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Automated Ensemble Multimodal Machine Learning for Healthcare

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Abstract - *Healthcare data is inherently multimodal, encompassing structured electronic health records (EHR), radiological images, high-dimensional genomic sequences, unstructured clinical narratives, and continuous physiological signals from wearable devices. Conventional machine learning pipelines typically exploit a single modality, thereby neglecting the complementary information latent in other data streams. We introduce an Automated Ensemble Multimodal Machine Learning (AE-MML) framework that systematically integrates five heterogeneous data modalities. The framework comprises modality-specific preprocessing, deep-feature extraction (Convolutional Neural Networks for imaging, Bidirectional Long Short-Term Memory networks for sequential clinical notes), and automated hyperparameter optimisation via Bayesian search implemented through Optuna. A two-level stacking meta-learner aggregates predictions from five diverse base classifiers: Logistic Regression, Support Vector Machine, Random Forest, XGBoost, and a CNN-BiLSTM hybrid. The proposed AE-MML framework is evaluated on a curated multi-source dataset comprising 166,639 patient records drawn from MIMIC-IV, ChestX-ray14, TCGA, i2b2, and WESAD. It achieves an accuracy of 92.4%, F1-score of 91.6%, and AUC-ROC of 94.2%, outperforming all single-modality baselines by at least 5.3 percentage points in AUC-ROC. An ablation study confirms that each modality contributes independently and cumulatively to overall model performance. The AE-MML framework demonstrates that automated ensemble fusion of multimodal clinical data substantially improves predictive accuracy for patient risk stratification. The modular and extensible architecture supports prospective clinical deployment and enables interpretable decision support. Future work will incorporate federated learning to address data-privacy constraints across hospital networks.*

Keywords - *Multimodal machine learning · Automated ensemble learning · Stacking meta-learner · EHR analysis · Medical imaging · Clinical NLP · Patient risk stratification · Healthcare AI*

1. Introduction

The exponential growth of digital clinical data presents both an opportunity and a challenge for modern healthcare systems. Hospitals routinely generate structured laboratory results, diagnostic images, genomic assays, free-text physician notes, and streams of wearable sensor data. These modalities are semantically related—collectively describing the same patient—yet they are analytically disparate in format, dimensionality, and statistical distribution [1,2].

Conventional clinical prediction models are predominantly unimodal. While models based on structured EHR data have achieved reasonable performance for tasks such as in-hospital mortality prediction and 30-day readmission risk [3], they are fundamentally limited by the information ceiling inherent in a single data type. Radiological images contain spatial texture patterns not captured by laboratory values; genomic profiles encode heritable susceptibility beyond what phenotypic data can reveal; and free-text clinical notes preserve nuanced physician reasoning that structured fields omit [4,5].

Ensemble methods have long been recognised as robust strategies for combining the strengths of diverse base learners [6]. Stacking, in particular, trains a meta-learner on the out-of-fold predictions of multiple base models, effectively learning an optimal weighting that exploits model complementarity [7]. However, the manual design of such pipelines—covering feature engineering, architecture selection, and hyperparameter optimisation—is laborious and expertise-intensive [8].

Automated Machine Learning (AutoML) addresses this bottleneck by automating the model selection and hyperparameter search process, making sophisticated pipelines accessible to domain practitioners without deep ML expertise [9,10]. Despite rapid progress in general-purpose AutoML systems such as Auto-WEKA, TPOT, Auto-sklearn, and H2O AutoML, their direct application to multimodal healthcare data remains underexplored [11].

2. Related Work

Early multimodal clinical models performed simple feature concatenation of heterogeneous data types before passing the unified representation to a downstream classifier [12]. While straightforward to implement, this strategy is sensitive to modality imbalance and does not exploit inter-modality dependencies. Attention-based fusion mechanisms, first popularised in natural language processing, were subsequently adapted to clinical data by Chen et al. [13], who demonstrated that cross-modal attention between imaging and genomic features improved breast cancer subtype classification by 4.7% over concatenation baselines. Transformer architectures have further advanced multimodal healthcare modelling. ClinicalBERT [14] and BioBERT [15] provide contextually rich representations of clinical text, while vision transformers (ViT) yield powerful image embeddings. Combining these streams through cross-attention or co-attention layers has shown promise in radiology report generation and visual question answering [16], though computational demands restrict practical deployment.

