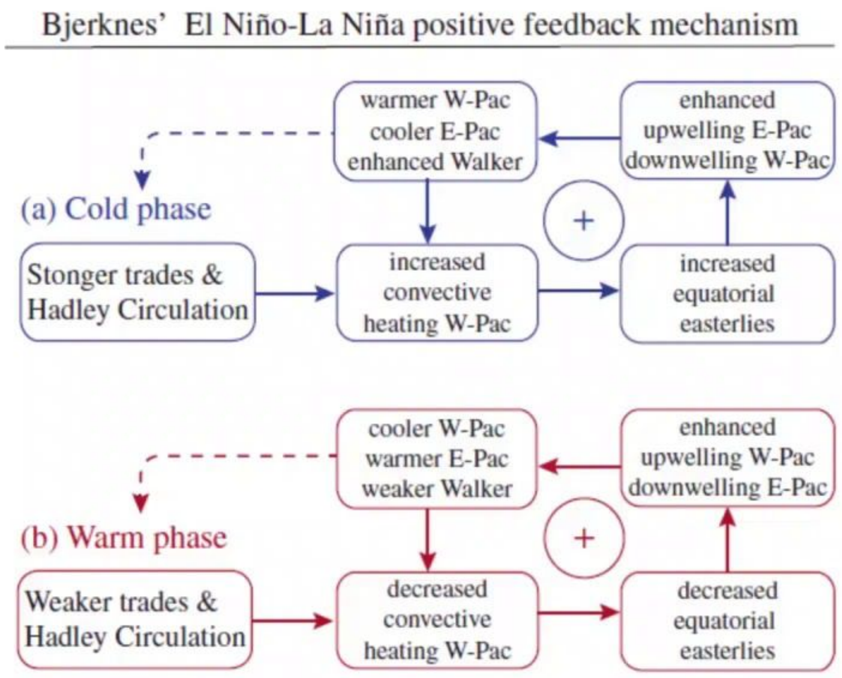
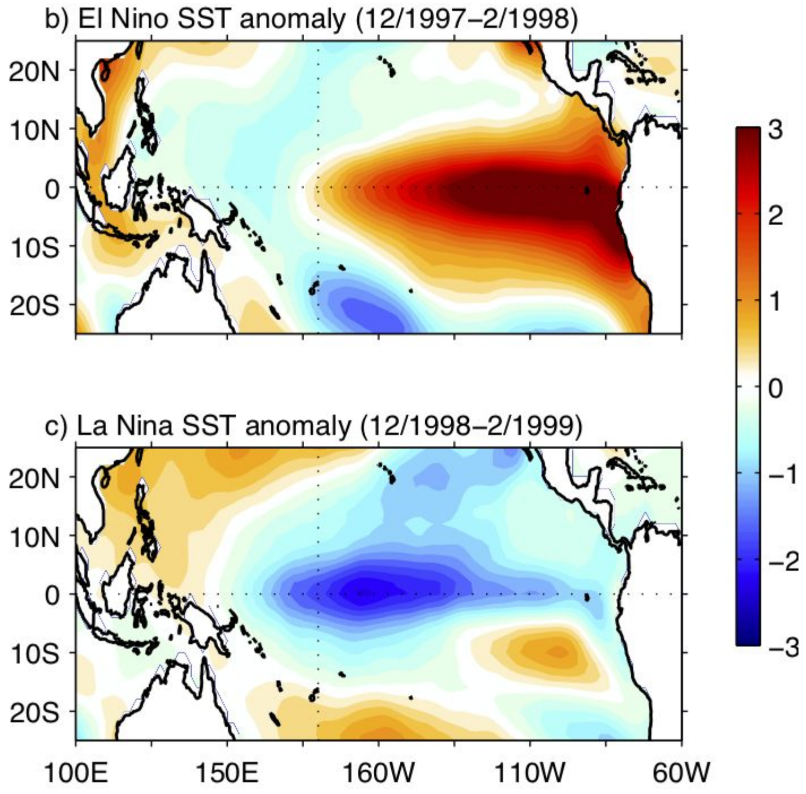
ENSO Prediction Using Deep Learning

