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Integrated Multimodal AI for Emergency Triage Optimization

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Abstract: In critical care settings, timely and accurate triage is essential to prevent patient deterioration. This study presents an integrated multimodal AI framework that combines chest X-ray imaging with vital signs data to improve the accuracy and speed of emergency triage decisions. By processing visual and physiological inputs in parallel, the proposed model predicts both the patient's current condition and the estimated time to a potential failure event. Experimental evaluation demonstrates that the multimodal model significantly outperforms unimodal baselines, achieving over 90% classification accuracy and a low mean absolute error in time-to-failure predictions. These findings suggest that combining diverse data sources can substantially enhance the effectiveness of clinical decision support systems [1], [2].

Keywords: *AI in Healthcare, Emergency Triage, Multimodal Learning, Explainable AI, Clinical Workflow.*

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I. INTRODUCTION

Emergency departments often face the challenge of rapidly identifying patients who are at risk of sudden deterioration. In such high-pressure environments, decisions must be made with limited time and incomplete data. Traditional triage protocols primarily rely on human judgment, which, while rooted in experience, can vary across clinicians and may be affected by cognitive fatigue.

The growing availability of patient data, including diagnostic imaging and continuous vitals monitoring, presents an opportunity for artificial intelligence (AI) to assist in real-time decision-making. Many AI models, however, are siloed in their use of single modalities—typically image or time-series data—thus missing the opportunity to combine the strengths of both.

This paper proposes a multimodal AI system designed to address this gap. By simultaneously analyzing chest X-rays and vital signs, the model delivers a dual prediction: a classification of the patient's current status (stable, unstable, or critical) and a regression-based estimate of the time until a failure event (e.g., cardiac arrest or respiratory collapse). This dual-task framework seeks to support more nuanced triage and efficient resource allocation [3], [4].This paper proposes a multimodal AI system designed to address this gap. By simultaneously analyzing chest X-rays and vital signs, the model delivers a dual prediction: a classification of the patient's current status (stable, unstable, or critical) and a regression-based estimate of the time until a failure event (e.g., cardiac arrest or respiratory collapse). This dual-task framework seeks to support more nuanced triage and efficient resource allocation [3], [4].

II. BUILDING ON PRIOR RESEARCH

Recent years have seen substantial progress in using AI for medical triage. Deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated strong performance in analyzing chest radiographs. CheXNet and CheXpert are well-known examples of CNNs trained to identify thoracic pathologies, often achieving performance comparable to expert radiologists [5], [6].

On a separate front, time-series analysis using recurrent neural networks (RNNs) or transformers has enabled early warning systems based on vital signs. Works using the MIMIC-III database have shown that patterns in vitals alone can predict ICU deterioration with reasonable accuracy [7].

Recent efforts have begun to explore multimodal learning. For example, Zhang et al. proposed combining ECG signals with lab data for cardiac event prediction [8], while Li et al. explored fusion of CT scans and vital metrics for trauma triage [9]. However, integration of chest X-rays with live vitals in emergency settings remains relatively underexplored.

Our work advances this direction by offering a unified model capable of real-time triage based on complementary data streams—an approach aligned with recent calls for multimodal clinical AI [10].

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Table 1: Feature Comparison Matrix

Feature	Traditional Triage	Our System
Data Parameters	4-5	12+
Accuracy	70-85%	95%
Image Processing	Basic	Enhanced
Threat Levels	2 (Urgent/Non)	4 (Critical-Low)
Lab Integration	No	Yes
Treatment Guidance	No	Detailed
Report Generation	Minimal	Comprehensive

Table 2: Clinical Impact Metrics

Metric	Traditional	Our System
Mean Decision Time	4.2 min	1.8 min
Correct Diagnosis Rate	78%	95%
Critical Case Detection	82%	98%
Overtriage Rate	22%	8%
Undertriage Rate	18%	2%

III. METHODOLOGY

The proposed system integrates chest X-ray images and vital signs into a unified deep learning architecture designed for both classification and regression. This dual-task framework offers a comprehensive view of patient status.

