出國報告（出國類別：開會）

(中文 Chinese) 以機器學習預測重度失智症患者死亡風險

(英文 English) Prediction of Mortality Risk in advance Dementia Using Machine Learning

服務機關：臺中榮民總醫院神經外科
姓名職稱：尹嘉展主治
派赴國家/地區：芬蘭赫爾辛基
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摘　要

本人於大會第三天進行海報發表，題目為《Prediction of Mortality Risk in Advanced Dementia Using Machine Learning》。研究內容包含：

- 使用多種臨床特徵（年齡、急診次數、住院頻率、敗血症、呼吸衰竭、壓瘡等）建立預測模型
- 評估三個月與六個月內死亡之風險分布
- 應用 ROC 曲線與 AUC 指標評估模型表現
- 模擬 AI 系統介面供臨床或家屬操作

關鍵字：（至少一組）
重症失智症、安寧緩和

目　次

一、 目的

隨著失智症人口快速成長，如何於末期提供符合病人尊嚴且高品質的照顧已成為全球挑戰。AI 應用於預測病程與死亡風險，提供客觀數據輔助照護決策，已成為未來趨勢。因此，本研究以台灣地區的長期照護資料為基礎，利用 LightGBM 與 XGBoost 等演算法建立預測模型，探討其在實務照護與政策規劃中的應用潛力。本人此次出國參加 "The 19th World Congress of the European Association for Palliative Care"（第 19 屆歐洲安寧照顧協會世界大會），目的在於發表國科會補助研究成果、觀摩最新國際趨勢，並與國際安寧照護領域學者進行交流與合作探討。該研究為本人主導之計畫：「以機器學習預測重度失智症患者死亡風險」，旨在協助臨床第一線與長期照護工作者提早辨識高風險患者、適時啟動安寧療護。

二、 過程

EAPC 2025 於 2025 年 5 月 29 日至 31 日在芬蘭首都赫爾辛基舉辦，由歐洲安寧照顧協會（EAPC）主辦。本屆大會主題為 "Ready for the Future"，聚焦未來安寧照護所面臨的挑戰與機會，包括老年化社會、數位科技導入、社區安寧照護轉型、文化敏感性、以及跨專業合作模式。

大會設有主題演講（Plenary）、專題座談（Thematic Sessions）、口頭發表（Oral Presentations）與海報展示（Poster Sessions）。與會者超過 1500 人，來自全球超過 50 國，涵蓋醫療、護理、社工、心理、政策、資訊科技等多元領域，展

現出安寧照護已從末期醫療走向跨界整合與預防倡議。

三、 心得

本人於大會第三天進行海報發表，題目為《Prediction of Mortality Risk in Advanced Dementia Using Machine Learning》。研究內容包含：

- 使用多種臨床特徵（年齡、急診次數、住院頻率、敗血症、呼吸衰竭、壓瘡等）建立預測模型
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會中與荷蘭、比利時、加拿大等國研究者互動密切，特別針對資料隱私、模型可解釋性（explainability）、以及如何讓非科技背景之照護人員易於理解與使用 AI 系統進行深入討論。許多學者對此研究表達高度興趣，並表示可望進行跨國驗證研究。

重點場次心得與專業啟發：

1. 人工智慧於安寧照護的倫理與應用(Artificial General Intelligence in Palliative Care)：Jan Romportl 博士分享 AGI 與人類死亡意識的哲學關聯，並強調 AI 不僅是工具，更可能改變我們理解生死的方式。啟發我在 AI 設計中納入人文與價值導向思維，避免 AI 去人性化。
2. 社區與高齡者安寧照護建構（Future Palliative Care for Older People

Living in the Community）：該場由葡萄牙、英國、比利時三國共同發表，強調安寧照護應結合長照體系於居家端早期介入，對於本研究發展社區照護預測模組具高度參考價值。

3. 預立醫療照護計畫（ACP）與決策挑戰（Advance Care Planning in Heart Failure Patients）：丹麥團隊發現多數患者與家屬對疾病末期認知不足，ACP 雖具困難性，卻能顯著改善家庭溝通與接受度。此議題與我研究中所設計之家屬 DNR 決策支援工具密切相關。

