Predicting Survival Status of Patients with Liver Cirrhosis

Matt Wang, Lena Wang, Yiyu Yao, Chuan Lin

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Cirrhosis Overview

- Cirrhosis: A chronic liver disease with high mortality.
- Traditional diagnostics are invasive and costly.
- Aim: Use machine learning to determine the effectiveness of D-penicillamine and to predict the survival status of patients.

Dataset Description

Cirrhosis Dataset Overview

- 424 patient records from Mayo Clinic (1974–1984).
  - 312 patients in clinical trial (112 did not join but agreed to record basic metrics)
  - 6 patients dropped out
- Features: Demographics, clinical metrics, and survival data.

Dataset Challenges

Limitations in Data

- Small dataset: 418 usable records.
- Missing data: $\sim 33\%$ of values missing (mainly due to 112 patients not participating in the trial).

Missing Data Handling

Analysis and Solution

Method Evolution

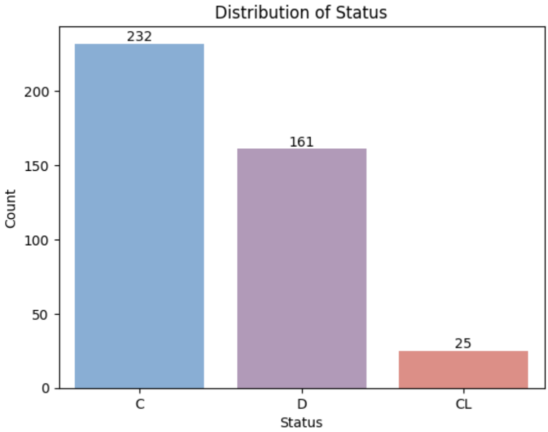
- Simple deletion → Data loss
- Median/Mode → Bias
- EM only → Limited
- Combined approach ✓
  - EM with Proportional
  - Statistical Imputation

ID	0
N_Days	0
Status	0
Drug	106
Age	0
Sex	0
Ascites	106
Hepatomegaly	106
Spiders	106
Edema	0
Bilirubin	0
Cholesterol	134
Albumin	0
Copper	108
Alk_Phos	106
SGOT	106
Tryglicerides	136
Platelets	11
Prothrombin	2
Stage	6

Categorical Encoding

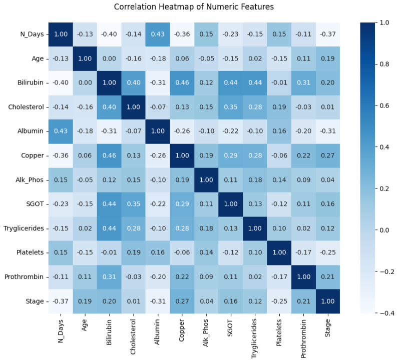
Transforming Features

- One-hot encoding applied to categorical variables.
- Survival status simplified to binary: 0 (Alive), 1 (Deceased).



Feature Engineering

New Features Introduced



- **DiagnosedDay**
- **Age Group**
- **BA Ratio**
- **CA Ratio**
- **RiskScore**
- **Liver Complication Index**

Models Evaluated

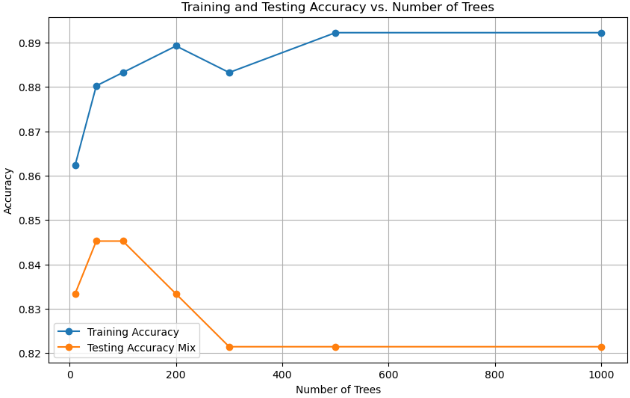
Machine Learning Techniques

- Random Forest (RF): Handles non-linear relationships.
- Support Vector Machine (SVM): Classification with kernels.
- K-Nearest Neighbors (KNN): Local pattern detection.
- Multilayer Perceptron (MLP): Neural network architecture.

