GraphMMP: A Graph Neural Network Model with Mutual Information and Global Fusion for Multimodal Medical Prognosis

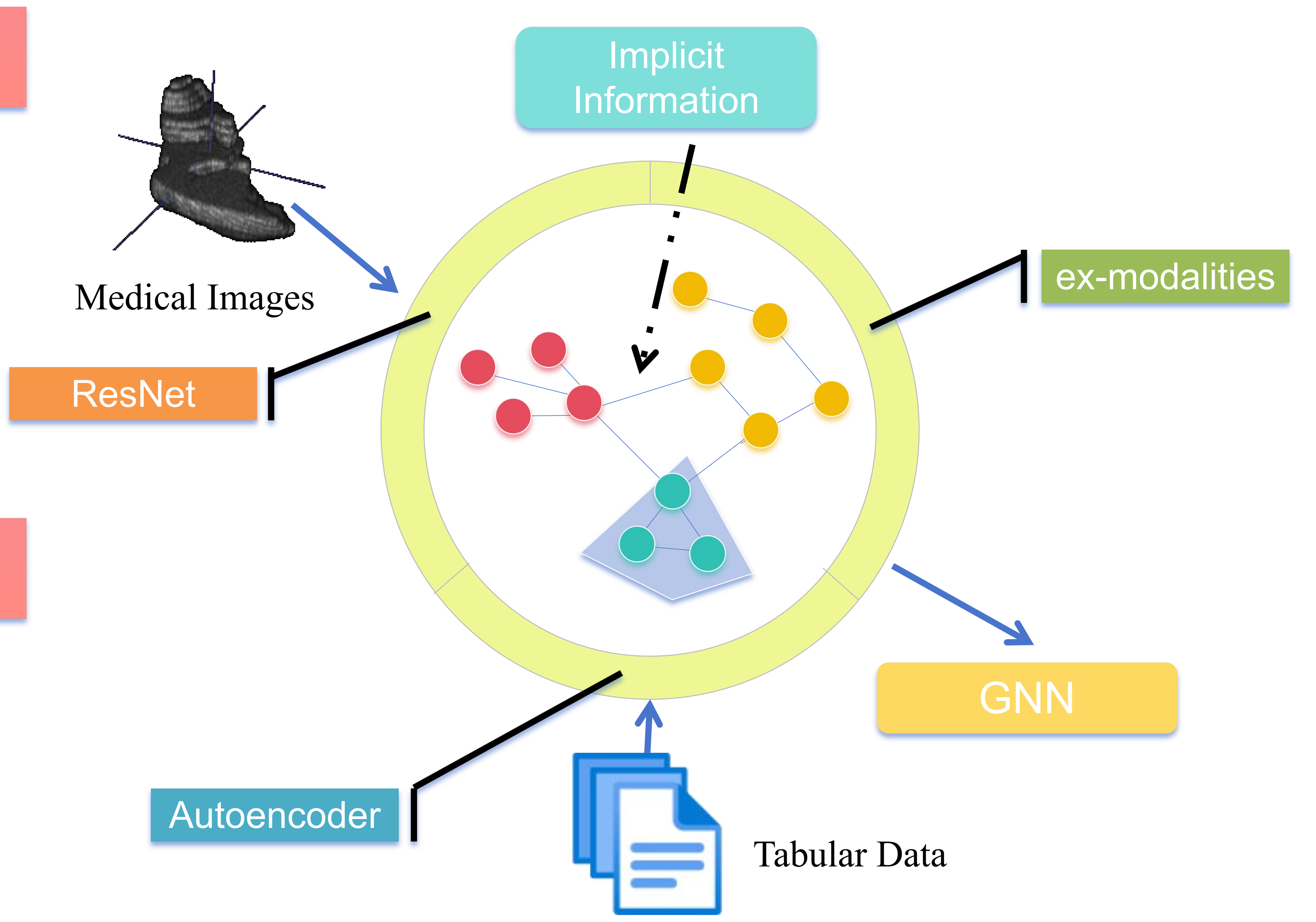
Xuhao Shan ,Ruiquan Ge✉,Jikui Liu ,Linglong Wu ,Chi Zhang ,Siqi Liu ,Wenjian Qin ,Wenwen Min ,Ahmed Elazab ,and Changmiao Wang✉