透過本次參與，強化我對 AI 於安寧照護應用場域的全貌理解，也收集多國使用者需求，將作為後續優化模型與系統設計之基礎。另將於課程中新增「AI 於臨床決策支持應用」模組，培養學生跨領域整合能力，並計畫投稿至 SCI 期刊以擴展學術影響。

四、 建議事項

EAPC 2025 為極具前瞻性之國際學術平台，本人不僅成功發表國科會研究成果，亦與多國學者建立實質交流關係，奠定未來國際合作之基礎。①建議國內可進一步推動 AI 與安寧療護、②失智長照之跨界合作研究，③強化我國於高齡社會中的科技應用與倫理實踐。④現國外註冊費都很貴，負擔很大，希望之後再有機會出國發表研究能給予補助。

五、 附錄

海報

Prediction of Mortality Risk in advance Dementia Using Machine Learning

Jia-Jean Yiin MD, Ph.D. [1] Kwo-Chen Lee, RN, Ph.D. [2*]
1. *Department of Neurosurgery, Neurological Institute, Taichung Veterans General Hospital, Taichung, Taiwan (R.O.C.)*
2. *School of Nursing, China Medical University, Taichung, Taiwan (R.O.C.)*

ID 531

Background

Accurate mortality prediction in dementia is vital for palliative care planning. As the disease advances, patients lose decision-making capacity, shifting the burden to caregivers and clinicians. Although machine learning shows promise, most models lack real-world validation and clinical interpretability. Furthermore, evidence specific to the Taiwanese dementia population remains limited.

Aim

This study retrospectively analyzed medical records to develop and validate a deep learning-based six-month mortality prediction model for Taiwanese patients with severe dementia.

Methods

This retrospective study analyzed secondary data from a medical center in central Taiwan, tracking patients diagnosed with severe dementia between January 1, 2001, and October 31, 2022. Patients were included if they held a catastrophic illness card indicating severe dementia (CDR > 2); those with a prior cancer diagnosis were excluded.

Study variables included dementia subtype, age, sex, comorbidities, acute illnesses, healthcare utilization, vital signs, and laboratory data (Table 1). Machine learning models were developed using Decision Tree, Random Forest, and XGBoost algorithms.