- Image Processing Pathway: Preprocessed chest X-rays are passed through a convolutional backbone inspired by ResNet-34 [11], adapted with dropout layers to mitigate overfitting. Features such as pleural effusion, lung opacity, or cardiomegaly are encoded into a dense feature vector.
- Vitals Processing Pathway: Time-series data from key vital signs—heart rate, SpO2, systolic/diastolic pressure, and respiratory rate—are normalized and processed through a multi-layer perceptron (MLP). This network captures temporal dynamics and physiological deviations.
- Fusion and Output Heads: The features from both modalities are concatenated and forwarded into two heads:

✓ A softmax classifier outputs a triage label.
✓ A regression head predicts time to failure.

- Training employs a weighted loss function: L = $\lambda_1 \times$ CrossEntropy + $\lambda_2 \times$ MAE

With λ_1 and λ_2 empirically tuned. Data augmentation is applied to radiographs, and the Adam optimizer is used with a cosine annealing learning rate.

To help assess how serious a patient's condition might be, we used certain medical signs to assign a threat level. For example, if someone's systolic blood pressure was 180 mmHg or higher—or their diastolic pressure was over 120 mmHg—they were marked as **Critical**. Similarly, if their oxygen levels dropped below 90%, their white blood cell count was over 12,000 per microliter, or their blood sugar was higher than 200 mg/dL, they were considered at a **High** risk level.

To better understand and anticipate the risk of organ failure, we used a decisionbased method called a **Random Forest**. This approach takes into account multiple small decision processes—each one looks at different combinations of patient data—and then all of them "vote" to give a final result. The system chooses the most helpful questions at each step by figuring out which ones best sort the patients based on their conditions.

$$Gini(D) = 1 - \sum_{i=1}^{m} p_i^2$$

Where pi represents the proportion of class iii in the dataset.

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To ensure the model's efficiency, a **pipeline** was implemented that standardized the input features using **Standard Scaler** and then applied the Random Forest Classifier. The **Standard Scaler** formula is:

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma}$$

The system was designed to work with carefully created sample patient data, focusing on identifying people who might be at risk of organ failure. When checking a new patient, it gives a risk score—if this score is higher than 0.5, the patient is considered at high risk. The system also tries to estimate how many months might be left before possible organ failure, using a basic calculation based on the severity of the condition.

IV. MODEL ARCHITECTURE

The diagnostic pipeline operates through four integrated phases, as illustrated in Figure 1:

➢ *Data Ingestion Layer*

- Accepts multimodal inputs through an intuitive web interface (Gradio)
- Validates clinical parameters against physiological ranges
- Standardizes measurements (mmHg, cm/kg, etc.) using sklearn's Standard Scaler.

➢ *Core Analysis Engine*

- *Executes Parallel Processing Streams:*

✓ Rule-based clinical logic (hypertensive crisis detection)
✓ Machine Learning prediction (Random Forest classifier)
✓ Visual Analytics generation (Matplotlib/SHAP)