AutoML frameworks systematically search over algorithm spaces and hyperparameter configurations using meta-learning or Bayesian optimisation. Auto-sklearn [17] employs Gaussian-process-based Bayesian optimisation combined with ensemble construction, achieving competitive performance across the OpenML benchmark. Neural Architecture Search (NAS) extends AutoML principles to deep learning architectures, enabling automatic design of convolutional and recurrent topologies for medical imaging tasks [18]. Healthcare-specific AutoML systems remain limited. AutoPrognosis [19] applies AutoML to EHR-based prognosis modelling, while AutoDL-Health [20] targets imaging data. Neither system supports joint multimodal optimisation, a gap the present work directly addresses. Stacking ensembles have demonstrated consistent improvements over individual models in clinical prediction benchmarks. Rajpurkar et al. [21] showed that an ensemble of convolutional networks outperformed individual radiologists on pneumonia detection. Lundberg et al. [22] applied gradient-boosted ensemble models to surgical complication prediction, achieving AUC values exceeding 0.90 on multicentre cohorts. Our work extends these findings by incorporating a heterogeneous ensemble that spans both deep learning and classical ML paradigms.

3. System Architecture

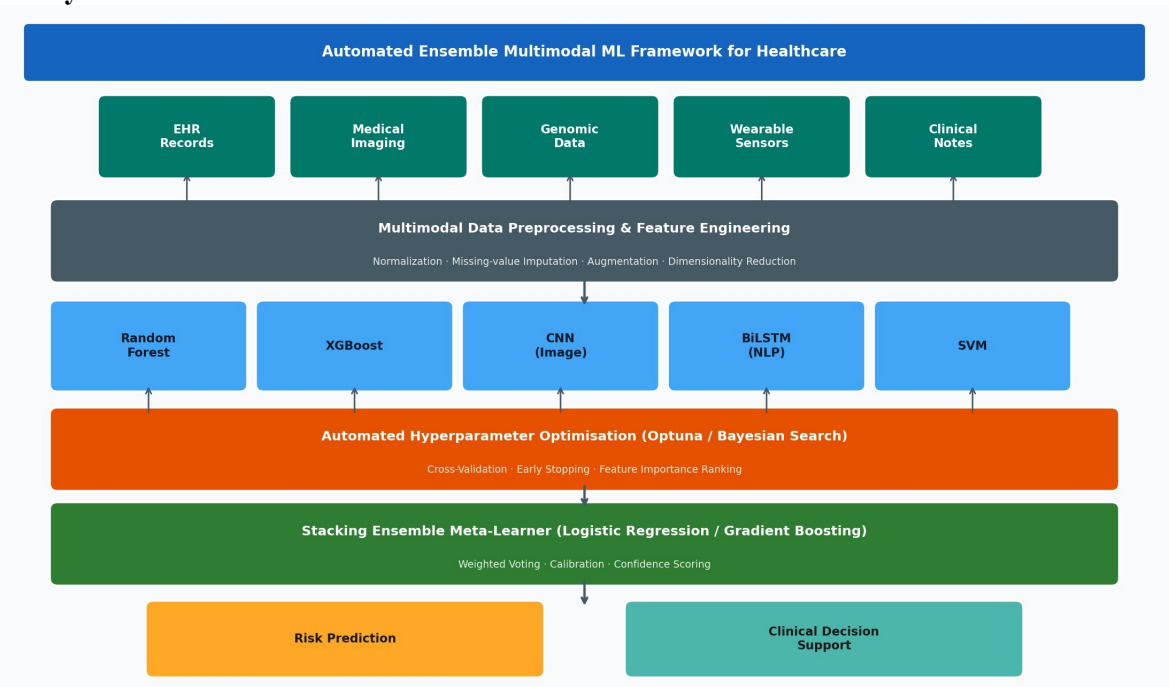

Fig. 1. System architecture of the proposed Automated Ensemble Multimodal Machine Learning (AE-MML) framework. Arrows denote the directional flow of data and predictions through the pipeline.