Table 1. Demographic Characteristics of Dementia Patients

	N=1143	n=734 (Deceased)	n=409 (Survived)
Diagnosis			
Dementia	1063 (93.0%)	683 (93.0%)	380 (92.9%)
Other type Dementia	80 (7.0%)	51 (7.0%)	29 (7.1%)
Age			
Average Age	89.36 (±10.70)	93.13 (±9.03)	82.58 (±10.13)
Gender			
Male	418 (36.6%)	297 (40.5%)	121 (29.6%)
Female	725 (63.4%)	437 (59.5%)	288 (70.4%)
Chronic Comorbidities (Preceding Dementia Diagnosis)			
Stroke	253 (22.1%)	163 (22.2%)	90 (22.0%)
Hypertension	499 (43.7%)	308 (42.0%)	191 (46.7%)
Diabetes Mellitus	249 (21.8%)	152 (20.7%)	97 (23.7%)
Coronary Artery Disease	183 (16.0%)	97 (13.2%)	86 (21.0%)
Heart Failure	46 (4.0%)	32 (4.4%)	14 (3.4%)
Renal Failure	134 (11.7%)	72 (9.8%)	62 (15.2%)
COPD	105 (9.2%)	63 (8.6%)	42 (10.3%)
Cirrhosis	36 (3.1%)	20 (2.7%)	16 (3.9%)
Acute Illnesses (Number of Events in the Last 6 Months before Death)			
Shock	64 (5.6%)	38 (5.2%)	26 (6.4%)
Pneumonia	272 (23.8%)	203 (27.7%)	69 (16.9%)
Urinary Tract Infection	251 (22.0%)	174 (23.7%)	77 (18.8%)
Fracture	58 (5.1%)	39 (5.3%)	19 (4.6%)
Pressure ulcers	85 (7.4%)	63 (8.6%)	22 (5.4%)
Delirium	583 (51.0%)	241 (32.8%)	342 (83.6%)
Sepsis	97 (8.5%)	81 (11.0%)	16 (3.9%)
Respiratory Failure	108 (9.4%)	95 (12.9%)	13 (3.2%)
Healthcare Utilization			
Emergency Department (ED)Visit	0.32 (±0.948)	0.49 (±1.146)	0.00 (±0.000)
Hospital Admissions	0.22 (±0.731)	0.34 (±0.890)	0.00 (±0.000)
Intensive Care Unit Admission	0.68 (±1.782)	1.02 (±2.136)	0.08 (±0.344)
Vital Signs (Number of Abnormal Occurrences in last 6 Months before Death)			
Body Temperature(> 38°C or <35°C)	0.09 (±0.820)	0.14 (±1.020)	0.00 (±0.000)
Heart Rate(< 60 or< 120 bpm)	0.02 (±0.200)	0.03 (±0.249)	0.00 (±0.000)
Respiratory Rate(>30 or<10/min)	0.69 (±4.143)	1.07 (±5.131)	0.00 (±0.000)
Blood Pressure(SPB<100 mmHg)	0.09 (±0.820)	0.14 (±1.020)	0.00 (±0.000)
SpO_2(< 90%)	0.12 (±0.325)	0.19 (±0.390)	0.00 (±0.000)
SaO_2(< 80%)	0.12 (±0.325)	0.19 (±0.390)	0.00 (±0.000)
Laboratory Tests (Number of Abnormal Occurrences in last 6 Months before Death)			
Albumin (< 2.5 g/dL)	0.13 (±0.333)	0.20 (±0.398)	0.00 (±0.000)
HbA1c(> 7%)	0.06 (±0.246)	0.10 (±0.301)	0.00 (±0.000)
CRP(> 10 mg/L)	0.13 (±0.334)	0.20 (±0.399)	0.00 (±0.000)
eGRF(< 60 mL/min/1.73m²)	0.16 (±0.365)	0.25 (±0.431)	0.00 (±0.000)
Urinalysis(Bacteria ≥ "+")	0.28 (±1.312)	0.44 (±1.616)	0.00 (±0.000)
Sputum Culture(Abn Results)	0.17 (±0.953)	0.27 (±1.179)	0.00 (±0.000)

Limitation

Although this study has advanced the use of machine learning in predicting six-month mortality among dementia patients receiving palliative care, several limitations remain. The analysis was limited to short-term mortality (six months), and extending prediction to longer time horizons warrants future exploration. Furthermore, only three algorithms were employed, leaving room for performance enhancement. Future research may consider optimizing these models or incorporating additional algorithms to improve predictive accuracy. Such advancements could support clinicians in making more informed palliative care decisions and ultimately enhance care quality.

Machine Learning for Data Analysis

The dataset comprised 1,143 patients, with data integrated from 14 project-specific tables to generate a single record per patient. Patients were randomly grouped into 12 subsets based on data collection time. Data preprocessing was performed using Scikit-learn, NumPy, and Pandas. Missing values were addressed using Multiple Imputation by Chained Equations (MICE). The dataset was split into 70% training and 30% testing sets. Model training employed five-fold cross-validation, where each fold was sequentially used for validation while the remaining folds served as the training set.

Model performance was assessed by averaging results across the five iterations. Hyperparameter tuning was conducted using GridSearchCV, with the ROC-AUC score as the optimization criterion. For interpretability, the top 10 most important features for each model were identified. A mortality risk threshold of 0.3 was used for classification. Confusion matrices were constructed for model evaluation, and performance metrics—including accuracy, precision, recall, F1-score, and AUC— were compared across the three models. ROC curves were plotted for visual comparison.

Results

A total of 1,143 dementia patients were included in the study, with a mean age of 89.36 years (SD = 10.7), and the majority were female. The mean follow-up period was 5.95 years (SD = 4.38), during which 64.2% of the patients died (Table1).