Lilian Zhu
Anomaly Detection Aces
Final Presentation

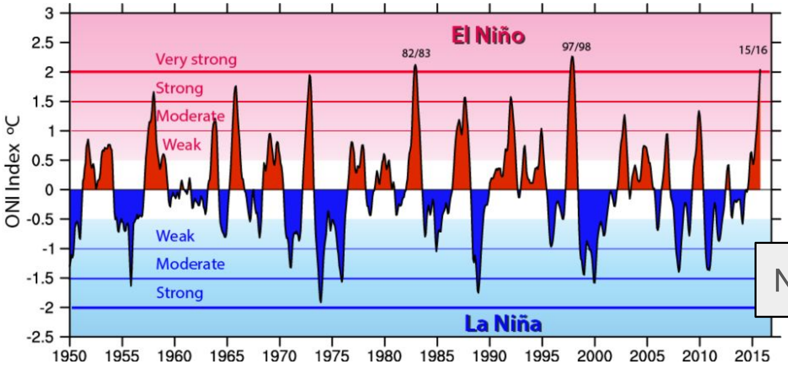
El Nino-Southern Oscillation (ENSO)



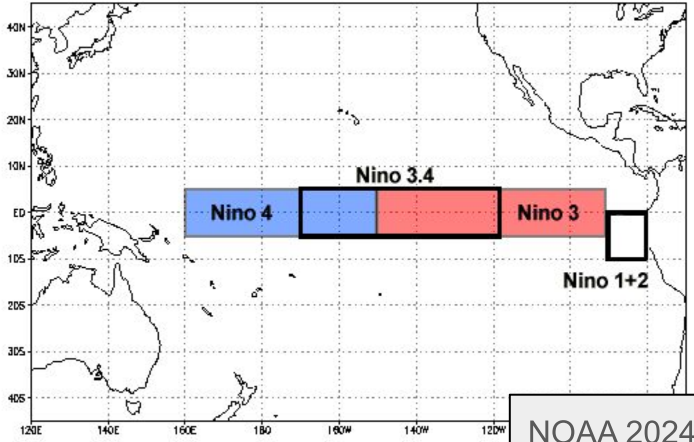


NCAR 2019

ONI - Defining Phases of ENSO



NCAR 2024



NOAA 2024

ONI from 2012 to 2024

Year	DJF	JFM	FMA	MAM	AMJ	MJJ	JJA	JAS	ASO	SON	OND	NDJ
2012	-0.9	-0.7	-0.6	-0.5	-0.3	0.0	0.2	0.4	0.4	0.3	0.1	-0.2
2013	-0.4	-0.4	-0.3	-0.3	-0.4	-0.4	-0.4	-0.3	-0.3	-0.2	-0.2	-0.3
2014	-0.4	-0.5	-0.3	0.0	0.2	0.2	0.0	0.1	0.2	0.5	0.6	0.7
2015	0.5	0.5	0.5	0.7	0.9	1.2	1.5	1.9	2.2	2.4	2.6	2.6
2016	2.5	2.1	1.6	0.9	0.4	-0.1	-0.4	-0.5	-0.6	-0.7	-0.7	-0.6
2017	-0.3	-0.2	0.1	0.2	0.3	0.3	0.1	-0.1	-0.4	-0.7	-0.8	-1.0
2018	-0.9	-0.9	-0.7	-0.5	-0.2	0.0	0.1	0.2	0.5	0.8	0.9	0.8
2019	0.7	0.7	0.7	0.7	0.5	0.5	0.3	0.1	0.2	0.3	0.5	0.5
2020	0.5	0.5	0.4	0.2	-0.1	-0.3	-0.4	-0.6	-0.9	-1.2	-1.3	-1.2
2021	-1.0	-0.9	-0.8	-0.7	-0.5	-0.4	-0.4	-0.5	-0.7	-0.8	-1.0	-1.0
2022	-1.0	-0.9	-1.0	-1.1	-1.0	-0.9	-0.8	-0.9	-1.0	-1.0	-0.9	-0.8
2023	-0.7	-0.4	-0.1	0.2	0.5	0.8	1.1	1.3	1.6	1.8	1.9	2.0
2024	1.8	1.5	1.1	0.7	0.4	0.2						

ONI (Oceanic Nino Index) = 3 month Rolling mean of SST anomaly
in NINO3.4 region

- El Nino: ONI > 0.5
- La Nina: ONI < -0.5

ENSO Using Sea Surface Temperature Anomalies Zonal Pattern

This paper uses SST anomalies zonal pattern. However, since ENSO is a very time-dependent process, I will use time lags as my input.