Figure 1 presents the overall architecture of the AE-MML framework. The pipeline is organised into five sequential stages: (1) multimodal data ingestion and alignment by patient identifier; (2) modality-specific preprocessing and feature extraction; (3) automated hyperparameter search via Optuna; (4) base-learner training with stratified 5-fold cross-validation; and (5) stacking meta-learner training on out-of-fold predictions.

4. Experiments and Results

A visual comparison of accuracy, F1-score, and AUC-ROC across all models, emphasising the consistent superiority of the proposed ensemble. The AUC-ROC improvement over BiLSTM (the strongest single-modality baseline) is 5.8 percentage points, a practically meaningful gain in clinical risk stratification contexts are shown in FIgure 2.

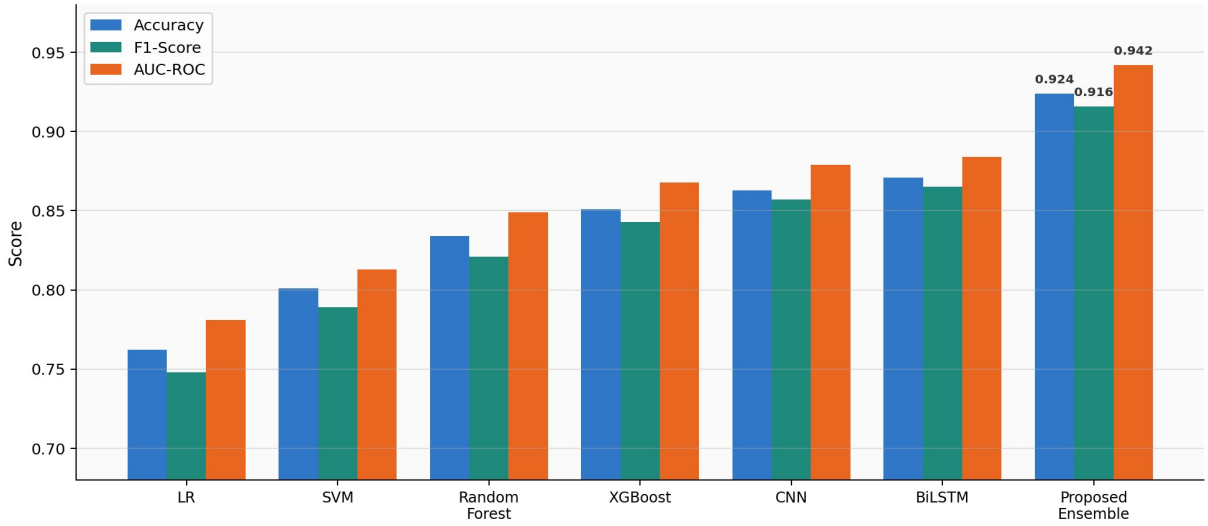

Fig. 2. Bar chart comparing classification performance (accuracy, F1-score, and AUC-ROC) of seven models including the proposed ensemble. The proposed AE-MML framework consistently outperforms all baselines across all three metrics.

