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Abstract

The integration of heterogeneous healthcare data modalities presents a significant opportunity to enhance diagnostic accuracy and clinical decision-making. This chapter proposes a hybrid framework that combines deep autoencoders for unsupervised feature representation with Gradient Boosting classifiers for robust prediction in healthcare diagnostics. By leveraging multimodal data sources—including electronic health records, medical imaging, and biosensor signals—the model captures complex interdependencies and reduces high-dimensional data into informative latent embeddings. The subsequent Gradient Boosting classification effectively handles feature heterogeneity and missing data, achieving superior diagnostic performance compared to unimodal and conventional methods. Experimental evaluations on benchmark healthcare datasets demonstrate the framework's ability to improve disease detection accuracy, interpretability, and scalability in real-world clinical environments. The findings highlight the potential of deep representation learning integrated with ensemble techniques to address challenges of multimodal data fusion, offering a promising direction for precision medicine and intelligent healthcare systems.

Keywords: Multimodal Data Fusion, Deep Autoencoders, Gradient Boosting, Healthcare Diagnostics, Feature Representation, Ensemble Learning

Introduction

The rapid advancement of healthcare technologies and digitization has resulted in an unprecedented growth of clinical data, collected from diverse sources such as electronic health records (EHRs), medical imaging, wearable sensors, and genomic profiling [1]. These heterogeneous data types encapsulate complementary information that, if properly integrated, can significantly enhance disease diagnosis, prognosis, and treatment planning [2]. The high dimensionality, varying formats, and intrinsic noise within these multimodal datasets' present substantial challenges for conventional analytical methods [3]. Existing unimodal approaches often fail to capture the complex interdependencies across modalities, which are critical for comprehensive clinical understanding [4]. Consequently, there is a growing need for sophisticated

data fusion techniques that can learn robust, informative representations from heterogeneous inputs and leverage these features for accurate and reliable healthcare diagnostics [5].

Deep learning has revolutionized many areas of data analysis by enabling hierarchical feature extraction and nonlinear transformations that uncover latent structures in complex datasets [6]. Among these techniques, deep autoencoders have demonstrated notable success in unsupervised representation learning by encoding high-dimensional inputs into lower-dimensional latent spaces that retain salient characteristics [7]. This capability is particularly valuable in healthcare, where the curse of dimensionality and limited labeled data often impede effective model training [8]. Autoencoders facilitate noise reduction and dimensionality compression, allowing for more manageable and interpretable feature spaces [9]. While deep networks excel at learning representations, their predictive performance can be further enhanced by coupling with powerful classifiers that are adept at handling diverse feature distributions and mitigating overfitting [10].

Gradient Boosting algorithms, including XGBoost, LightGBM, and CatBoost, have emerged as state-of-the-art ensemble methods capable of delivering superior classification accuracy on structured data [11]. These algorithms iteratively build an ensemble of weak learners, typically decision trees, that progressively correct prediction errors [12]. Their ability to model complex nonlinear relationships, manage missing data, and provide interpretable feature importance metrics makes them particularly suitable for healthcare applications involving tabular and multimodal data [13]. Integrating Gradient Boosting with deep autoencoders offers a hybrid approach that combines the representational strengths of deep learning with the robust decision-making of ensemble methods, ultimately leading to enhanced diagnostic capabilities and clinical decision support [14], [15].