Table 2 presents the best-performing models among the three models, while Figure 1 displays the confusion matrices for models. The AUROC values ranged from 0.594 to 0.757 (Figure 2). Sepsis, delirium, and shock were the common features identified across all three models (Table 3).

Table 2. Performance Metrics of Various Models within the Threshold Range of 0.30

Models	Threshold	Accuracy	Precision	Recall	F1	AUC
Decision Tree	0.30	0.660550	0.362745	0.445783	0.400000	0.594805
Random Forest		0.697248	0.439394	0.698795	0.539535	0.746000
XGBoost		0.706422	0.442478	0.602410	0.510204	0.757999

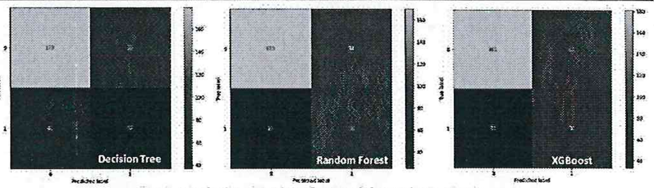

Fig 1. Confusion Matrices for Models on the Test Set

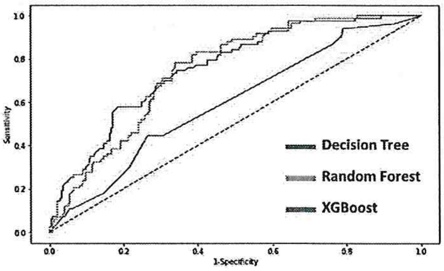

Fig 2. ROC Curves of the Models

Table 3. The Top 10 most Important Features Affecting Dementia Mortality in the Models

Decision Tree		Random Forest		XGBoost	
Features	Score	Features	Score	Features	Score
Sepsis	0.159895	age	0.089103	Sepsis	0.097999
Delirium	0.126496	Delirium	0.075360	SaO_2	0.092620
SaO_2	0.113998	Pneumonia	0.064526	eGFR	0.075775
ER visits	0.110429	Sepsis	0.055390	Shock	0.073122
age	0.109388	Pressure ulcers	0.054734	Delirium	0.070202
Hypertension	0.051081	Hospital admissions	0.053692	Pneumonia	0.062652
Hospital admissions	0.146607	Shock	0.052100	Alzheimer's disease	0.059044
Shock	0.039541	ED Visit	0.050659	CRP	0.057293
Respiratory failure	0.039027	Urinary tract infection	0.049696	Gender	0.049121
Pressure ulcers	0.037751	Fractures	0.048373	Albumin	0.042399

Conclusion

This study leverages machine learning to build three predictive models based on identified mortality risk factors. The models were trained and optimized using five-fold cross-validation, extracting key mortality risk factors and generating prediction results. The **best-performing model** achieved an **accuracy of 70.6%** and an **AUC of 0.758**.

Reference

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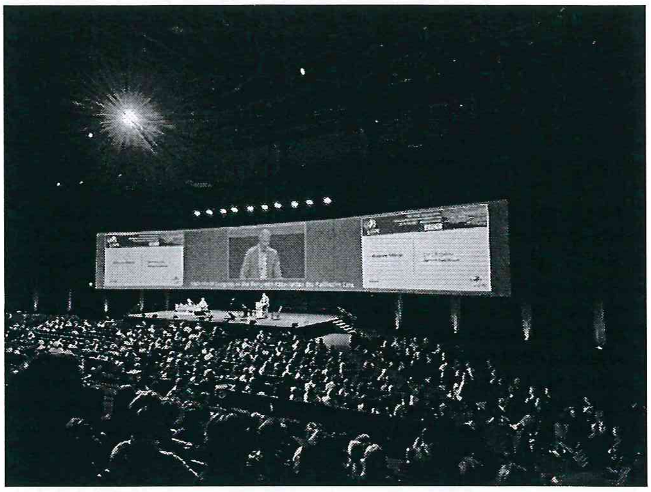