Introduction

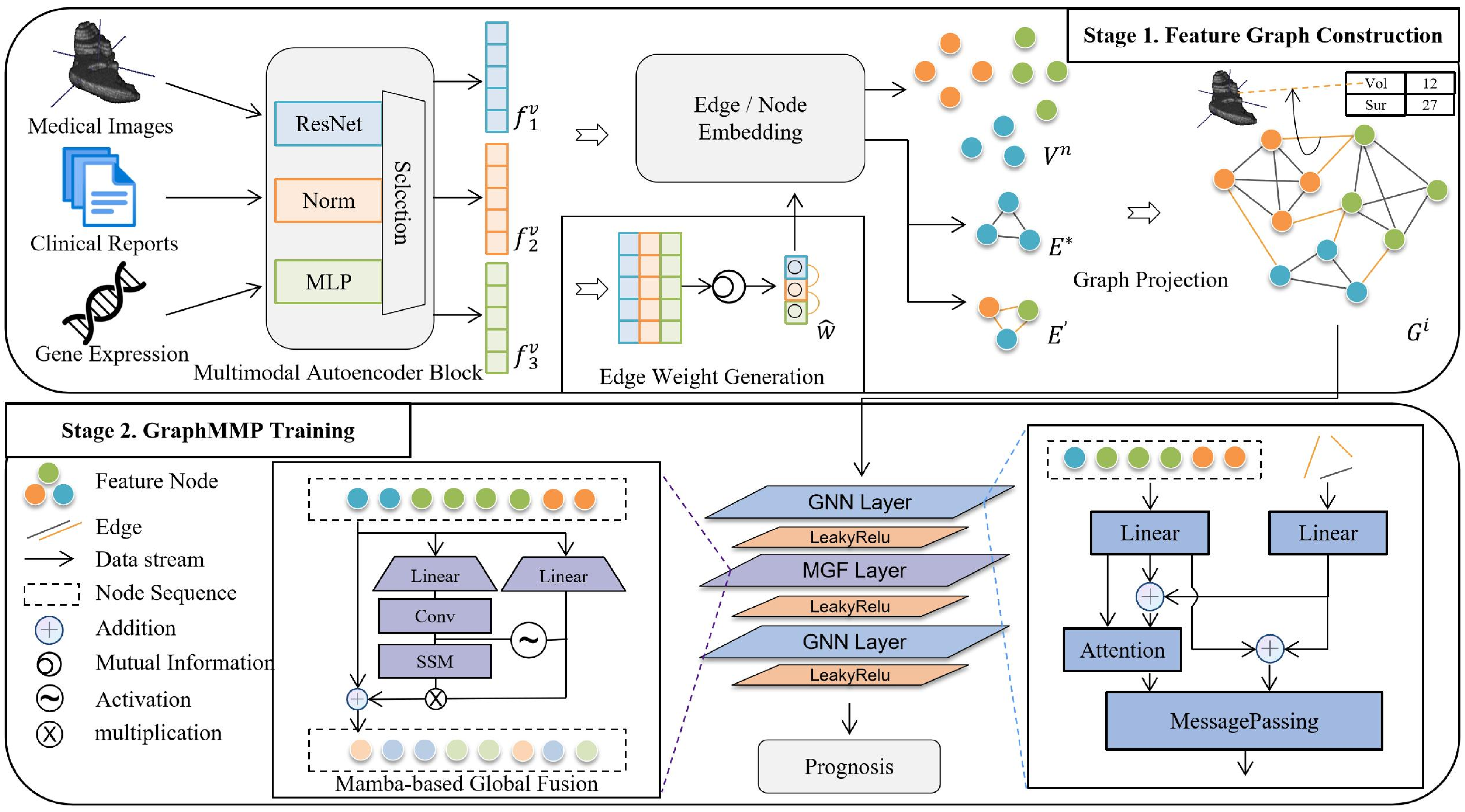
Multimodal data integration is crucial for medical prognosis. Deep learning methods excel at analyzing such **heterogeneous data**. While **Graph Neural Networks (GNNs)** show promise in modeling relational data, existing methods often fail to capture hidden **cross-modal relationships and global dependencies**, limiting their performance in complex prognosis tasks.

challenges

1. **Effectively modeling** complex interactions between highly heterogeneous data modalities.
2. **Capturing both local and global dependencies** across modalities within a unified model.
3. Overcoming the limited global perception of standard GNNs for **comprehensive data integration**.



Method



Two-Stage Architecture

Feature Graph Construction:
Builds a feature graph where nodes are multimodal features and edges are weighted by **Mutual Information (MI)** to capture hidden inter-modal relationships.

GraphMMP Training:
A lightweight GNN with a novel **Mamba-based Global Fusion (MGF)** module to enhance global contextual understanding.

