



Project Objective

Hospitals vary in how they manage staff, beds, and patient services.

Our goal is to use machine learning to:

- 1. Predict hospital resource usage
- 2. Identify high-demand hospitals
- 3. Group hospitals based on efficiency

The goal is to help healthcare administrators make smarter, datadriven decisions.



Dataset Overview

- 1. We used a publicly available dataset on California hospitals.
- 2. The dataset contains over 578,000 records.
- 3. Key features we used in our project include:
 - Licensed, available, and staffed bed counts (BED_LIC, BED_AVL, BED_STF)
 - Number of days per report (DAY_PER)
 - Hospital name and county (FAC_NAME, COUNTY)
 - Type of service (Variable)
 - Total resource usage (Amount)
- 4. We focused mainly on data related to hospital operations, regional context, and service utilization.



CRISP-DM Process

- **Business Understanding**: Optimize hospital performance and planning
- Data Understanding: Explored key operational metrics
- Data Preparation: Cleaned, encoded, and scaled features
- Modeling: Trained and tested three ML models
- Evaluation: Compared model performance using R², RMSE, Accuracy
- **Interpretation:** Used PCA to visualize hospital clusters and highlight efficiency patterns.



Machine Learning Approach

We used three types of machine learning models:

- Regression To predict resource usage (Amount)
- Clustering To group hospitals by efficiency levels
- Classification To predict if a hospital will face high demand



Models

Regression Models

Target: Amount (Resource Use)

Models Used:

- Linear Regression
- Random Forest
- XGBoost

Best Result:

Random Forest

RMSE: 61.6 million

 R^2 : 0.916

Relative Error: 0.37%

Clustering Models

Goal: Group hospitals by efficiency

Algorithms:

- K-Means
- DBSCAN (sample only)
- Agglomerative (sample only)

Best Output:

K-Means with 3 clusters
Visualized using PCA

Classification Models

Goal: Predict high demand (binary label using median Amount)

Models Tested:

- Logistic Regression
- Gradient Boosting
- Random Forest

Best Model:

Random Forest 83.5% accuracy



Regression Models

Algorithm	R ² Score	RMSE (Millions)	Relative Error (%)	Notes
Linear Regression	0.0128	211.7	1.29%	Underfitting; poor predictive power
Random Forest Regressor	0.9164	61.6	0.37%	Best model for predicting Amount
XGBoost Regressor	0.8679	77.4	0.47%	Strong, but slightly behind RF

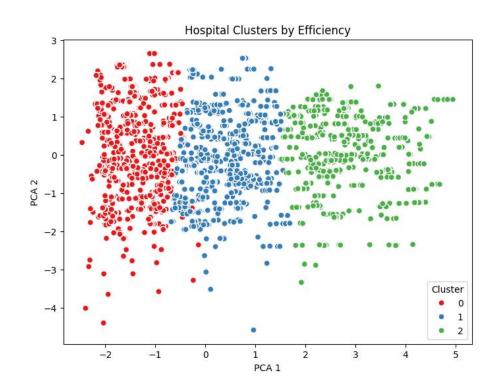


Clustering Models

Algorithm	Sample Size	Clusters Found	Notes
K-Means	Full	3	Clear clusters; interpretable PCA
DBSCAN	50,000	Mostly 1 + noise	Runtime constraints; not suitable for full dataset
Agglomerative Clustering	20,000	3	Good structure, but not scalable to full dataset



- Clustering (K-Means) Visualized using PCA
- 3 Efficiency Groups:
 - Cluster 1: High capacity
 - Cluster 2: Moderate
 - Cluster 0: Underutilized





Classification Models (Without Outliers)

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	Notes
Logistic Regression	54.2	0.54	0.54	0.54	Weak linear model baseline
Random Forest Classifier	60.3	0.61	0.60	0.60	Best without outliers
Gradient Boosting	58.0	0.58	0.58	0.58	Balanced but slightly lower than RF



Classification Models (With Outliers)

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	Notes
Logistic Regression	54.2	0.54	0.54	0.54	No performance improvement
Random Forest Classifier	83.5	0.84	0.84	0.84	Excellent performance w/ outliers
Gradient Boosting	82.3	0.83	0.83	0.83	Strong alternative, close to RF



Limitations & Future Work

Limitations:

• DBSCAN, Agglomerative Clustering not scalable to full dataset

Future Work:

- Add time-based forecasting
- Build dashboard (Tableau/Power BI) for hospital insights



Final Thoughts

- ML models forecast hospital needs effectively
- Classification helps in early planning
- Clustering reveals operational disparities
- Our approach aligns with CRISP-DM and project goals



Conclusion

- Models can reliably forecast hospital needs and reveal performance gaps.
- Insights support better staffing, budgeting, and hospital policy decisions.



THANK YOU