LSTM-based Recurrent Neural Network Predicts Influenza-like-illness in Variable Climate Zones

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Background

- Influenza virus is responsible for a recurrent, yearly epidemic in most temperate regions of the world.
- For the 2021-2022 season the CDC reports 5000 deaths and 100,000 hospitalizations [1].
- The mechanisms behind seasonal variance in flu burden are not well understood.
- Based on a previously validated model, this study seeks to expand understanding of the impact of variable climate regions on seasonal flu trends.
- To that end, three climate regions have been selected.
- Each region represents a different ecological region and provides different weather patterns showing how the climate variables impact flu transmission in different regions.

Methods

- An **LSTM-Based recurrent neural network** was used to predict influenza-like-illness trends for three separate locations: Hawaii, Vermont, and Nevada.
- Flu data were gathered from the **CDC** as weekly influenza-like-illness (ILI) percents [2].
- Weather data were collected from **Visual Crossing** [3].
- Data were prepared and the model trained as described previously [4].

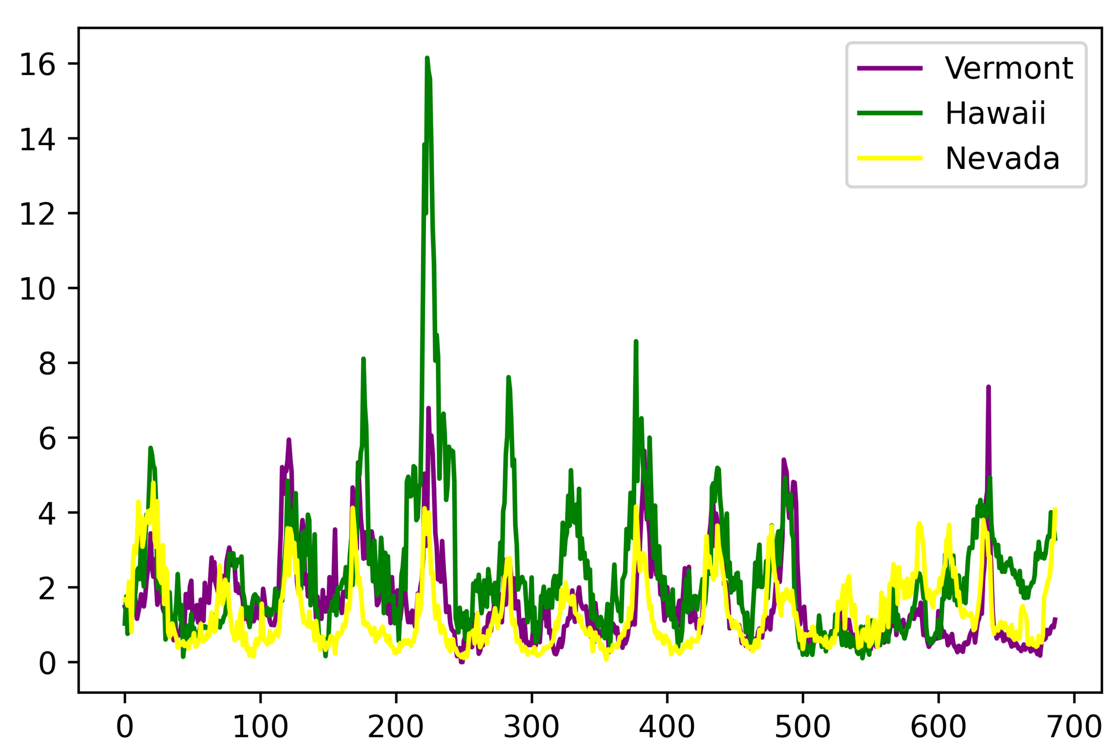

Figure 1. Comparison of flu trends from 2010 to 2023.

Results

Table 1. Correlation matrixes for Vermont, Nevada, and Hawaii flu and climate data. Temperature showed a moderate negative correlation with ILI in all three regions (Vermont = -0.54, Nevada = -0.56, Hawaii = -0.44). Humidity was moderately correlated in Nevada (0.47) and weakly correlated with ILI in Hawaii (0.22). Vermont ILI did not correlate with humidity. Precipitation and wind speed were weakly correlated in all three regions. Solar radiation and UV index showed moderate correlation in Vermont (-0.33, -0.36) and Nevada (-0.5263, -0.55) however only weak correlation in Hawaii (-0.15, -0.18).

Vermont

	% ILI	*tempmax*	*tempmin*	*temp*	*humidity*	*precip*	*windspeed mean*	*solarradiation*	*uvindex*
% ILI	1.00								
tempmax	-0.53	1.00							
tempmin	-0.54	0.97	1.00						
temp	-0.54	0.99	0.99	1.00					
humidity	-0.01	0.04	0.16	0.09	1.00				
precip	-0.13	0.23	0.29	0.26	0.37	1.00			
windspeedmean	0.19	-0.42	-0.41	-0.41	-0.41	-0.04	1.00		
solarradiation	-0.34	0.79	0.71	0.77	-0.28	0.09	-0.23	1.00	
uvindex	-0.36	0.81	0.73	0.78	-0.30	0.08	-0.22	0.97	1.00

Nevada

	% ILI	*tempmax*	*tempmin*	*temp*	*humidity*	*precip*	*windspeed mean*	*solarradiation*	*uvindex*
% ILI	1.00								
tempmax	-0.56	1.00							
tempmin	-0.55	0.92	1.00						
temp	-0.57	0.98	0.97	1.00					
humidity	0.47	-0.84	-0.69	-0.79	1.00				
precip	0.11	-0.32	-0.16	-0.25	0.41	1.00			
windspeedmean	-0.09	-0.05	0.15	0.07	-0.10	0.30	1.00		
solarradiation	-0.53	0.68	0.68	0.71	-0.67	-0.23	0.19	1.00	
uvindex	-0.55	0.75	0.71	0.76	-0.74	-0.29	0.20	0.90	1