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Research Letter | Open Access

CNN-Based ENSO Forecasts With a Focus on SSTA Zonal Pattern and Physical Interpretation

Historically, ENSO prediction beyond 6 months is very inaccurate.

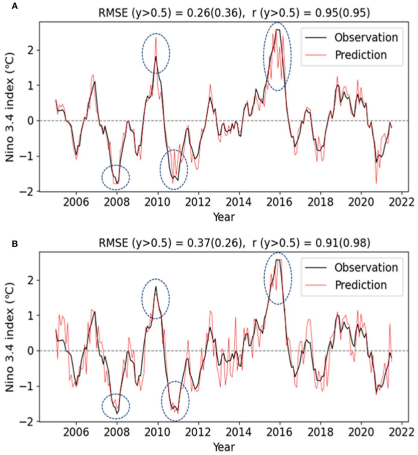
Rapid Development of Systematic ENSO-Related Seasonal Forecast Errors

J. D. Beverley[1,2], M. Newman[2], and A. Hoell[2]

[1]Cooperative Institute for Research in Environmental Sciences (CIRES), University of Colorado Boulder, Boulder, CO, USA, [2]NOAA Physical Sciences Laboratory, Boulder, CO, USA

Abstract Climate models exhibit known systematic errors in their representation of the El Niño-Southern Oscillation (ENSO). In this study, we show that such simulation errors are largely present in tropical seasonal prediction, even for short lead times. Regressing monthly forecast errors from 11 different operational models upon the observed ENSO state, we find that predicted ENSO-related sea surface temperature anomalies (of either sign) for winter/spring are significantly extended or shifted to the west and are also too persistent during the ENSO decay phase, both common climate model errors. There are also corresponding precipitation forecast errors, most notably a robust westward shift of the ENSO-related precipitation dipole that may impact predictions of extratropical teleconnections. These ENSO-related errors develop within days after initialization regardless of month, including significant errors appearing in anomalous surface trade winds, and saturate so rapidly that they primarily depend upon the seasonal cycle rather than lead time.

Modifying weight function of CNN



- Weight function that reduces weight of high-frequency normal events
- Significant improvement in ENSO predictions

Previous Work

CESM (Train + Val)

- Ensemble of 40 climate models from around the world
- Use for training and validation data (9 + 1 ensemble members)
- Variables
  - Sea Surface Temperature
  - Quarter degree grid
  - 1959 to 2015
  - NetCDF file

```
sst_test_data.SST
```

xarray.DataArray 'SST' (**ensemble_member**: 10, **time**: 673, **lat**: 22, **lon**: 46)

ERA5 (Test)

- Reanalysis product (Observations + Model)
  - Proxy for observations
- Use for testing data
- Variables
  - Sea Surface Temperature
  - Eighth degree grid
  - 1959 to 2021
  - NetCDF file

```
era
```

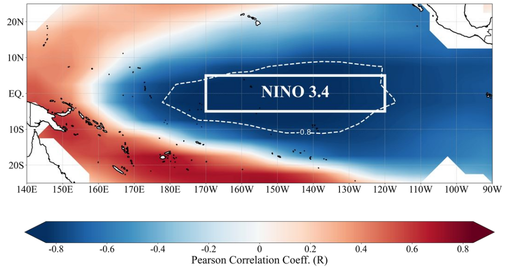
xarray.Dataset

▸ Dimensions: (**time**: 756, **lat**: 180, **lon**: 360)

Expected outcome: accurate predictions of ONI based off sea surface temperature averages in NINO3.4 region.

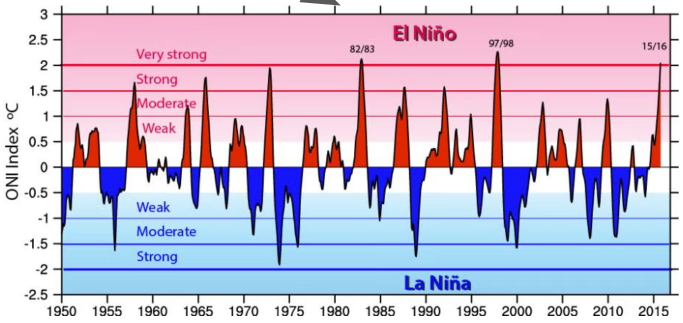
Input:

