Orchestrating LLMs to Explain Shock Predictions by DL Model for ICU Care: A Reasoning Scorecard Approach

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Abstract

Shock prediction in critical care settings remains a major challenge, requiring both accurate early detection and explainable reasoning to support clinicians. We present a novel pipeline where a Transformer-based deep learning (DL) model predicts shock probability based on ICU vitals and labs, followed by explanation generation using multiple large language models (LLMs) — GPT-4, Gemini 1.5 Pro, and Mistral. To evaluate explanation quality, we introduce an orchestration strategy with DeepSeek R1 to score reasoning outputs on *Transparency*, *Consistency*, *Clarity*, and *Completeness*. Our scorecard results show strengths and weaknesses of each LLM, providing insights for developing more reliable explainable AI in healthcare.

Keywords

Shock Prediction, ICU Care, Explainable AI, Large Language Models, Reasoning Scorecard, Deep Learning, Healthcare AI

ACM Reference Format:

Bhanu Pratap Singh. 2025. Orchestrating LLMs to Explain Shock Predictions by DL Model for ICU Care: A Reasoning Scorecard Approach. In . ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 Introduction

Shock is a life-threatening condition in ICU settings that demands early detection and intervention [5]. Predictive models, especially deep learning-based, have shown potential for identifying shock onset [3]. However, clinical adoption remains hindered by a lack of transparent and trustworthy explanations [1].

We propose a two-stage system: (1) a Transformer-based DL model trained on MIMIC-III data to predict shock probability, and (2) an explainability layer where GPT-4, Gemini 1.5 Pro, and Mistral generate clinical reasoning based on the model's output. We further design a **reasoning scorecard** evaluated by DeepSeek R1 LLM to systematically benchmark the quality of generated explanations.

Contributions:

- A shock prediction model achieving AUC of 0.8226 on ICU patient data.
- An orchestration framework combining GPT-4, Gemini, Mistral for explanation generation.
- A novel Reasoning Scorecard evaluating *Transparency*, *Consistency*, *Clarity*, and *Completeness*.
- A comparative analysis identifying LLM strengths and limitations in medical explainability.

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Conference'17, Washington, DC, USA
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ACM ISBN 978-x-xxxx-xxxx-x/YYYY/MM
https://doi.org/10.1145/nnnnnnn.nnnnnnn

2 Related Work

Early works such as [5] demonstrated the feasibility of shock prediction using vital signs. Explainability in healthcare has gained traction with methods like SHAP [2] and LIME [4], yet generating coherent clinical reasoning remains challenging [9]. Recent studies [8] have explored LLMs for medical reasoning but lack quantitative scorecard-based evaluations.

3 Methodology

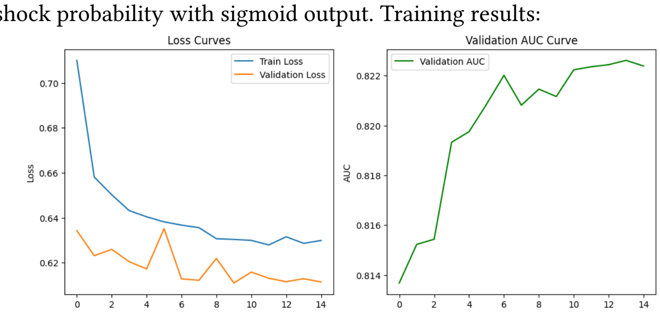
3.1 Data Processing

We extract ICU vitals and lab measurements from MIMIC-III database for the first 12 hours after admission. Records missing essential vitals/labs were filtered to ensure meaningful prediction. Final dataset: **4,957 patients**.

The generated patient summaries [6] and model explanation reasoning dataset [7] have been made publicly available to support reproducibility and further research.

3.2 Transformer Shock Prediction Model

Our DL model projects input features using a linear layer, applies 2-layer Transformer encoding (4 heads, 32-d embedding), and predicts shock probability with sigmoid output. Training results:



Final model achieves **AUC = 0.8226**. Confusion matrix and SHAP global feature importance are shown in Figures 1 and 2.