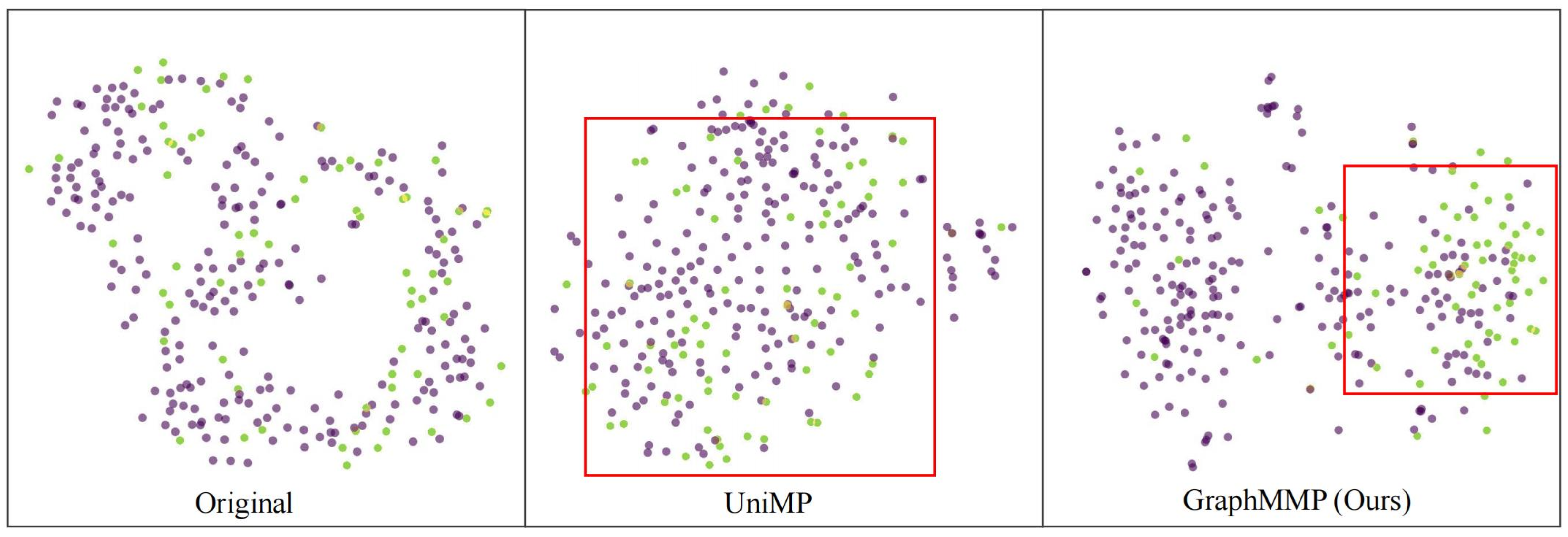
MI-based Edge Weighting: Quantifies feature associations to build a semantically meaningful graph.

MGF: A novel module that flattens the graph into a sequence, processes it and fuses it back, boosting performance.

QUALITATIVE RESULTS

Comparisons results and t-SNE on our private dataset

Method	Modality	ACC	Precision	Recall	F1-score	AUC
GraphConv	T	0.7823	0.8252	0.5883	0.6708	0.7661
UniMP	T	0.7931	0.7962	0.6797	0.7147	0.7861
GraphMMP (Ours)	T	0.8099	0.8182	0.6429	0.7222	0.8037
SimpleFF	I+T	0.7275	0.7472	0.5410	0.6218	0.7050
HFBSurv	I+T	0.7945	0.8201	0.6432	0.7233	0.8015
MMD	I+T	0.7722	0.8125	0.6063	0.6772	0.7344
TMI-CLNet	I+T	0.8312	0.8438	0.7428	0.7805	0.8223
GraphMMP (Ours)	I+T	0.8514	0.8462	0.7857	0.8106	0.8411



Comparisons results on our METABRIC dataset

Method	ACC	Precision	Recall	F1-score	AUC
GraphConv	0.8056	0.6571	0.4646	0.5562	0.8502
UniMP	0.8369	0.7263	0.6346	0.6819	0.8573
GCN	0.7626	0.6111	0.1112	0.1897	0.7116
ChoqFuzGCN	0.8200	0.7142	0.5983	0.6470	0.8301
MOGAT	0.8056	0.6279	0.5455	0.5838	0.8463
GraphMMP (Ours)	0.8535	0.7368	0.6796	0.7129	0.8649

Xuhao Shan| Email: 242050182@hdu.edu.cn
ChangmiaoWang| Email: cmwangalbert@gmail.com
RuiquanGe| Email: gespring@hdu.edu.cn

arXiv

Code