Random Forest Results

Optimized Tree Numbers

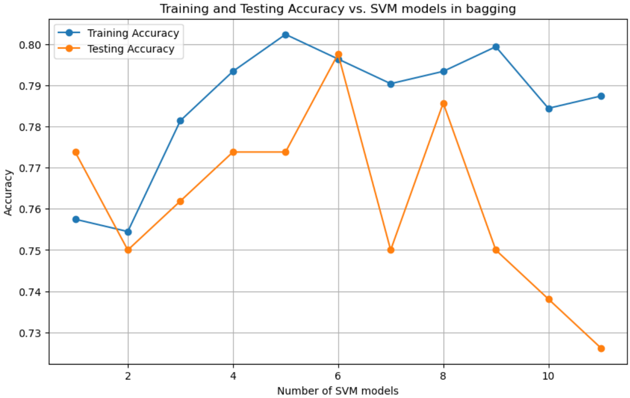
- Best performance: 21 trees (Accuracy: 87%).
- Higher trees led to overfitting.



SVM Results

Key Findings

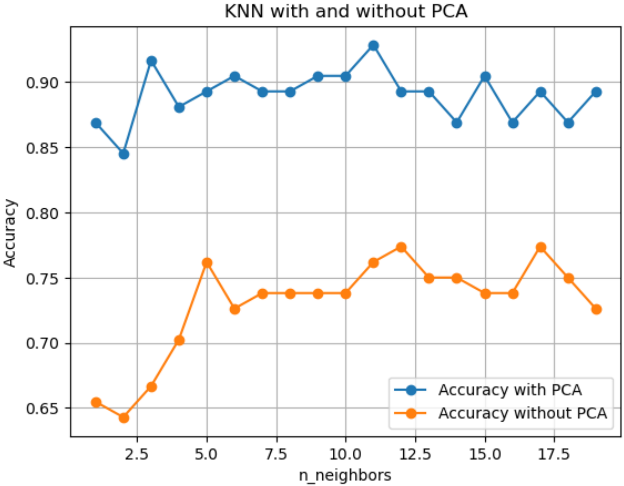
- Best accuracy: 79.8% with linear kernel.
- Non-linear kernels reached an even lower accuracy (rbf = 61.9%).



KNN Results

Key Findings

- PCA improved accuracy to 92.8% with k=11.



MLP Results

Neural Network Findings

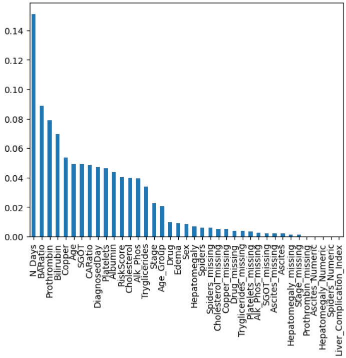
- Optimal learning rate: 0.001.
- Simple architectures performed better: Single layer (128 units).

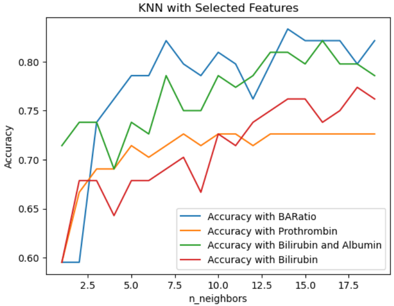
hidden_units	learning_rate	test_accuracy
[64]	0.001	0.761905
[64]	0.010	0.730159
[64]	0.100	0.746032
[128]	0.001	0.809524
[128]	0.010	0.777778
[128]	0.100	0.746032
[64, 64]	0.001	0.809524
[64, 64]	0.010	0.761905
[64, 64]	0.100	0.682540
[128, 64]	0.001	0.761905
[128, 64]	0.010	0.730159
[128, 64]	0.100	0.761905

Feature Importance Analysis

Key Insights

- Drug feature (D-penicillamine) has a minimal correlation with the survival status.
- Top three informative Features: BA Ratio (Bilirubin/Albumin), Prothrombin, Bilirubin.





Conclusion

Key Takeaways

- KNN achieved highest accuracy (92.8%).
- D-penicillamine had limited effect on cirrhosis treatment.
- BA Ratio as a cost-effective and non-invasive predictor.

Limitations and Future Work

Next Steps

- Expand dataset to improve robustness.
- Validate BA Ratio in real-world clinical settings.
- Using prediction results to generate the probability of death