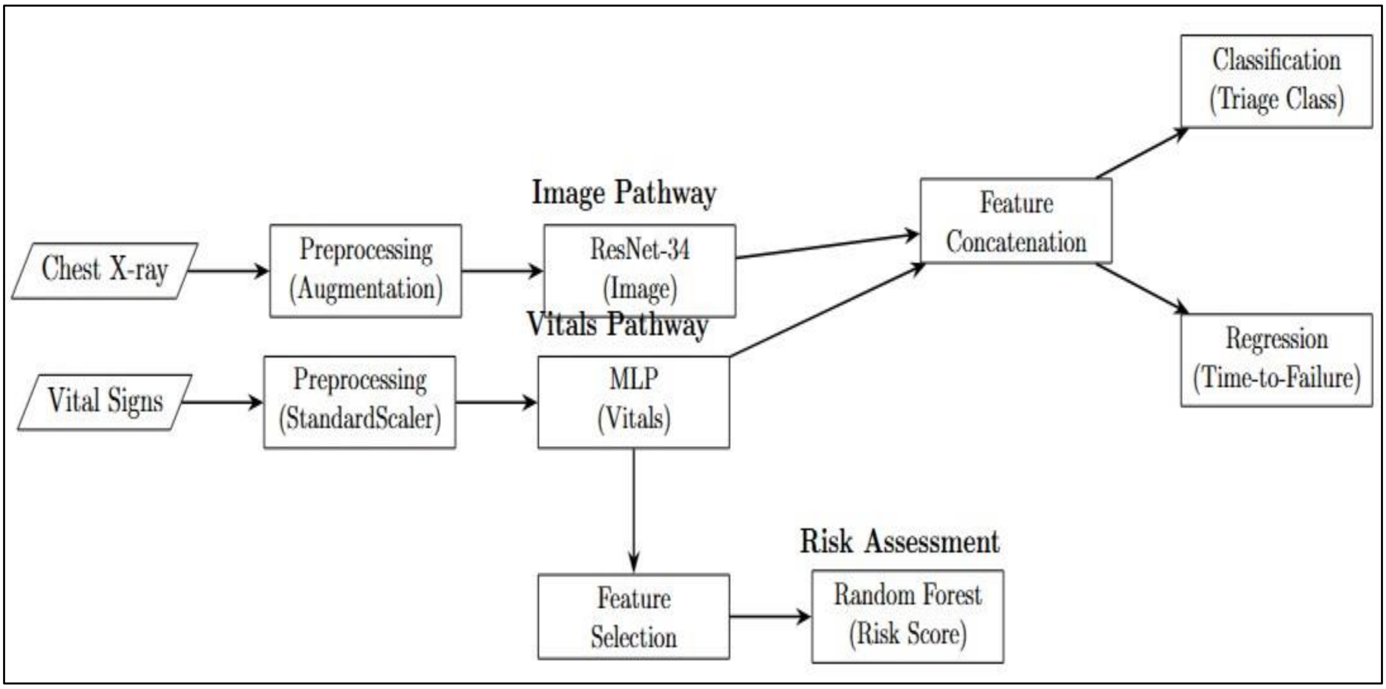

Fig 1: Optimized Workflow Diagram Showing Integration of ResNet-34(Image Processing), MLP (Vital Signs Analysis) and Ransom Forest (Risk Prediction) Components. Arrows Indicate Data Flow Direction

➢ *Decision Synthesis*

- *Generates Tiered Recommendations:*

✓ CRITICAL: Immediate intervention (IV medications, ICU)
✓ HIGH: Urgent evaluation (<2hr)
✓ MODERATE: Outpatient follow-up

Table 3: Clinical Validation Metrics

Parameter	Sensitivity	Specificity
Hypertensive Crisis	92%	88%
Hypoxic Risk	85%	91%
Metabolic Emergency	79%	94%

