Predicting Survival Status of Patients with Liver Cirrhosis

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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 (424 - 6 that dropped out).
- Missing data: $\sim 33\%$ of values missing (mainly due to 106 patients not participating in the trial).

Missing Data Handling

Analysis and Solution

Method Evolution

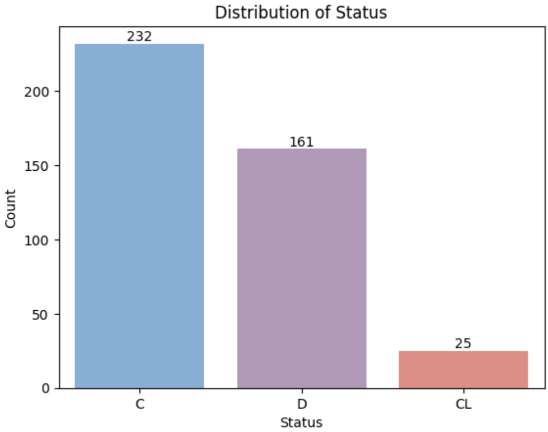
- Simple deletion → Data loss
- Median/Mode → Bias
- EM only → Limited
- Combined approach ✓
  - EM
  - Proportional & Statistical Imputation

```
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

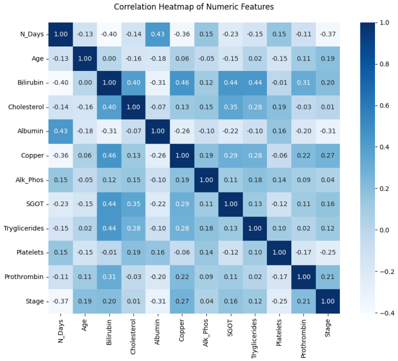
Transforming Features

- 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

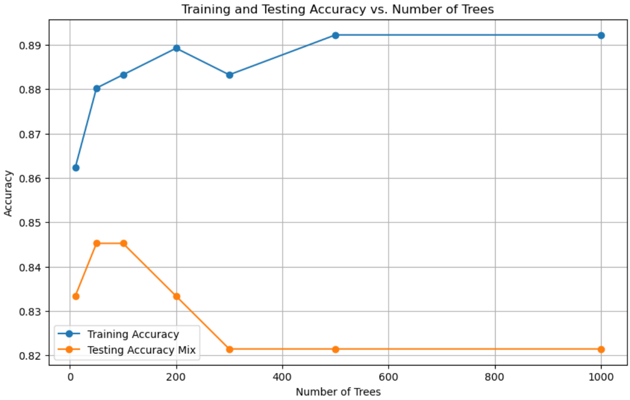
Machine Learning Techniques

- Random Forest (RF)
- Support Vector Machine (SVM)
- K-Nearest Neighbors (KNN)
- Multilayer Perceptron (MLP)

Random Forest Results

Optimized Tree Numbers

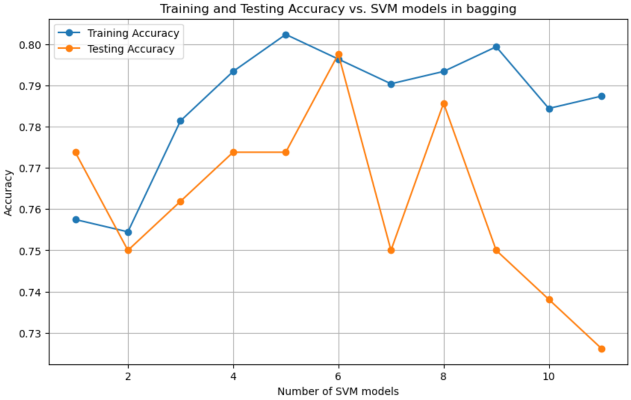
- Best performance: 21 trees (Accuracy: 87%).
- Higher trees led to overfitting.



SVM Results

with Bagging and Kernel

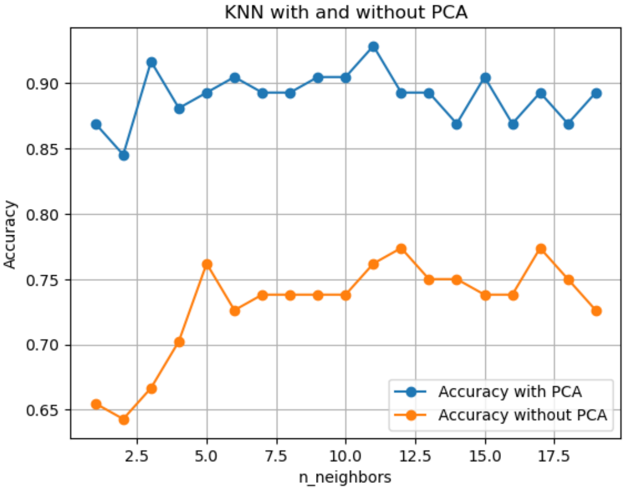
- Best accuracy: 79.8% with linear kernel.
- Non-linear kernels reached an even lower accuracy (rbf = 61.9%).



KNN Results

with/withoPCA

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



MLP Results

Neural Network Findings

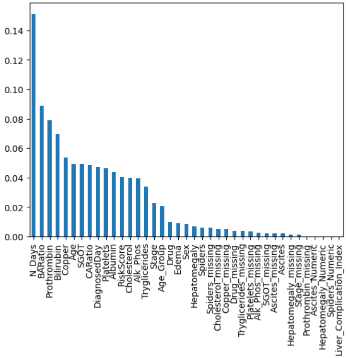
- Optimal learning rate: 0.001.
- Simple architectures performed better: Single layer (128 units).

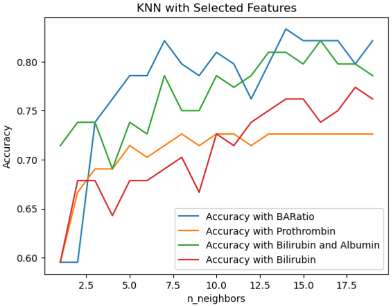
hidden_units	learning_rate	test_accuracy
[64]	0.001	0.761905
[64]	0.010	0.730159
[64]	0.100	0.746032
[128]	0.001	0.809524
[128]	0.010	0.777778
[128]	0.100	0.746032
[64, 64]	0.001	0.809524
[64, 64]	0.010	0.761905
[64, 64]	0.100	0.682540
[128, 64]	0.001	0.761905
[128, 64]	0.010	0.730159
[128, 64]	0.100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