Virtual Care Assistant from home

Presentation Part Two

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Project Description

Project

Virtual Care Assistant from home : predict patient status from vitals & text

Task

- Multi-modal classifier for Normal / Improvement / Deterioration
- Fuse structured vitals + free-text complaints

Data

- Synthetic data
- 700 patient-episodes (HR, SpO_2, Temp, RR + free text)
- Preprocessing: impute & normalize vitals, TF-IDF & RandomForest or BERT embeddings

Evaluation

- Stratified 5-fold CV
- Metrics: Accuracy, Macro-F1
- Baseline vs. Deep-Learning comparison

Prior Art

Source / Title (Year)	Approach / Model	Data (size)	Metrics	Results
"Deep learning for early warning of inpatient deterioration" (Nature Digit. Med., 2021) https://did.li/1otx5	LSTM with attention on vital-sign time-series	2,100 patient episodes (minute-by-minute vitals)	AUC, Macro-F1	AUC 0.87, Macro-F1 0.71; attention maps showed SpO_2 drops and HR spikes as strongest early-warning signals; model predicts deterioration up to 12 h in advance.
"Fusion of clinical notes and vitals using BERT + MLP" (J. Gen. Intern. Med., 2023) https://did.li/fAVaa	BERT encoder on free-text notes + MLP head for vitals	800 home-hospitalization episodes	Accuracy, Precision, Recall	Accuracy 0.76; Precision 0.74; Recall 0.72; text+vitals fusion improved Macro-F1 by 8 pp over vitals-only baseline; ablation confirmed synergy of both modalities.
"Combining vital signs and free-text for deterioration detection" (PMC, 2019) https://did.li/dR7CN	TF-IDF vectorization on clinical notes + LightGBM	1,200 inpatient stays (notes + vitals)	ROC-AUC, Sensitivity, Specificity	ROC-AUC 0.79; Sensitivity 0.81; Specificity 0.75; top predictive text tokens included "pain," "breathlessness," "fatigue"; combining features outperformed single-modality.

Market Solutions

Examples of Existing Market Solutions:

Current Health (USA)

- AI-powered remote monitoring platform that combines wearable sensors and patient-reported data to detect early clinical deterioration. www.currenthealth.com

Datos Health (Israel)

- Automated remote-care system integrating physiological signals and patient self-reports to personalize treatment plans using AI. www.datos-health.com

Our Approach:

Active, Proactive Classification

- Real-time prediction of patient status (Stable / Improving / Deteriorating), not just passive monitoring.

Fusion of Free-Text Reports & Vitals

- Applying NLP to unstructured patient complaints and descriptions alongside physiological measurements.

Clinical Decision Support Focus

- Prioritizing patients who need immediate intervention and aiding medical teams on the ground with rapid, data-driven decisions.

Data Construction Process:

During the project, a Synthetic data was developed to handle free-text inputs and patient-reported clinical measures. The goal was to extract meaningful clinical, emotional, and functional insights from the data. The process involved building, processing, and organizing the data in a way that enables effective and insightful analysis.

1. Data Ingestion and Sources:

The data consisted of free-text entries written by patients as part of a home hospitalization service. A dedicated ingestion interface was developed, integrating with the OpenAI API to enable automated submission of texts for processing.

2. Technical Setup and Work Environment

Essential helper libraries were imported, including: os, json, time, random, and openai.
The API key was configured securely using environment variables (os.getenv) to ensure data protection and privacy.

