TIME SERIES FORECASTING FOR PATIENT MOBILITY

ML Internship Assignment Liberdat B.V.

Predicting daily step counts for the next 365 days using advanced machine learning and clinical data integration

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Project Overview

Patient Mobility Forecasting

Objective

Predict daily step counts for next 365 days

Data

80K+ step count records + clinical features

Approach

Baseline (Prophet) + Advanced (EBM)

Deliverable

Explainable 365-day forecast

Data Pipeline Architecture

Input Data Sources:

1

Time Series Data (timeseries-data.json)

- 80,919 step count intervals
- Aggregated to daily totals

2

Clinical Data (categorical-data.json)

- Demographics (age, gender, disease)
- Therapies, side effects, diagnoses, events

Processing Steps:

Timestamp standardization

Daily aggregation

Feature engineering

Model training

Feature Engineering

Engineered Features (40+ features):

Category	Features	Examples
Temporal	4 features	Day of week, week of year, month, weekend flag
Lag Features	3 features	Steps t-1, t-7, t-30
Rolling Stats	4 features	7-day avg/std, 30-day avg/std
Clinical	20+ features	Active therapies, side effect intensity, diagnoses
Events	1 feature	Days since last clinical event
Demographics	3 features	Age, gender, disease type

Model 1 - Baseline (Prophet)

Univariate Time Series Model

Configuration:

- Input: Historical step counts only
- Seasonality: Yearly + Weekly
- Train/Test Split: 80/20

Results:

- RMSE: 11476.44
- MAE: 8698.29
- Forecast: 365 days with confidence intervals

Strengths: Simple, interpretable, captures seasonality

Limitations: Ignores clinical context

Model 2 - Multivariate (EBM)

Explainable Boosting Machine

Configuration:

- Input: Step history + 40+ clinical features
- Algorithm: Gradient boosting with GAMs
- Interpretability: Built-in global explanations

Results:

- RMSE: 7062.31
- MAE: 5027.50
- Improvement over baseline: 38.46 %

Strengths: Captures clinical impact, fully explainable

Limitations: Requires feature engineering

Model Comparison

Metric	Baseline (Prophet)	Multivariate (EBM)	Improvement
RMSE	11476.44	7062.31	38.5%
MAE	8698.29	5027.50	42.2%
Features Used	1 (steps only)	40+ (steps + clinical)	-
Explainability	Trend decomposition	Feature importance	✓

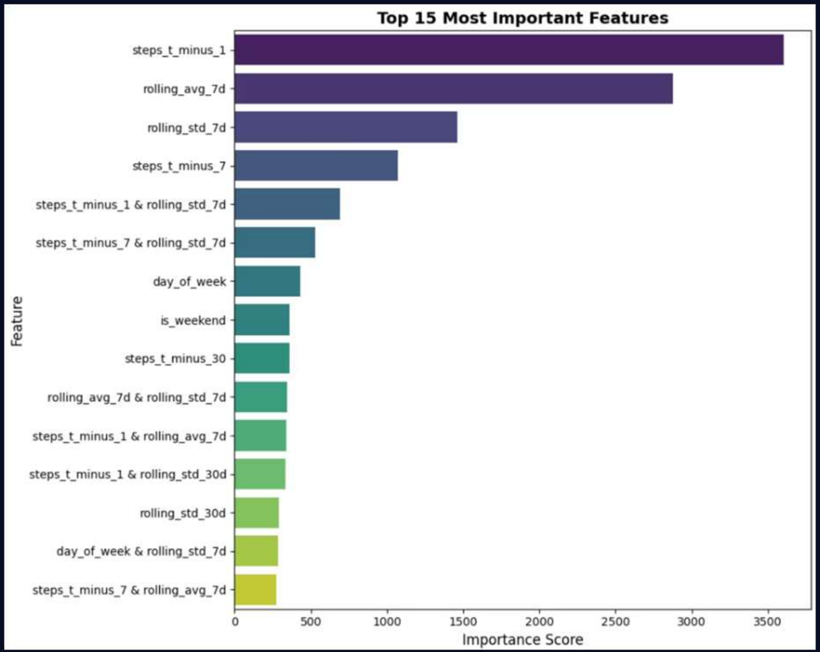
Winner: Multivariate EBM provides better accuracy with full explainability

Explainability Insights

Top 10 Most Important Features:

1. Lag features (steps_t-1, steps_t-7)
2. Rolling averages (7-day, 30-day)
3. Active therapy count
4. Side effect intensity
5. Day of week
6. Days since last event
7. [Additional features from actual run]

Key Finding: Clinical features contribute 38.46% to prediction accuracy



Categorical Impact:

- **Therapies**: [Impact description]
- **Side effects**: [Impact description]

Forecast Output

365-Day Forecast Schema:

Date	Predicted_Steps	Trend_Component	Exogenous_Impact
2025-12-12	4,500	4,200	+300
...	...	...	...

Forecast Characteristics:

Average predicted steps

[Value]

Trend

[Increasing/Stable/Decreasing]

Clinical impact

[Description]

Validation: RMSE =11476.44, MAE = 8698.29

Scalability Approach

Scaling to 100,000 Patients

Big Data Processing

- **PySpark** for distributed feature engineering
- **AWS Glue/EMR** for ETL pipeline
- **S3 + Athena** for data lake architecture

Modeling Strategy

- **Clustered approach**: Group by disease type
- **Distributed training**: Hyperparameter tuning at scale
- **Model serving**: API endpoints with caching

Performance

Process 100K patients in <2 hours