Sea surface temperature time lagged in three month intervals up to 2 years

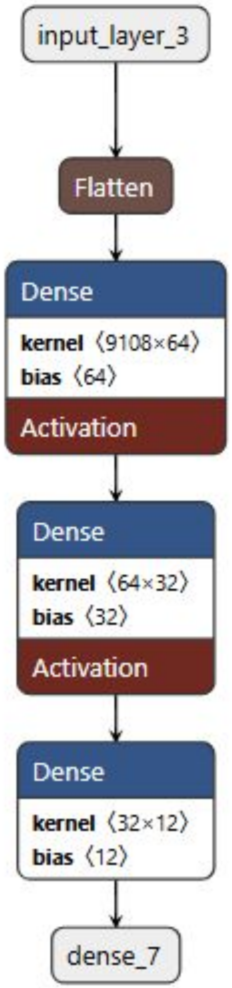


Output:

Oceanic Nino Index (ONI)



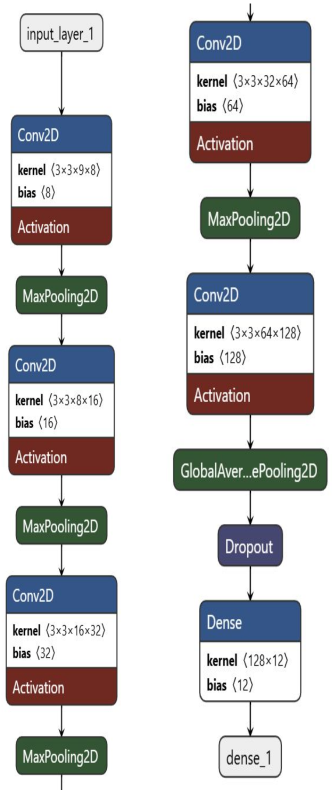
Baseline MLP Model



Optimizer = adam
Loss = mse
Metrics = accuracy

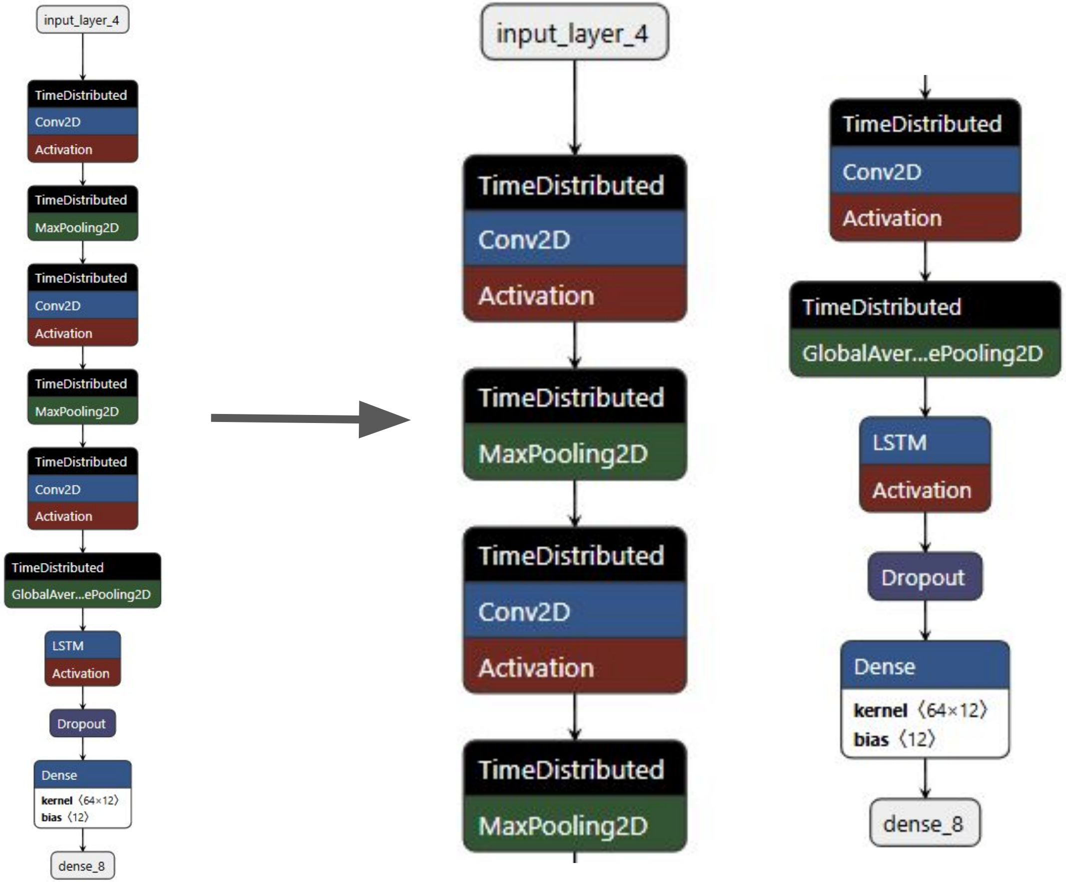