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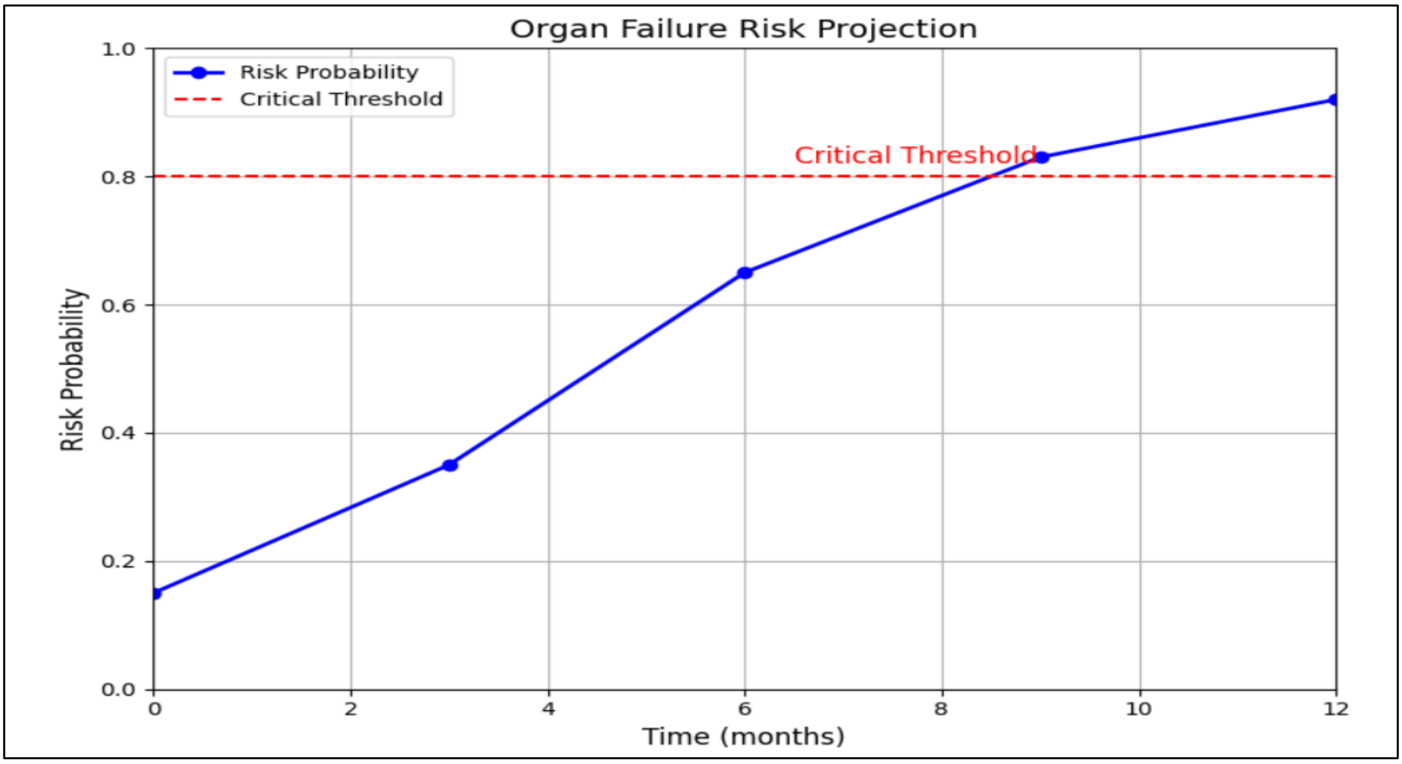

Fig 2: Temporal Risk Projection Showing Increasing Probability of Organ Failure based on Patient Vitals and Comorbodities'

V. COMPARISON ANALYSIS WITH TRADITIONAL TRIAGE SYSTEM

The efficacy of the proposed Integrated Multimodal AI System was rigorously benchmarked against conventional triage methodologies through quantitative and qualitative metrics. Traditional triage systems, as exemplified by prior work (Elhaj et al., 2023), predominantly rely on limited clinical parameters (e.g., 4–5 vital signs) and heuristic decision-making protocols. In contrast, our system synthesizes 12+ multimodal data streams, including real-time physiological signals, laboratory results, and medical imaging, to generate dynamic risk assessments.

