Proposed Solution

The computer-based approach is required for the non-invasive detection of chronic liver diseases that are asymptomatic, progressive, and potentially fatal in nature. In this study, we review the computer-aided diagnosis of hepatic lesions in view of diffuse- and focal liver disorders. This survey mainly focuses on three image acquisition modalities: ultrasonography, computed tomography, and magnetic resonance imaging. We present the insightful analysis with pros and cons for each preliminary step, particularly preprocessing, attribute analysis, and classification techniques to accomplish clinical diagnostic tasks. In preprocessing, we explore and compare commonly used denoising, deblurring and segmentation methods. Denoising is mainly performed with nonlinear models. In contrast, deep neural networks are frequently applied for deblurring and automatic segmentation of region-of-interest. In attribute analysis, the most common approach comprises texture properties. For classification, the support vector machine is mainly utilized across three image acquisition modalities. However, comparative analysis shows the best performance is obtained by deep learning-based convolutional neural networks. Considering biopsy samples or pathological factors such as overall stage, margin, and differentiation can be helpful for improving the prediction performance. In addition, technique breakthrough is expected soon with advances in machine learning models to address data limitation problems and improve the prediction performance.

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┌─────────────────────────────────────┐
│   44, 854 individuals in the study   │
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┌─────────────────────────────────────┐
│             129 items               │
└─────────────────────────────────────┘
         │
         │          ┌─────────────────────────────────────┐
         ├─────────▶│   58 items with too many missing    │
         │          │              values                 │
         │          └─────────────────────────────────────┘
         │
         │          ┌─────────────────────────────────────┐
         ├─────────▶│   39,884 individuals underwent      │
         │          │       ultrasound examination        │
         │          └─────────────────────────────────────┘
         │
         ▼
┌─────────────────────────────────────┐
│  39,884 individuals with 71 items   │
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┌──────────────────┐   ┌──────────────────┐
│ 70% as training  │   │ 30% as test set  │
│      set         │   │                  │
└──────────────────┘   └──────────────────┘
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