- 2 Dense layers

CNN Model



Optimizer = adam
Loss = mse
Metrics = accuracy

- MaxPooling2D
- GlobalAveragePooling2D
- Dense layers
- Conv2D layers
    - relu



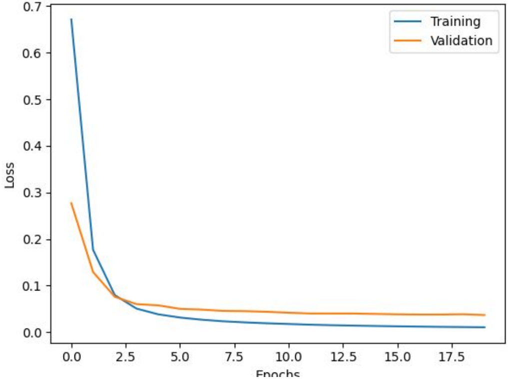
CNN + LSTM Model

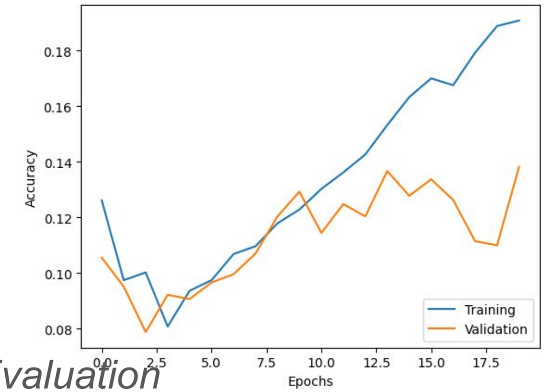
Optimizer = adam
Loss = mse
Metrics = accuracy