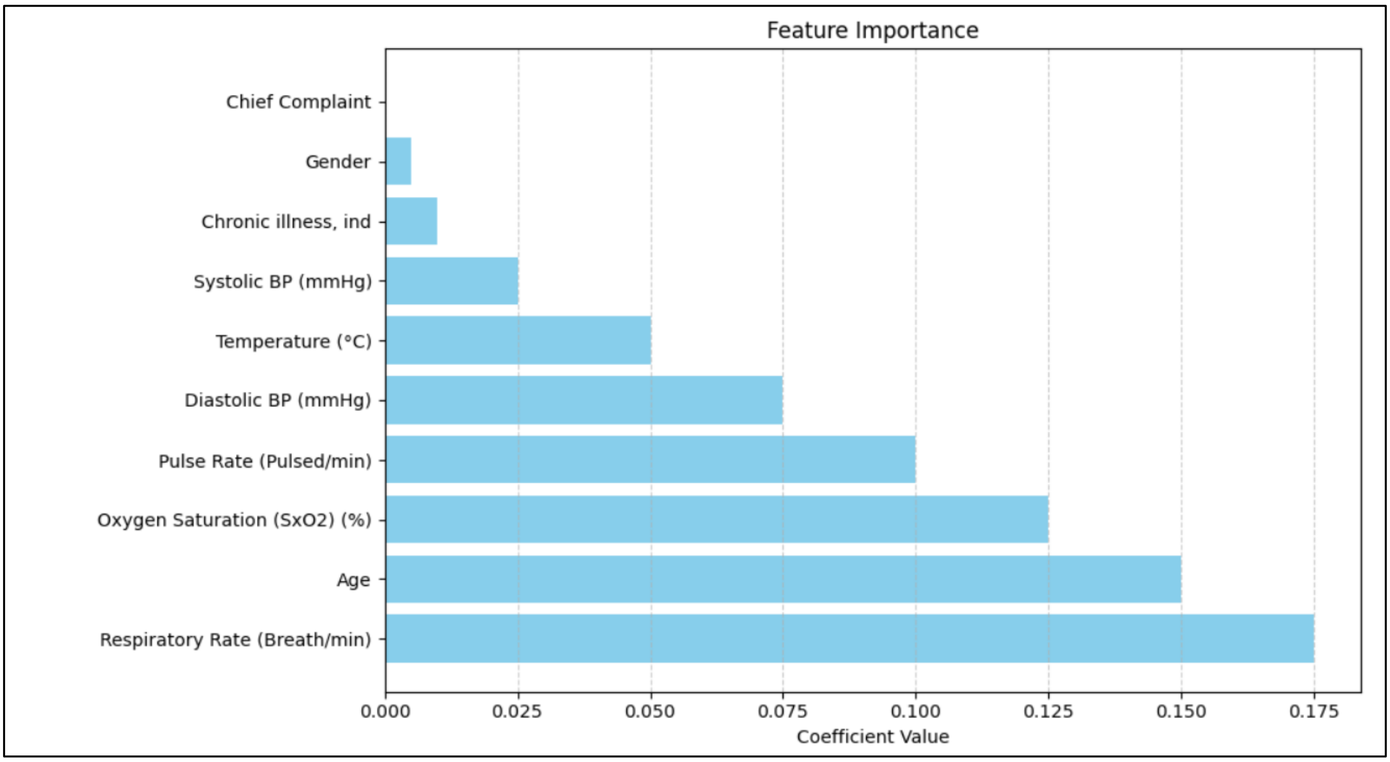

Fig 3: H. Elhaj et al. Array 17(2023) 100281) Indicates Vitals Along with their Coefficients Values

