# Detection of Hepatic Encephalopathy Using Machine Learning

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# **Motivation & Objective**

Hepatic encephalopathy (HE) is a serious neuropsychiatric complication of liver disease which affects **30–45% of patients** with cirrhosis and 24–53% of patients after TIPS [1].

Conventional diagnostics rely on **subjective** and **time-consuming neuropsychological tests**, which often delay detection and require trained personnel to evaluate them .

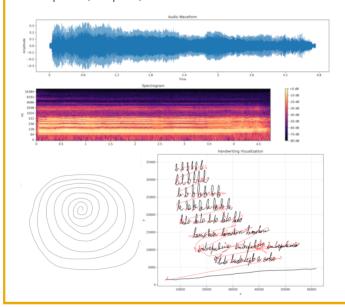
In this thesis, we address this challenge by proposing a machine learning solution based on non-invasive digital biomarkers. A multimodal approach was developed and evaluated by fusing handwriting and voice signals, with models trained for both a binary classification (HE vs. non-HE) and a more challenging three-class classification distinguishing healthy controls, cirrhotics without HE, and cirrhotics with HE.

### **Data**

The dataset consisted of 62 participants across the three groups.

Handwriting data were collected from writing and spiral tasks and analyzed through kinematic, pressure, and geometric features.

**Voice data** came from sustained **vowel recordings (A and E)**, from which spectral, temporal, and harmonic features were extracted.



# Methodology



#### Data collection

Handwriting signals from writing and spiral tasks and sustained vowel recordings (A/E) were acquired from 62 participants, including healthy controls and cirrhotic patients with and without HE.



#### Preprocessing

Data were cleaned, normalized, and split using patient-wise cross-validation.



#### Feature extraction & selection

A total of 68 handwriting features and 36 voice features were computed using task-specific pipelines. Then feature selection with 3 stages was applied, retaining the most informative descriptors for classification.



#### Model training

Machine learning models (e.g. SVM, RF, XGBoost) were trained on individual modalities with tuned hyperparameters.



#### Multimodal ensemble

The best handwriting and voice models were combined, using weighted averaging of prediction probabilities across modalities.



#### **Evaluation**

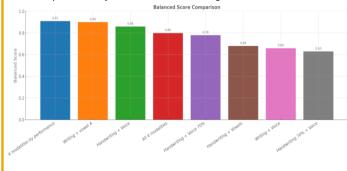
Performance was assessed using various evaluation metrics and a custom balanced score emphasizing sensitivity and AUC.

## Results

For single modalities, the best 3-class model was **XGBoost on vowel A**, reaching **79.0% accuracy** and **85.0% sensitivity**, outperforming handwriting-based models.

The performance-weighted multimodal ensemble (A: 40%, Writing: 30%, E: 20%, Spiral: 10%) further improved results to **85.1%** accuracy, **90.0%** sensitivity, and **94.6%** specificity.

In binary classification, the **Writing + Voice ensemble** achieved **93.4% accuracy**, **100% sensitivity**, and **86.7% specificity**, confirming the complementary nature of handwriting and voice.



# **Key findings**

**Voice-based models** consistently outperformed handwriting-only approaches, especially when trained on **vowel A**, highlighting that vocal features capture clinically relevant neurocognitive changes. Handwriting still provided complementary information, with **writing tasks more informative than spiral drawing**.

Feature analysis showed that **spatio-temporal** and **pressure parameters** were key for handwriting, while **spectral features** and **MFCCs** dominated in voice.

These findings demonstrate that handwriting and voice capture different but complementary aspects of motor and cognitive impairment in hepatic encephalopathy.

### Conclusion

This study demonstrates the potential of machine learning for non-invasive detection of hepatic encephalopathy using handwriting and voice analysis. Both modalities provided valuable diagnostic information, with voice features showing consistently higher performance, while handwriting contributed complementary cues.

The multimodal ensemble further improved classification and proved to be the most reliable approach, capturing different aspects of motor and cognitive impairment. The non-invasive and automatable nature of this method makes it a promising tool for early and objective HE screening in clinical practice.

The study is limited by the **small cohort size** and **class imbalance**, which restrict generalizability. Future work should therefore validate these findings on **larger patient populations**, expand the dataset with **additional speech and handwriting tasks**, and explore more **advanced deep learning methods** for feature representation. These steps could further enhance accuracy and robustness and support the practical integration of this approach into hospital workflows.