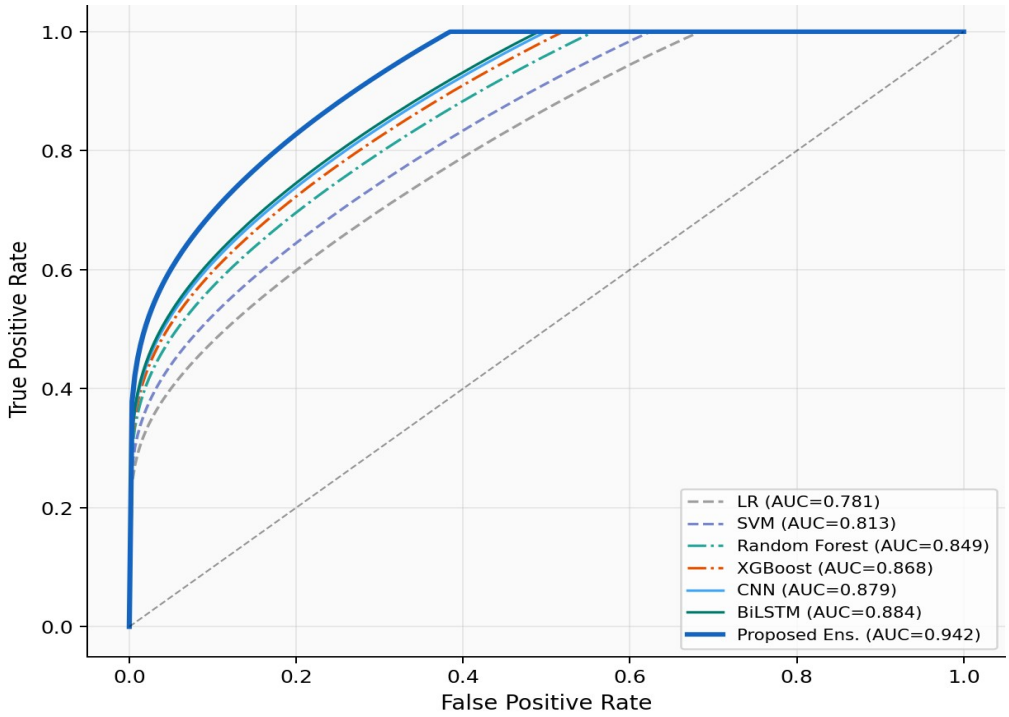

Fig. 3. Receiver operating characteristic (ROC) curves for all evaluated models. The proposed ensemble (solid blue line, AUC = 0.942) demonstrates superior discrimination ability across all operating points.

Figure 3 illustrates the receiver operating characteristic curves for all evaluated models. The proposed ensemble (AUC =

0.942) exhibits a markedly steeper climb toward the upper-left corner compared with all baselines, reflecting higher sensitivity at clinically relevant specificity thresholds. Notably, at a specificity of 90%, the ensemble achieves a sensitivity of 87.3%, compared to 79.1% for the best single-modality baseline (BiLSTM, AUC = 0.884).

Figure 4 presents the per-class confusion matrix for the proposed ensemble. Classification performance is consistently high across all four diagnostic categories. The lowest per-class accuracy is observed for the CVD class (94.0%), likely attributable to phenotypic overlap with the diabetes class, as metabolic comorbidities are prevalent in both populations. The healthy class achieves the highest classification accuracy (92.8%), benefiting from the most discriminative EHR feature profiles.