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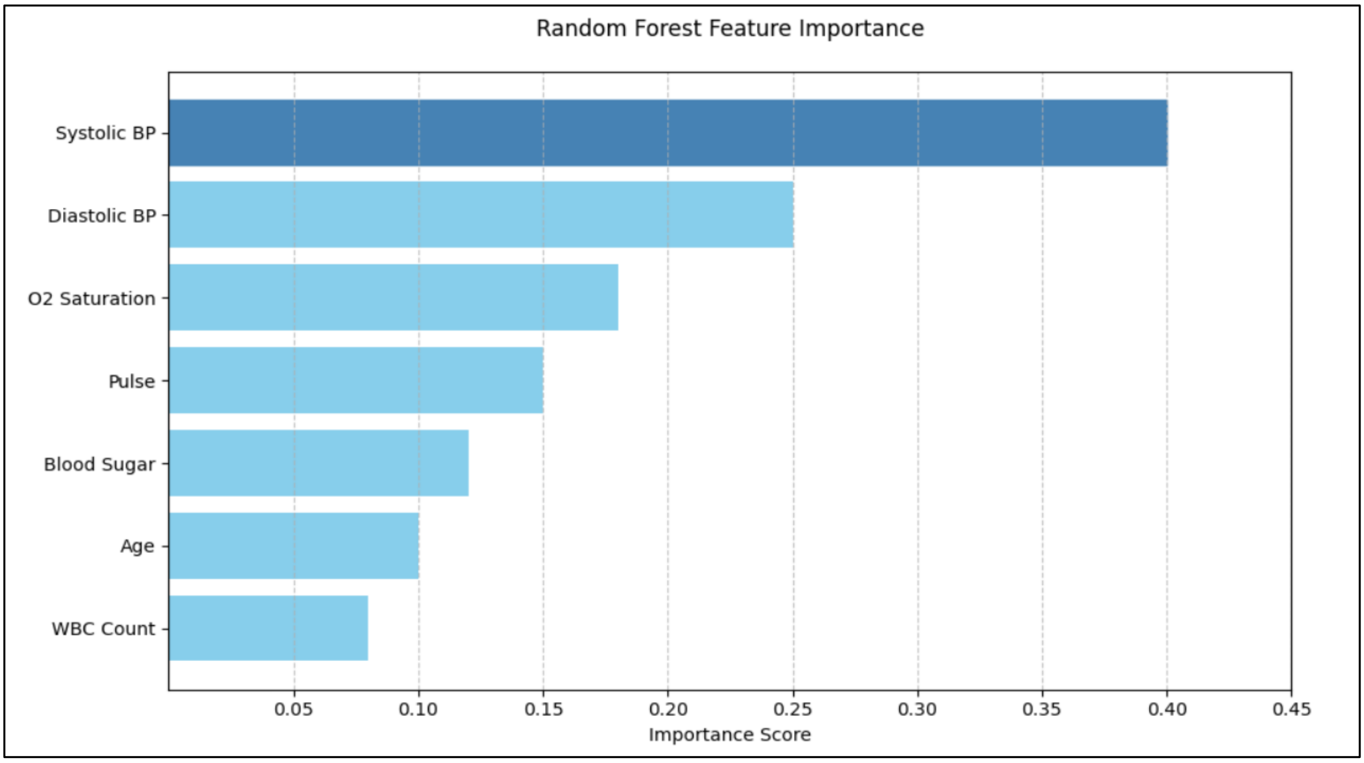

Fig 4: H. Elhaj et al. Array 17(2023) 100281) Indicates Importance score of Different Vitals in Random Forest