3. Natural Language Processing (NLP)

Each text was analyzed using OpenAI language models.
The processing aimed to:

- Summarize the texts to identify key points
- Extract clinical indicators, emotions, and patient-reported experiences
- Detect recurring patterns such as functional decline, worsening conditions, or signs of improvement

4. Feature Construction for Insight Extraction

Following the processing phase, the output was structured into a standard format (JSON/CSV) for further analysis.
Each record included the following features:

- **day1_note and day2_note:** First-person, simple, everyday-style text
- **Daily vitals:** Heart Rate (HR), Blood Pressure (BP), Body Temperature (Temp), Respiratory Rate (RR)
- **Status change direction:** Aligned with both the free-text entries and vital signs
- **Reasoning:** Objective explanation of the change observed between Day 1 and Day 2
- **Randomized parameters**: Age (25–110), gender, medical diagnosis
- **Labeling & Classification:** Improvement/ Deterioration/ No Change

Steps

1.Preprocessing:

Dataset:

home-hospitalization episodes

Vitals

- Impute missing values
- Smooth sensor spikes & cap extreme outliers (e.g. HR <40 or >180, SpO_2 <80)
- Normalize with StandardScaler

Text

- Lowercase, strip punctuation & stopwords
- Option A: TF-IDF vectorization
- Option B: extract contextual embeddings (e.g. BERT)

2.Labeling

- **Classes:**
  - no change : 37.2%
  - Improvement: 31.5%
  - Deterioration: 31.3%
- **Preparation:**
  - Ensure correct mapping of status codes
  - Stratify splits to preserve class ratios

3.Model Comparison

- **Vitals-only (baseline)**
  - Logistic Regression
  - Random Forest
- **Text-only**
  - TF-IDF → Logistic Regression
  - Frozen BERT embeddings → Random Forest
- **Classical Fusion**
  - [TF-IDF + Vitals] → Random Forest
- **Deep-Learning Fusion**
  - Fine-tune BERT on text + MLP head on vitals features

4.Evaluation

- Stratified 5-fold CV
- **Metrics:** Accuracy | Macro-F1 |
- **Ablation studies:** compare
  a. Vitals-only
  b. Text-only
  c. Combined modalities

Exploration & Baseline

Exploration

Label distribution:

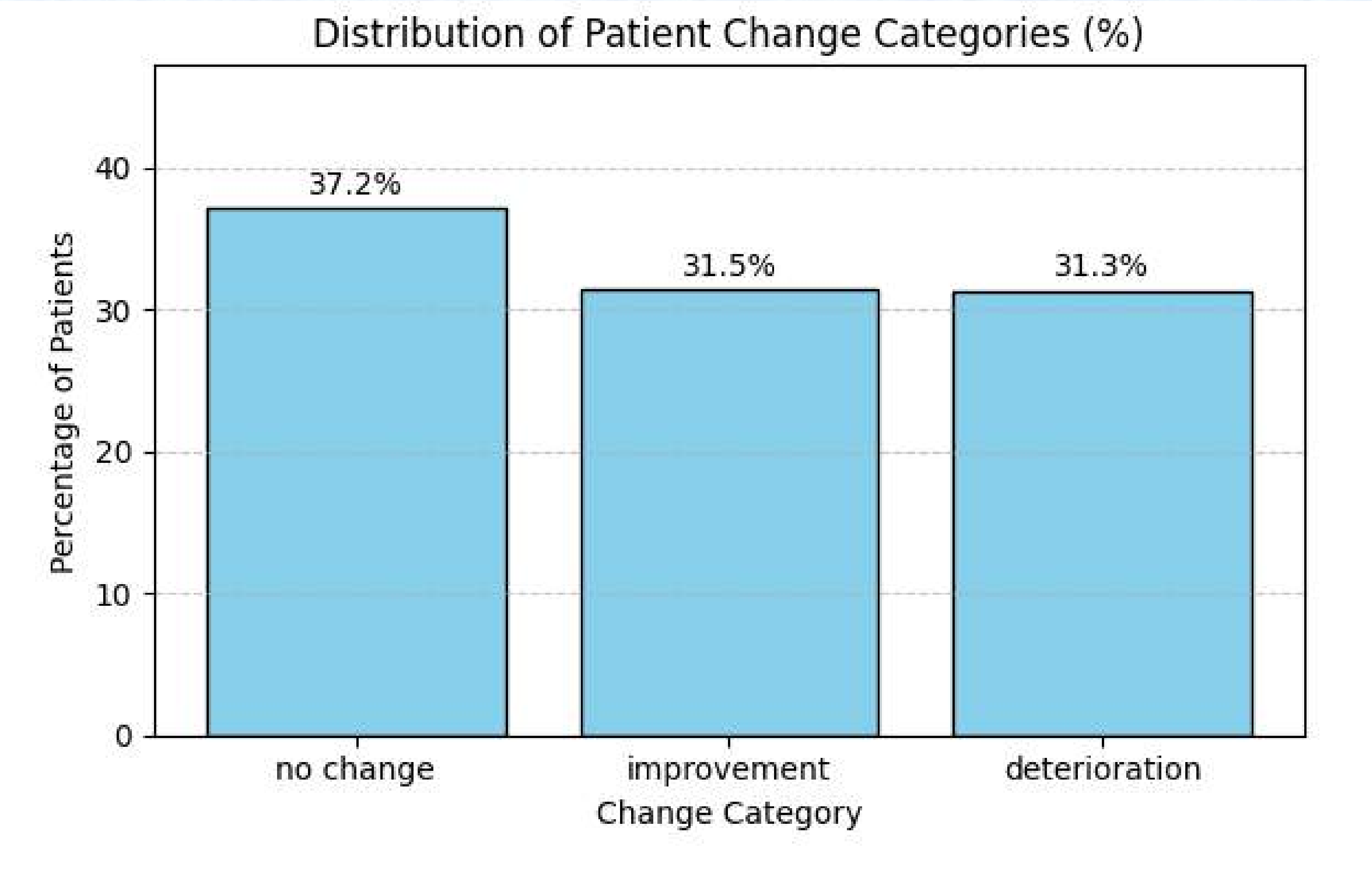
- no change : 37.2%
- Improvement: 31.5%
- Deterioration: 31.3%

