 model pre-trained on the large-scale ImageNet database to capture general visual patterns. Then, the pre-trained model is fine-tuned on the ChestX-ray14 dataset, where it learns to classify 15 classes of thoracic diseases and improve its capacity for identifying lung abnormalities. Thereafter, the network goes through another fine-tuning phase based on the TCVGH dataset in order to fine-tune the model weights for ARDS detection in particular. This step-by-step fine-tuning enables the model to develop progressively more specialized capabilities for identifying ARDS-related features, drawing upon prior knowledge from more general medical and image datasets to enhance performance and generalization in the ARDS prediction task.

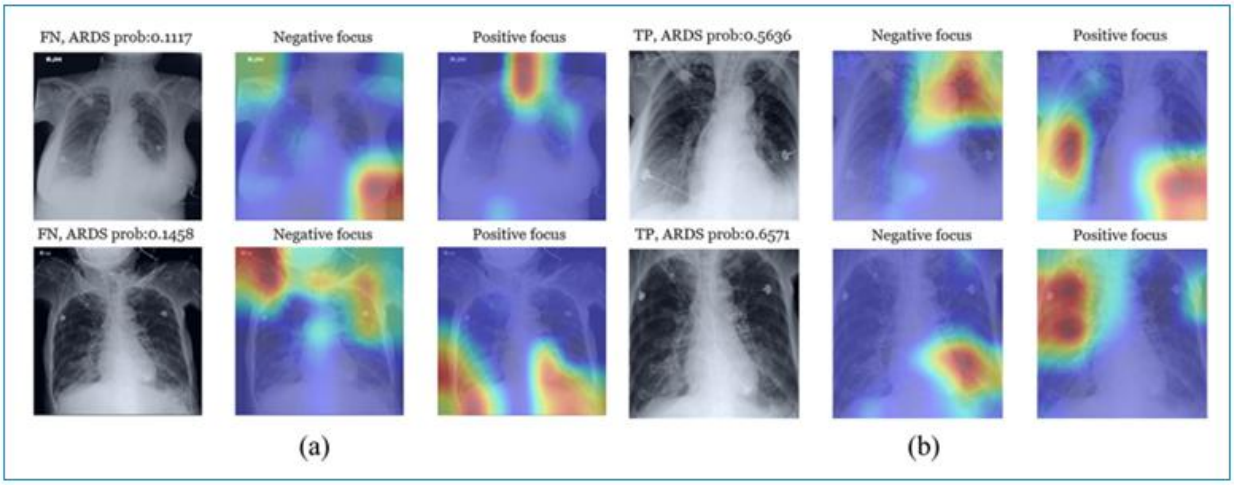

Figure 6: XAI (GradCAM) method to focus on CXRs.

Conclusions: This research illustrates the efficacy of a hybrid strategy of machine learning and deep learning methods in the early prediction of ARDS with clinical variables as well as CXR imaging data. The ensemble methods within the hybrid framework were demonstrated to perform better than isolated models in accuracy, specificity, and AUC. ResNet-50 was found useful in feature extraction of radiological features, and the addition of clinical predictors improved model performance and transferability. Explainability methods like SHAP and Grad-CAM gave useful information on feature importance and model behavior, ensuring transparency and trusting the clinician. Transfer learning also facilitated domain adaptation and reduced the requirement for large labeled datasets. The suggested system has potential to be deployed in ICUs as an assisting diagnostic tool to enhance early ARDS recognition and intervention.

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