OmniMedAI: Omni Medical AI Platform

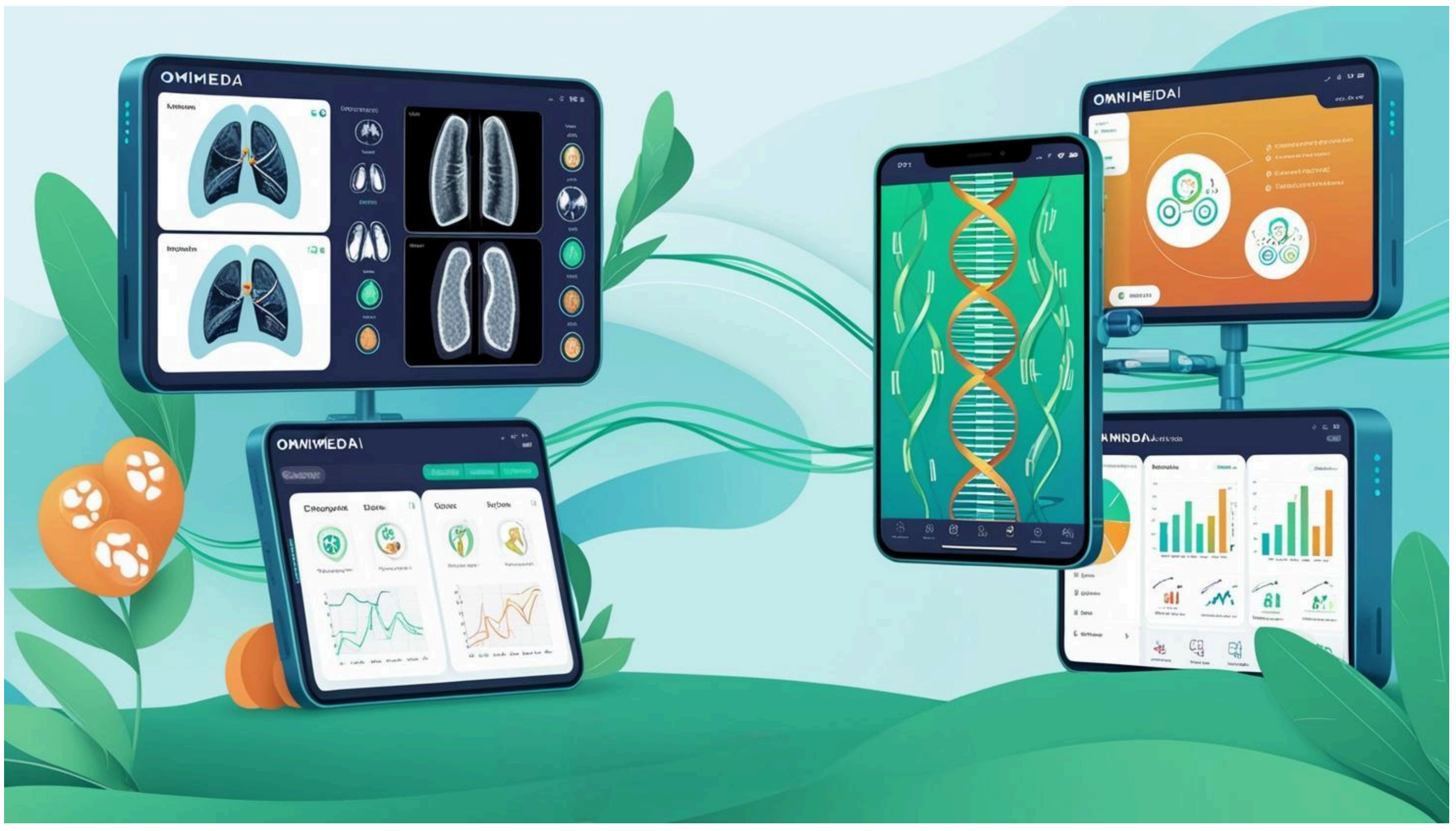
OMNIMEDAI
AI-DRIVEN DIAGNOSIS

Abstract

OmniMedAI is an advanced AI-driven platform designed to integrate and analyze heterogeneous medical data, including radiological imaging, digital pathology, genomics, and clinical records. Leveraging cutting-edge techniques in radiomics, deep learning, habitat analysis, and multi-instance learning, the platform enables researchers and clinicians to build robust predictive models for disease diagnosis, prognosis, and personalized treatment planning.