Vitals (mean ± std):

- HR: 74 ± 15 bpm
- SpO_2: 96 ± 2 %
- Temp: 36.8 ± 0.4 °C

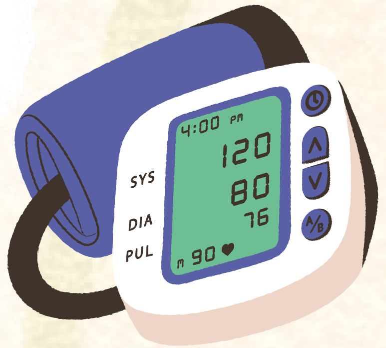
Age:

- Mean: 109 ± 25 yrs, peak 39–109
- Text insights
- WordCloud tokens: “pain”, “breath”, “chest”, “tired”



Baseline

- **Features**
  - Standardized vitals
  - TF-IDF(500 features) on patient complaints
- **Model**
  - Logistic Regression (class_weight=balanced)
- **Evaluation**
  - Stratified 5-fold CV
  - Accuracy = 0.92
  - Macro-F1 = 0.90
- **Takeaway**
  - The results are impressive, indicating that even baseline simply manages to learn the change label well from the text and metrics.



Insights & Recommendations

Free-text patient reports provide valuable yet noisy information

- EDA revealed variability in report length and phrasing.
- Introducing more realistic linguistic noise and structure in synthetic data may improve generalization

Traditional models outperformed BERT in this setting

- Random Forest + TF-IDF + vitals outperformed the BERT-based model (Macro-F1 ~0.49 vs. ~0.40).
- Likely due to limited dataset size and class imbalance.

Class imbalance negatively affects model performance

- Rare classes such as Deterioration saw notably lower F1 scores.
- Applying class weights improved results marginally; data augmentation may be necessary.

Current multimodal fusion is too simplistic

- Simple feature concatenation was used.
- Future models should explore more advanced fusion techniques: cross-attention, co-training, or learned joint representations.

Multitask learning could boost both accuracy and relevance

- Simultaneous prediction of both status and recommended_action may better reflect clinical reasoning.
- Could also improve efficiency and robustness in deployment scenarios.

Thank You for listening