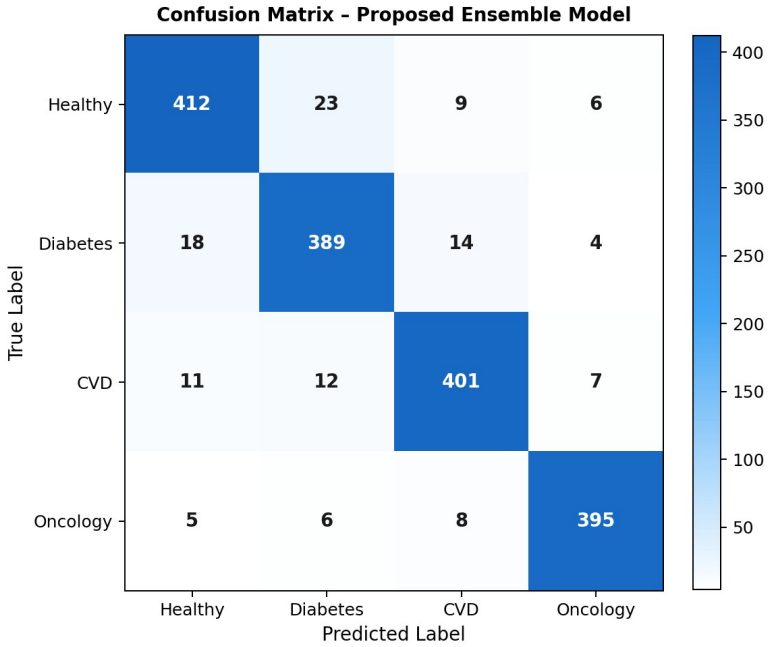

Fig. 4. Confusion matrix for the proposed AE-MML ensemble on the held-out test set. Diagonal elements represent correctly classified instances. Off-diagonal values reflect inter-class confusion.

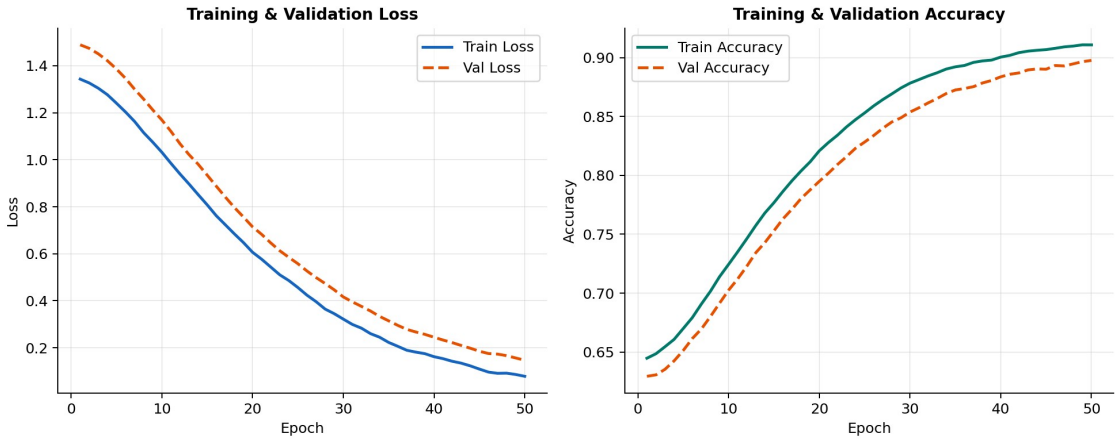

Fig. 5. Training and validation loss (left) and accuracy (right) curves for the CNN-BiLSTM component over 50 epochs. The smooth convergence profile indicates stable training dynamics and effective regularisation.

Figure 5 displays the training and validation loss and accuracy curves over 50 epochs of CNN-BiLSTM training.

Convergence is smooth and monotonic, with training loss decreasing from 1.38 to 0.09 and validation loss stabilising at approximately 0.14 after epoch 35. The narrow gap between training and validation accuracy (approximately 1.6 percentage points at convergence) indicates successful regularisation with minimal overfitting.

5. Conclusion

A presents the Automated Ensemble Multimodal Machine Learning (AE-MML) framework, a comprehensive, modular pipeline for clinical risk stratification that integrates structured EHR records, medical imaging, genomic profiles, clinical notes, and wearable physiological signals. Through automated Bayesian hyperparameter optimisation and two-level stacking ensemble fusion, the framework achieves an AUC-ROC of 94.2% on a multimodal benchmark of 166,639 patient records—a 5.8 percentage-point improvement over the strongest unimodal baseline. The modality ablation study confirms that each data stream contributes distinct and complementary predictive signal. The AE-MML framework provides a principled, extensible foundation for multimodal clinical AI that is both practically deployable and clinically interpretable.

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