System Architecture

> OmniMedAI adopts a modular architecture to support end-to-end multimodal data analysis:



1. **Data Integration Module**
   • Supports import of DICOM, CSV, HDF5, and other formats.
   • Integrates tools like ITK-SNAP (for ROI segmentation in radiology) and 3D Slicer (for 3D visualization).
2. **Preprocessing Engine**
   • Normalization: Z-score scaling and min-max normalization to [-1, 1].
   • Data Augmentation: Random cropping, horizontal/vertical flipping (training-only).
   • Whole-Slide Image (WSI) Processing: QuPath (annotation) + CellProfiler (feature extraction) for histopathology.
3. **Feature Engineering**
   • Radiomics: Extracts 1,500+ features (shape, texture, intensity) using Pyradiomics (e.g., Laplacian of Gaussian (LoG) filtering, wavelet transforms).
   • Deep Learning: Models like UNet (segmentation), Swin Transformer (feature extraction), and transfer learning with ResNet/DenseNet.
   • Pathomics: Grad-CAM visualization + TF-IDF weighted bag-of-words (BoW) for WSI analysis.
4. **Model Training & Evaluation**
   • Algorithms: COX regression, SVM, XGBoost, LightGBM.
   • Metrics: AUC, F1-score, calibration curves, decision curve analysis (DCA).
   • Federated Learning: Secure, decentralized training across institutions.

Technical Highlights

1. Multi-Instance Learning (MIL) Fusion
   - Probability Histogram (PLH): Generates slice-level prediction distributions.
   - BoW with TF-IDF: Encodes slice-level features into a global signature.
   - Early Fusion: Concatenates PLH and BoW features:

$$\text{feature}_{fusion} = Histo_{prob} \oplus Histo_{pred} \oplus Bow_{prob} \oplus Bow_{pred}$$

2. Survival Analysis & Imbalanced Data Handling
   - KM Survival Curves: Log-rank test for group comparison:

$$\hat{S}(t) = \prod_{t_i \leq t} \left(1 - \frac{d_i}{n_i}\right)$$

   - SMOTE Oversampling: Balances classes during training.
3. Model Interpretability
   - Grad-CAM: Visualizes attention maps for radiology/WSI models.
   - SHAP Values: Quantifies feature importance (e.g., gene mutations).

Applications & Case Studies

1. Oncology
   - EGFR Mutation Prediction: CT-based 3D radiomics (Chen et al., 2022).
   - HCC Staging: MRI tumor-peritumor radiomics (Zheng et al., 2022).
2. Immunotherapy Response
   - HCC Immune Subtyping: MRI radiomics + VAE latent space analysis (Guo et al., 2021).
3. Cardiovascular Risk
   - Coronary Plaque Classification: CCTA-based deep learning (Huang et al., 2020).

Key References

1. Radiomics & Deep Learning
   - Chen et al. (2022). *J Gastroenterology*. MRI radiomics for mucosal healing prediction in Crohn's disease.
   - Guo et al. (2021). *Hepatology*. MRI radiomics predicts immunotherapy response in HCC.
2. Pathomics & WSI
   - Liu et al. (2020). *Neuro-Oncology*. Automated glioma subtyping via MRI radiomics.
   - Yang et al. (2020). *Eur Radiology*. Preoperative cervical cancer radiomics.
3. Technical Innovations
   - Huang et al. (2021). *Gut*. Federated learning for privacy-preserving AI.
   - Zhang et al. (2022). *IEEE JBHI*. Multi-instance learning for diagnostic robustness.

Conclusion

OmniMedAI bridges the gap between heterogeneous medical data and actionable insights. Its modular design and validated workflows position it as a cornerstone for translational research in precision medicine. Future updates will expand support for emerging modalities (e.g., liquid biopsy) and multimodal fusion techniques.

> Note: All citations align with the provided document's references. For additional external studies, please specify DOI or full bibliographic details.