- Time Distributed layers
- LSTM layer
- Dense layer

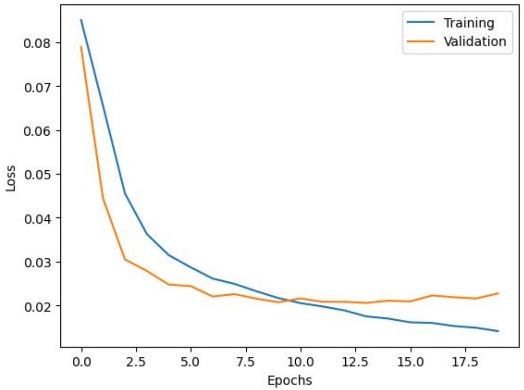
Evaluate model on test set

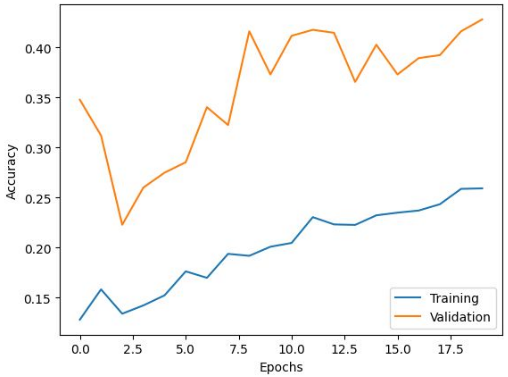
Baseline MLP



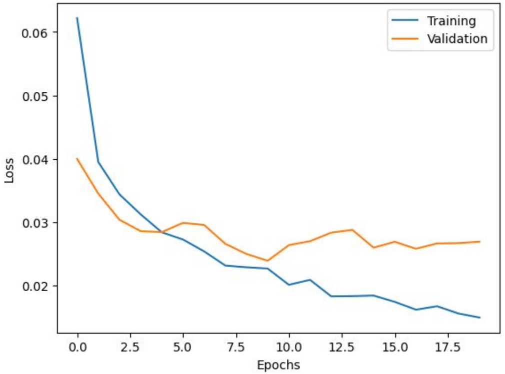


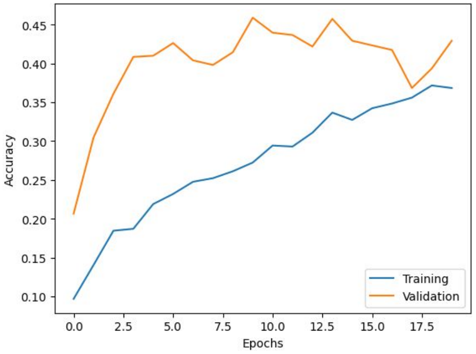
CNN



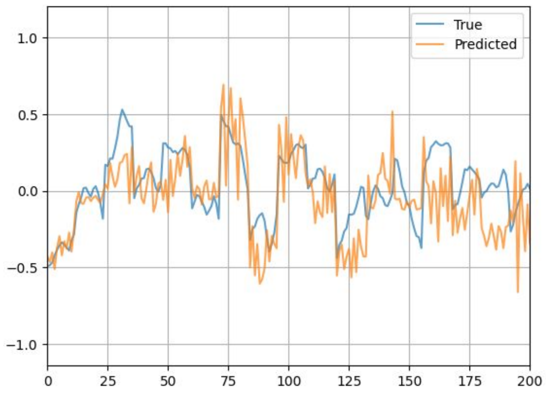


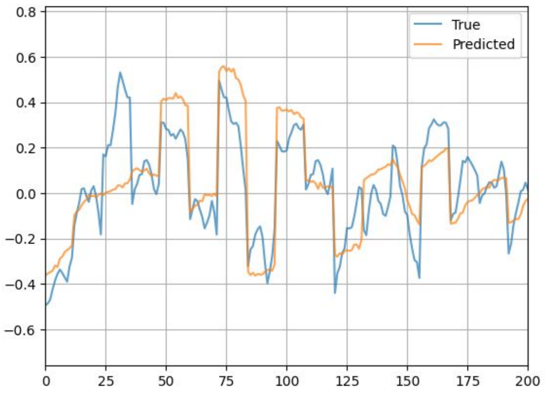
CNN + LSTM





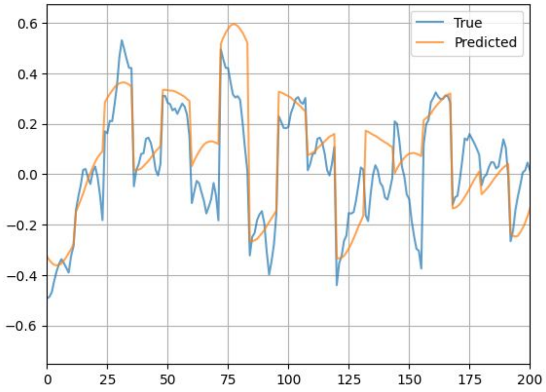
Baseline MLP Model vs CNN vs CNN+LSTM





```
print(base.evaluate(X_test, Y_test))
```

```
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.1048 - loss: 0.0625
[0.06247251480817795, 0.10252600163221359]
```



```
[26] print(CNN.evaluate(X_test, Y_test))
```

```
22/22 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.2307 - loss: 0.0247
[0.024480206891809434, 0.24368400621041727572]
```

```
print(model.evaluate(X_test_reshaped, Y_test))
```

```
22/22 ━━━━━━━━━━━━━━━━━━━━ 3s 152ms/step - accuracy: 0.2129 - loss: 0.0322
[0.03410351276397705, 0.23031203448877243]
```

Results

Discussion

- CNN and CNN + LSTM models learn patterns from SST anomalies
- CNN + LSTM validation accuracy improved more quickly than CNN
    - Temporal learning helps
- ENSO influenced by many variables

Next steps:

- Increase channels (ie more variables)
- Increase architecture complexity

Works Cited

Kim, Dong-Hoon, et al. “Improved Prediction of Extreme ENSO Events Using an Artificial Neural Network with Weighted Loss Functions.” *Frontiers in Marine Science*, vol. 10, 15 Jan. 2024, https://doi.org/10.3389/fmars.2023.1309609. Accessed 16 May 2025.

Wang, Gai-Ge, et al. “ENSO Analysis and Prediction Using Deep Learning: A Review.” *Neurocomputing*, vol. 520, Feb. 2023, pp. 216–229, https://doi.org/10.1016/j.neucom.2022.11.078.