

Early Prediction of Labour Force Dropout in SLE Patients

Integrating Longitudinal Deep Learning through an LSTM RNN with Random Forests

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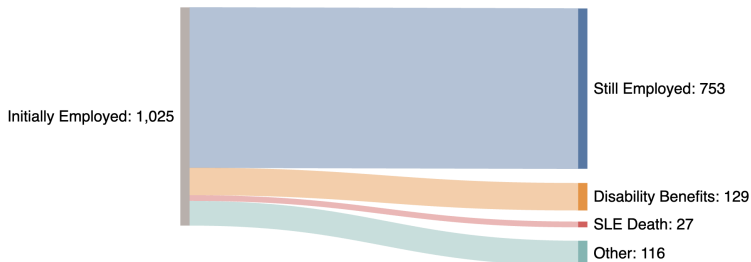
Background & Objectives

- SLE is a chronic autoimmune disease that affects functioning
- **Problem:** 20-40% of SLE patients exit workforce prematurely
- **Impact:**
 - Work gives financial stability and sense of purpose
→ Social isolation and mental health decline
 - Socioeconomic burden
- **Solution:**
 - Hybrid RF-LSTM tool to flag at-risk patients *before* departure to allow early clinical intervention

Employment Trajectories

Overview:

- Records at the Toronto Lupus Clinic (UHN) between 1996-2024



Source: Robroek et al., 2015 [1]

- Still employed includes actively working or retired after the retirement age
- Other states: Unemployed, Economically Inactive, Early Retirement

Long-Short Term Memory Model Architecture

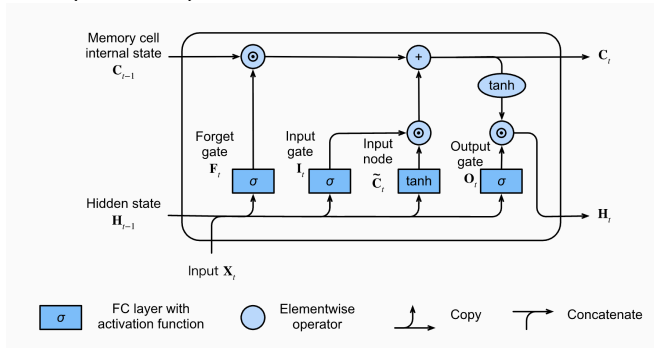
Why LSTMs?

- Capture **long-term dependencies** across years of patient visits

Input:

25 clinical features per visit selected w/RF and using class balancing via synthetic minority augmentation: $\mathbf{X} \in \mathbb{R}^{N \times T \times 25}$

Model cell at visit t ($1 \leq t \leq T$):



Prediction Pipeline

Hidden state at visit t :

$$\mathbf{H}_t = \text{LSTM}(\mathbf{X}_t, \mathbf{H}_{t-1}, \mathbf{C}_{t-1}) \quad (1)$$

Linear transformation:

$$\mathbf{z}_{t,k} = \mathbf{W}_k \mathbf{H}_t + \mathbf{b}_k \quad (2)$$

① Class prediction ($t = T$):

$$p(y = k) = \frac{\exp(z_{t,k})}{\sum_{j=1}^K \exp(z_{t,j})} \quad (K = 3 \text{ classes}) \quad (3)$$

$$\hat{y} = \underset{k \in \{\text{employed, disability, mortality}\}}{\arg \max} p(y = k) \quad (4)$$

② Risk score computation for disability and mortality resp. ($t \leq T$):

$$\text{risk}_{t,k} = \sigma(\mathbf{z}_{t,k}) = \frac{1}{1 + \exp(-\mathbf{z}_{t,k})} \quad (5)$$

Alert if $\text{risk}_{t,k} \geq \theta_k$ where θ_k is a hyperparameter that optimizes early detection time(Δt)

Model Performance Highlights

Final Employment State Classification

After 5-fold CV:

Overall balanced accuracy: **91%**

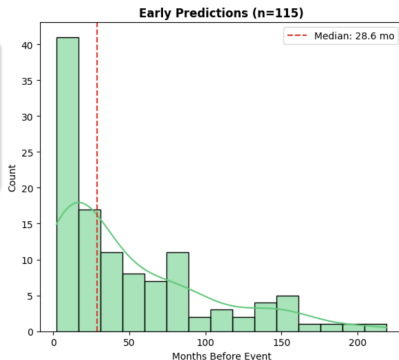
Early Warning System for Disability

Early warning system achieves **89% case detection**

It has a median lead time of **28.6 Months**
(IQR: 14.3–42.1)

Early Intervention Strategies:

- Proactive rehabilitation programs
- Multidisciplinary specialist coordination
- Workplace accommodation planning



Acknowledgements



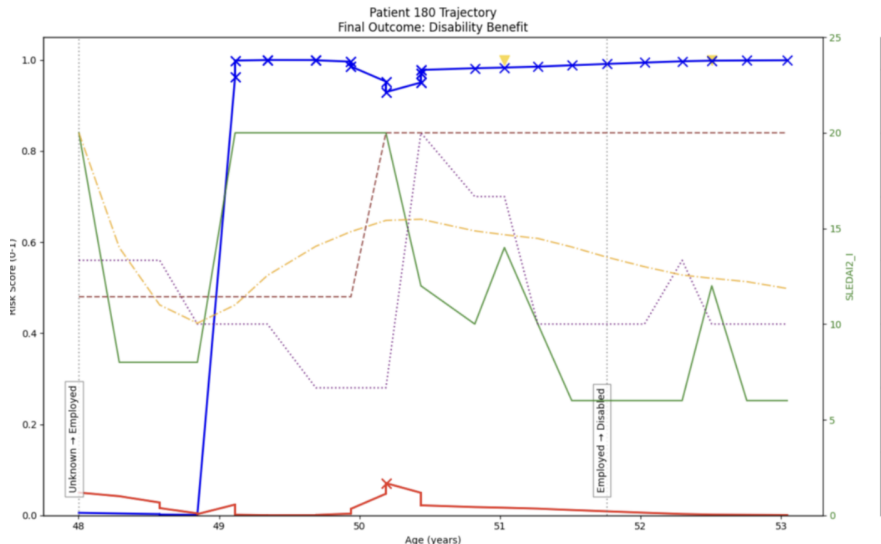
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Individual Patient Trajectory





Robroek, S. J., Rongen, A., Arts, C. H., Otten, F. W., Burdorf, A., & Schuring, M. (2015). Educational inequalities in exit from paid employment among Dutch workers: The influence of health, lifestyle and work. *PloS one*, 10(8), e0134867.
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