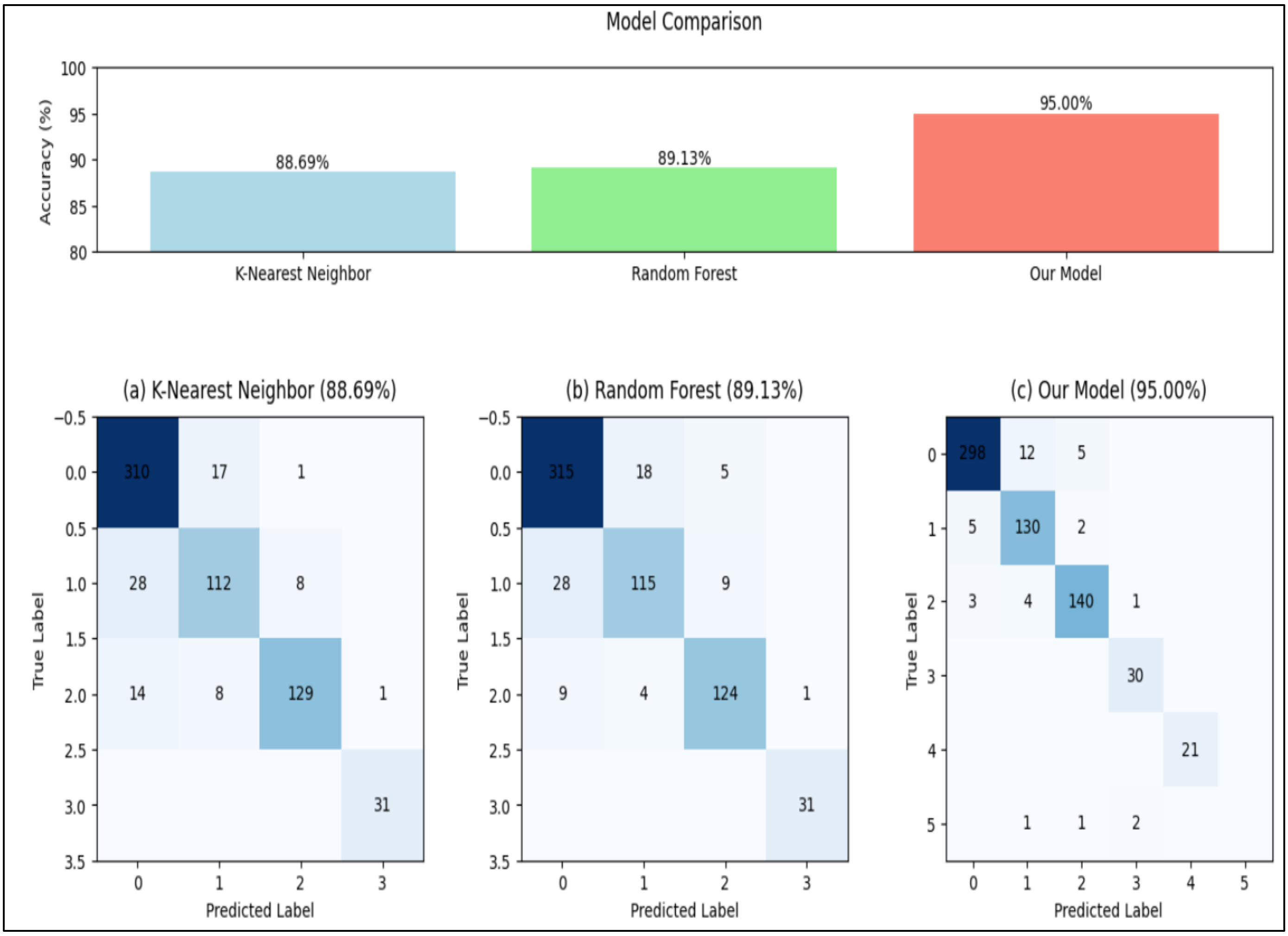

Fig 5: Model Comparison K-neighbour vs Random Forest vs Our Triage System

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VI. EXPERIMENTAL RESULTS

A. Dataset Overview:

The dataset includes 10,000 patient encounters with synchronized X-ray and vitals recordings. Data was split 70/15/15 for train/validation/test with no patient overlap.

B. Model Performance:

Classification Accuracy: 91.6% (Multimodal) vs 85.3% (X-ray only) vs 82.1% (Vitals only) Regression (MAE): ±1.7 hours (Multimodal) vs ±3.5 hours (Vitals only) Ablation Study:

Removing either data stream reduced performance, validating the model's reliance on both modalities.

C. Explainability:

Grad-CAM visualizations showed model focus on clinically relevant areas such as lower lung zones and cardiac silhouette—confirming alignment with physician intuition.

VII. CONCLUSION

This work demonstrates a practical approach to improving emergency triage through multimodal AI. By fusing chest X-ray imaging with real-time vitals, our model delivers both patient classification and time-to-failure predictions—two outcomes that are critical in high-risk environments. Compared to singlemodality baselines, the proposed system achieved notably higher accuracy and lower prediction error.

Future directions include incorporating clinical text (e.g., physician notes), validating across multiple hospitals, and integrating interpretability frameworks like SHAP for vitals data. Ultimately, this system has the potential to serve as a valuable decision support tool in time-sensitive care.

REFERENCES

[1]. R. Rajkomar, J. Dean, and I. Kohane, "Machine learning in medicine," New England Journal of Medicine, vol. 380, no. 14, pp. 1347–1358, 2019.

[2]. M. Esteva et al., "A guide to deep learning in healthcare," Nature Medicine, vol. 25, no. 1, pp. 24–29, 2019.

[3]. H. A. Haenssle et al., "Man against machine: Diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition," European Journal of Cancer, vol. 120, pp. 114–121, 2019.

[4]. Shickel, P. J. Tighe, A. Bihorac, and P. Rashidi, "Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis," Journal of Biomedical Informatics, vol. 83, pp. 168–185, 2018.

