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# 基於深度時空模型與三維雷達回波資料應用於臺灣地區雷達回波預測之研究

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## 摘　要

台灣在梅雨季常伴隨鋒面和中小尺度系統，導致劇烈降水事件。世界各地的極端天氣和異常降雨頻率增加，尤其是短延時強降雨，可能引發土石流和城市淹水等災害。然而，極端天氣和台灣複雜地形使現有預測方法的準確度仍需提升。

傳統預測方法依賴數值天氣預報和統計模型，需大量觀測資料和模型參數，且受物理方程式和模型假設的限制，無法充分考慮氣象系統的複雜性（Wu & Kuo, 1999）。隨著科技和人工智慧（AI）發展，AI 模型相比傳統方法大幅提高了預測準確度。深度學習技術具自學習、自適應、自調節特點，能自動提取和學習複雜特徵，更好地考慮時空特徵，對雷達回波預測具有潛力。

深度學習模型如 ConvLSTM、PredRNN 和 HPRNN 等已廣泛應用於降雨預報，但隨時間推移，模型準確度下降仍是挑戰。此外，台灣複雜的天氣型態和多樣降雨類型，導致雷達回波資料強度不平衡，特別是高強度降雨資料稀少，預測模型容易低報，難以有效預測高強度降雨。

本研究實驗以建構 Video Swin Transformer 模型結合不同注意力機制提升模型對於雷達回波之預測準確度。優於先前實驗 2020 年的梅雨個案中，RMSE 與 FAR 平均分數下降程度分別為 8.5%、21.2%，SSIM、CSI 平均分數提升程度分別為 2.4%、3.9%。2020 年的熱帶低氣壓個案中，RMSE 與 FAR 平均分數下降程度分別為 18.4%、18.7%，SSIM、CSI 平均分數提升程度分別為 7.8%、17.9%。2022 年的低強度個案中，RMSE 與 FAR 平均分數下降程度分別為 18.6%、21.1%，SSIM、CSI 平均分數提升程度分別為 18%、6%。

關鍵字：雷達回波外延法、降雨即時預報、深度學習、時空序列預測、注意力機制、損失函數

# Abstract

During the plum rain season in Taiwan, the presence of fronts and mesoscale systems often leads to intense rainfall events. Globally, extreme weather and abnormal rainfall events are becoming more frequent, especially short-duration heavy rainfall, which can cause disasters such as landslides and urban flooding. However, the accuracy of existing forecasting methods needs improvement due to extreme weather and Taiwan's complex terrain.

Traditional forecasting methods rely on numerical weather prediction and statistical models, requiring extensive data and parameters. Their accuracy is limited by physical equations and assumptions (Wu & Kuo, 1999). AI models, with advancements in technology, significantly improve forecast accuracy. Deep learning techniques, with self-learning and adaptive features, automatically extract complex features, making them promising for radar echo predictions.

Deep learning models such as ConvLSTM, PredRNN, and HPRNN have been widely applied to rainfall forecasting, but their accuracy decreases rapidly over time, presenting a challenge. Additionally, Taiwan's complex weather patterns and diverse rainfall types lead to imbalanced radar echo data. Specifically, high-intensity rainfall data is scarce, causing prediction models to underreport, making it difficult to effectively predict high-intensity rainfall.

This study aims to improve the accuracy of radar echo predictions by constructing a Video Swin Transformer model combined with different attention mechanisms. Compared to previous experiments, the average scores for RMSE and FAR in the 2020 plum rain season case decreased by 8.5% and 21.2%, respectively, while the average scores for SSIM and CSI increased by 2.4% and 3.9%, respectively. In the 2020 tropical depression case, the average scores for RMSE and FAR decreased by 18.4% and 18.7%, respectively, while the average scores for SSIM and CSI increased by 7.8% and 17.9%, respectively. In the 2022 low-intensity case, the average scores for RMSE and FAR decreased by 18.6% and 21.1%, respectively, while the average scores for SSIM and CSI increased by 18% and 6%, respectively.



Keywords: Radar Echo Extrapolation, Real-time Rainfall Forecasting, Deep Learning, Spatiotemporal Sequence Prediction, Attention Mechanism, Loss Function