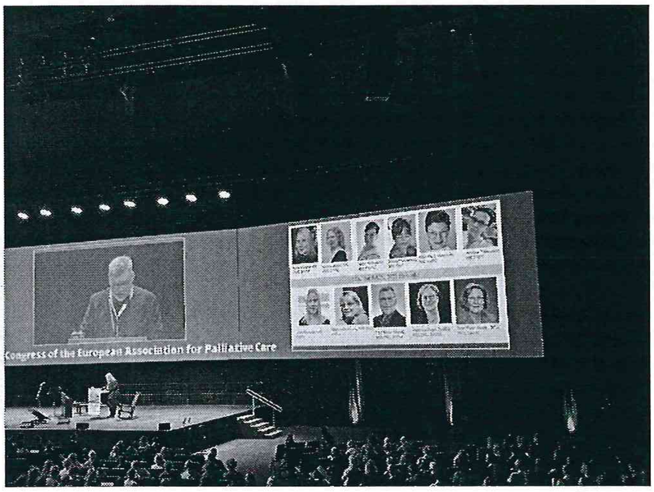
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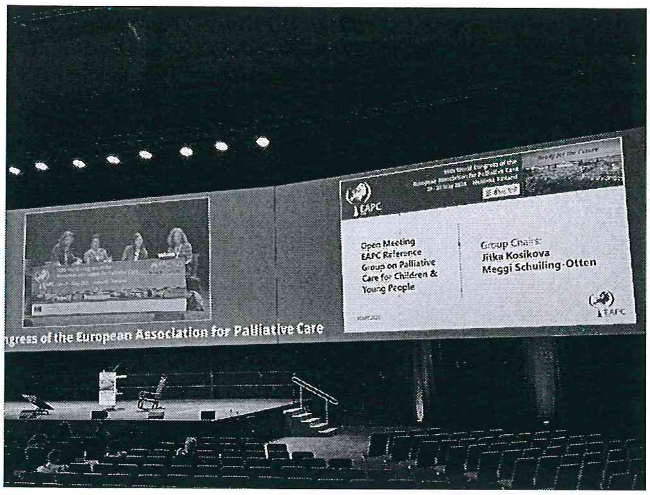
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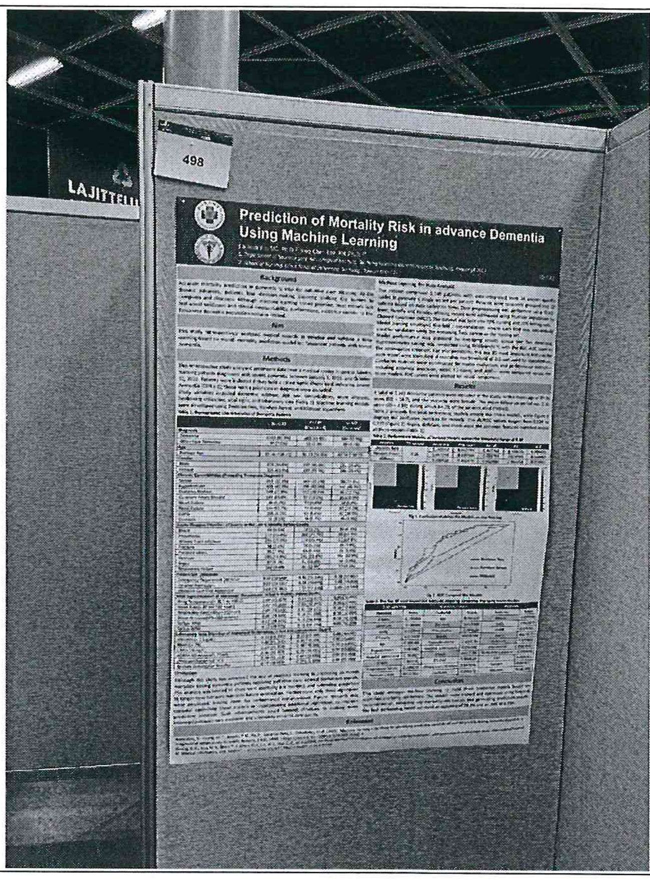
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