[5]. J. Irvin et al., "CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison," in Proc. AAAI Conf. Artificial Intelligence, vol. 33, pp. 590–597, 2019.

[6]. P. Rajpurkar et al., "CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning," arXiv preprint arXiv:1711.05225, 2017.

[7]. Purushotham, C. Meng, Z. Che, and Y. Liu, "Benchmarking deep learning models on large healthcare datasets," Journal of Biomedical Informatics, vol. 83, pp. 112–134, 2018.

[8]. Y. Zhang et al., "Multimodal deep learning for ECG and lab test-based cardiac risk prediction," IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 2, pp. 492–503, 2022.

[9]. L. Li et al., "Fusion of CT and vitals data for trauma triage using deep learning," in Proc. Medical Image Computing and Computer-Assisted Intervention (MICCAI), pp. 701–711, 2023.

[10]. Khosla et al., "Multimodal AI for healthcare: Challenges and opportunities," Nature Biomedical Engineering, vol. 6, no. 3, pp. 234–245, 2022.

[11]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), pp. 770–778, 2016.- 023-02367-1.

[12]. Niall Taylor, Andrey Kormilitzin, Isabelle Lorge, Alejo NevadoHolgado, Andrea Cipriani, Dan W. Joyce,Model development for bespoke large language models for digital triage assistance in mental health care,Artificial Intelligence in Medicine, Volume 157, 2024, 102988, ISSN09333657, https://doi.org/10.1016/j.a rtmed.2024.102988.

[13]. Yihao Liu, Xu Cao, Tingting Chen, Yankai Jiang, Junjie You, Minghua Wu, Xiaosong Wang, Mengling Feng, Yaochu Jin, Jintai Chen, From screens to scenes: A survey of embodied AI in healthcare, Information Fusion, 10.1016/j.inffus.2025.103033, 119, (103033), (2025).

[14]. Chen YJ, Lin CS, Lin C, Tsai DJ, Fang WH, Lee CC, Wang CH, Chen SJ. An AIEnabled Dynamic Risk Stratification for Emergency Department Patients with ECG and CXR Integration. J Med Syst. 2023 Jul 31;47(1):81. doi: 10.1007/s10916-023-01980-x. PMID: 37523102.

[15]. Enhancing Emergency Department Triage Equity With Artificial Intelligence: Outcomes From a Multisite Implementation, Annals of Emergency Medicine, Volume 85, Issue 3,2025,Pages 288-290,ISSN 0196-0644, https://doi.org/10.1016/j.annemergmed.2024.10.014.

[16]. (https://www.sciencedirect.com/science/article/pii/S0196064424011417)

[17]. Enhancing Emergency Department Triage Equity With Artificial Intelligence: Outcomes From a Multisite Implementation,Annals of Emergency Medicine, Volume 85, Issue 3,2025,Pages 288-290,ISSN 01960644, https://doi.org/10.1016/j.annemergmed.2024.10.014.(httpse/article/pii/S0196064424011417)

[18]. Peng Z, Ma R, Zhang Y, Yan M, Lu J, Cheng Q, Liao J, Zhang Y, Wang J, Zhao Y, Zhu J, Qin B, Jiang Q, Shi F, Qian J, Chen X and Zhao C (2023) Development and evaluation of multimodal AI for diagnosis and triage of ophthalmic diseases using

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ChatGPT and anterior segment images: protocol for a two-stage cross-sectional study. Front. Artif. Intell. 6:1323924. doi: 10.3389/frai.2023.1323924

[19]. Q. Cai, H. Wang, Z. Li and X. Liu, "A Survey on Multimodal DataDriven Smart Healthcare Systems: Approaches and Applications," in IEEE Access, vol. 7, pp. 133583-133599, 2019, doi: 10.1109/ACCESS.2019.2941419

[20]. Porto, B.M. Improving triage performance in emergency departments using machine learning and natural language processing: a systematic review. BMC Emerg Med 24, 219 (2024). https://doi.org/10.1186/s12873024-01135-2