

| Group | Test / Model | When to Use | Medical Example |
|---------------------------------|---------------------------------------|---|--|
| Correlation Tests | Pearson correlation | Correlation between two continuous, normal variables | Correlate age and blood pressure |
| | Spearman correlation | Rank-based correlation, non-normal/ordinal data | Correlate disease stage (ordinal) with symptom severity |
| | Kendall's Tau | Correlation for small samples or many tied ranks | Small sample: correlate pain score and functional score |
| | Point-Biserial correlation | Correlation: one binary, one continuous variable | Correlate gender (M/F) with hemoglobin |
| | Phi coefficient | Correlation between two binary variables | Correlate presence of diabetes with hypertension |
| | Tetrachoric correlation | Binary variables assumed to be underlying continuous | Smoking status and disease status, both coded as yes/no |
| Regression/ Prediction Tests | Simple linear regression | Predict a continuous outcome from one predictor | Predict cholesterol from BMI |
| | Multiple linear regression | Predict continuous outcome from multiple predictors | Predict BP from age, BMI, and physical activity |
| | Logistic regression | Predict binary outcome | Predict presence of diabetes (yes/no) from age, BMI |
| | Multinomial logistic regression | Predict categorical outcome with ≥3 unordered levels | Predict diagnosis category (diabetes, HTN, cancer) from lab data |
| | Ordinal logistic regression | Predict ordered categorical outcome | Predict severity (mild/moderate/severe) from vitals |
| | Poisson regression | Predict count data | Number of ER visits per year from comorbidities |
| | Negative binomial regression | Count data with overdispersion | Hospitalizations per year with variable frequency |
| | Zero-inflated models | Count data with many zeros | Predict number of asthma attacks (many patients have 0) |
| | Cox regression (proportional hazards) | Time-to-event prediction | Time to cancer recurrence post-treatment |
| | Linear mixed-effects regression | Repeated measures or hierarchical data | Track glucose levels across time within patients |
| | Quantile regression | Predict median or percentiles of outcome | Predict median hospital stay length by age, comorbidities |
| | Ridge/Lasso regression | High-dimensional data, feature selection | Predict gene expression outcome using many SNPs |
| | Decision Tree | Easy-to-interpret model for classification/regression | Predict diabetes from BMI, age, family history |
| | Random Forest | Ensemble method for better prediction | Predict mortality risk from clinical parameters |
| | Gradient Boosting (e.g., XGBoost) | High-accuracy prediction for tabular data | Predict cancer risk using clinical + genetic features |
| | Support Vector Machine (SVM) | Classification with complex boundaries | Classify tumor as benign/malignant |
| | K-Nearest Neighbors (KNN) | Prediction based on similarity | Predict disease based on symptom similarity |
| | Naive Bayes | Fast probabilistic classifier, especially for text | Classify radiology report as abnormal/normal |
| | Neural Networks / Deep Learning | Complex, nonlinear prediction with large datasets | Predict diabetic retinopathy from retinal images |
| | Time Series (ARIMA/Prophet/LSTM) | Forecast future values from past trends | Forecast hospital admissions or COVID cases over time |
| | Ensemble models (Bagging/Stacking) | Combine multiple models to improve performance | Predict sepsis using combined models of vitals, labs, and notes |