Hawaii

	% ILI	*tempmax*	*tempmin*	*temp*	*humidity*	*precip*	*windspeed mean*	*solarradiation*	*uvindex*
% ILI	1.00								
tempmax	-0.43	1.00							
tempmin	-0.45	0.91	1.00						
temp	-0.45	0.98	0.97	1.00					
humidity	0.22	-0.41	-0.32	-0.34	1.00				
precip	0.03	-0.24	-0.12	-0.17	0.48	1.00			
windspeedmean	-0.24	0.29	0.45	0.33	-0.60	-0.19	1.00		
solarradiation	-0.15	0.36	0.26	0.31	-0.38	-0.27	0.18	1.00	
uvindex	-0.18	0.44	0.29	0.37	-0.46	-0.36	0.17	0.91	1.00

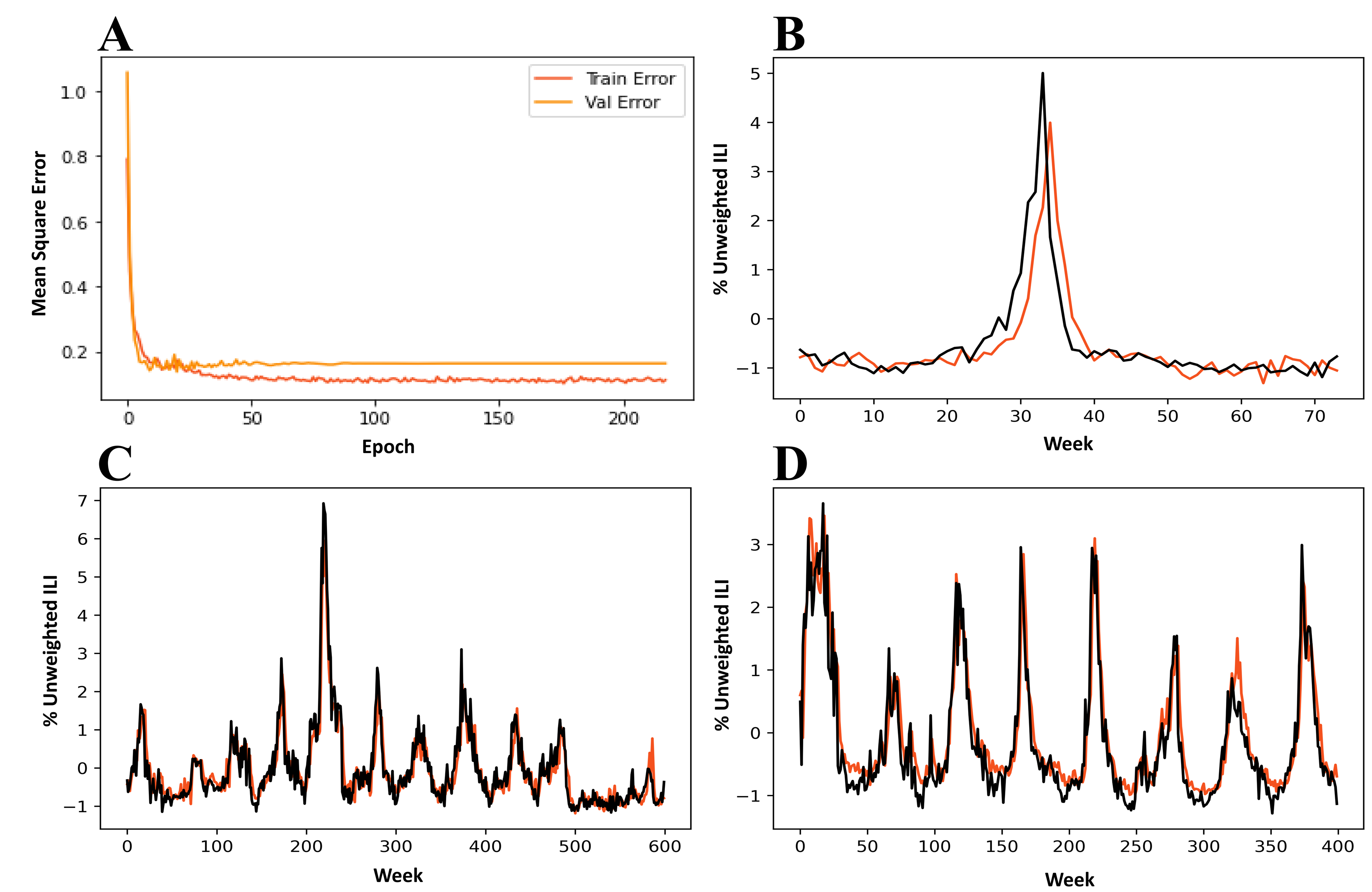

Figure 2. LSTM model trained on data from Vermont is able to predict trends in Hawaii and Nevada. (A) Training error of the Vermont-based data displayed as Mean Square Error. (B) +1-week predictions of reserved Vermont testing data. (C) +1-week predictions of all Hawaii data. (D) One-week predictions of all Nevada data.

Conclusions

Preliminary results indicate that temperature is a moderate predictor of ILI rates. Additionally, humidity, solar radiation, and UV index present promising prediction variables. Initial modeling attempts revealed acceptable performance in all regions. While seasonality appeared similar in each region, differences in correlation with weather variables may reveal variability in the driving forces behind ILI rates.

References
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