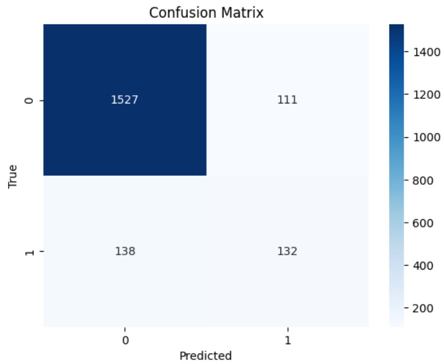


Figure 1: Confusion Matrix of Shock Prediction Model

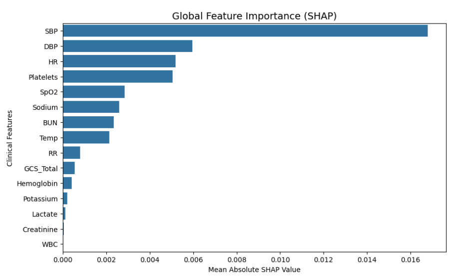


Figure 2: Global Feature Importance using SHAP

Note: SHAP values indicate the impact of each feature on the model's output. Higher absolute SHAP values signify greater influence.

3.3 Reasoning Generation by LLMs

Using top features + model prediction + probability, we generate prompts per patient. Three models: (1) GPT-4 via OpenAI API, (2) Gemini 1.5 Pro API, (3) Mistral 7B locally (Ollama).

3.4 Reasoning Scorecard

Each explanation was scored on 4 axes:

- **Transparency**: Are assumptions, risks discussed?
- **Consistency**: No contradictions or factual errors.
- **Clarity**: Easy for clinician to understand.
- **Completeness**: All key vitals/labs interpreted.

Scores were generated by DeepSeek R1 model prompting a formal rubric.

4 Results

4.1 LLM Performance

Radar plots and bar charts summarize average scores across models (Figures 3, 4, 5).

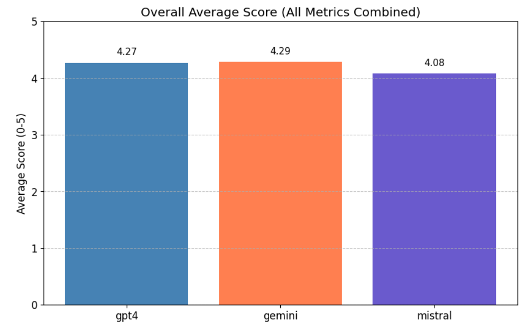


Figure 3: Overall Average Reasoning Score per LLM. Average scores across all axes for each LLM. Higher scores indicate better performance.

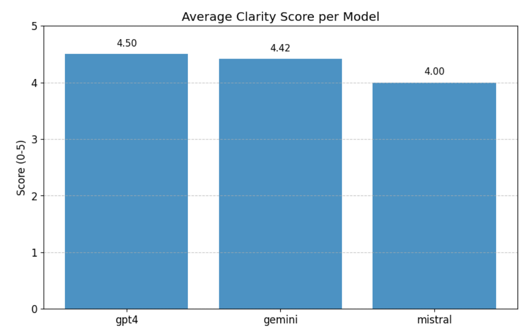


Figure 4: Clarity Score Comparison

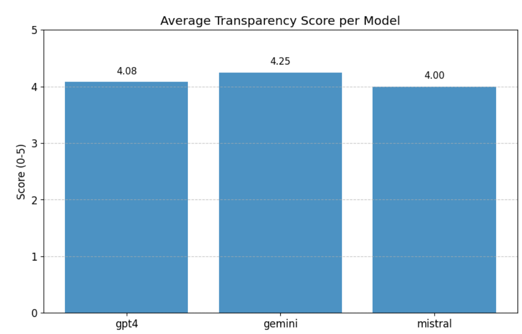


Figure 5: Transparency Score Comparison

4.2 Key Insights

- GPT-4 produced the most *Consistent* explanations.
- Gemini showed high *Transparency* but lower *Clarity*.
- Mistral explanations were more *Concise*, but missed detailed reasoning in some cases.
- DeepSeek R1 orchestration provided robust automated evaluation.

5 Conclusion

This work demonstrates that LLMs, when orchestrated carefully, can effectively generate clinical reasoning for shock prediction in ICU patients. Our scorecard approach surfaces model-specific tendencies and quality gaps. Future work will explore using ensembles of explanations, further fine-tuning LLMs for ICU context, and validating impact with real clinicians.

Acknowledgment

This project was completed as part of "AI in Healthcare" coursework at University of Texas at Austin.

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