Predicting El Niño-Southern Oscillation using Convolutional Neural Networks

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***Abstract*—The El Nino-Southern Oscillation (ENSO) is an interannual cycle in the Pacific ocean that happens every three to seven years, split into two phases: El Nino and La Nina. During El Nino, the ocean experiences a warm anomaly and decreased upwelling in the Eastern Pacific, as well as weakening of the easterly winds. During La Nina, we experience the opposite: cold anomalies, increased upwelling, and stronger easterlies. These two phases are identified using the Oceanic Nino Index (ONI) which is a three month rolling mean of sea surface temperature anomaly. In this work, we use ONI calculated from the Community Earth System Model (CESM) with time lags in intervals of three months up to two years in the past as historic input channels to a convolutional neural network. The model is evaluated using mean squared error loss and accuracy. We create two models, a CNN and a combined CNN and LSTM which achieved accuracies of 23 and 21 percent respectively. While there is room for improvement, these results demonstrate CNN's potential for capturing non-linear dynamics of the climate and ENSO prediction.**

I. Introduction

The El Nino-Southern Oscillation (ENSO) is a coupled ocean-atmosphere phenomenon which is one of the most dominant modes of interannual climate variability on Earth. ENSO is split into two phases, El Nino and La Nina, which have widespread effects on global weather patterns, agriculture, and more. For example, a strong La Nina phase in 2022 brought an extreme drought shock in 2022 to Hungary and central Europe, resulting in crop losses and economic impact. Thus, accurate forecasting of ENSO is critical to having risk management and early warning systems in place to minimize impact.

Traditionally, ENSO predictions have relied on statistical methods, but are often very computationally expensive. Advancements in machine learning have opened up promising avenues for ENSO prediction and climate modeling as a whole. Convolutional Neural Networks (CNN) are able to efficiently extract spatial features from gridded climate fields from variables like sea surface temperature. When trained on large datasets from climate models, CNNs can effectively learn patterns associated with ENSO that are otherwise difficult to predict with pure computational methods.

In this project, we built a CNN to predict the Oceanic Nino Index, a metric used for identifying phases of ENSO where ONI < -0.5 represents a La Nina Phase and ONI > 0.5 represents a El Nino phase. We use sea surface temperature (SST) anomalies in the Pacific Ocean from the ERA5 reanalysis dataset to forecast ONI values up to 12 months in advance using historic input of 3 month intervals up to two years in the past.

II. Previous Solutions

Previous solutions for ENSO prediction using neural networks have been very promising while still having limitations. In Wang et al. 2022 [2], the current deep learning model achieves a 20-month advance prediction but the accuracy of the intensity in different regions is lower. They note the Spring Prediction Barrier (SPB) where climate models struggle to forecast the transition between ENSO phases. SPB is apparent in deep learning models and still an area of active research. In Kim et al. 2022 [1], they use a weight function that reduces the weight of high-frequency normal events which when applied to a recurrent neural network, had shown significant improvement in ENSO predictions for all lead times from one to 12 months compared to a normal loss function.

III. Database

To train the CNN, we use data from the Community Earth System Model (CESM) which is an ensemble of 40 climate models from models around the world. The CESM is a widely used fully coupled global Earth system model which provides state-of-the-art computer simulations (cite). We use 10 ensemble members: 9 for training and 1 for validation.

Then to test our model, we use the ERA5 reanalysis dataset. ERA5 is commonly used as a baseline for observations since it uses observational data as forcing combined with models for a continuous climate dataset in both space and time.

We extract sea surface temperature variables from both datasets from 1980 to 2020 as monthly means over the Pacific Ocean. The data is presented as a netCDF file, which is a common file type for multidimensional, scientific data and the data can be easily manipulated through the Python library Xarray.

IV. Proposed Method

A. Baseline Model

The baseline model is a simple fully connected MLP model consisting of two dense layers with ReLU activation with 64 and 32 neurons.

B. CNN Model

Our proposed method is a convolutional neural network model to predict ONI up to twelve months in advance based on spatial patterns of sea surface temperature anomalies. The input to the model uses preprocessed SST anomalies from CESM where each input sample is a multi channel 2D grid of SST anomalies with time lagged steps of 3 month intervals in a 2 year time span. The CNN starts with a 2D convolutional layer with 8 filters and a 3x3 kernel and then a max pooling layer to reduce the spatial dimensions. The 2D convolutional and max pooling layer is repeated with increasing filter depths: 16, 32, 64, and 128. Each convolution uses the ReLU activation function. The model finishes off with a global pooling layer, a dropout layer with a rate of 0.5 to prevent overfitting, and a final dense layer to output the 12 dimensional vector that represents predicted ONI values for the next 12 months. We also use an Adam optimizer with a mean squared error loss function and accuracy as the evaluation metric.

C. CNN + LSTM with Time Distributed Layers

It was challenging to improve the CNN model as I tried to increase the model complexity, add batch normalization, and different weight techniques. While it is definitely possible to improve this model further, I suspect that there are definite limitations to only training the model on historic inputs since ENSO prediction depends on many other variables and confounding factors. Thus, I decided to make a new model that combines CNN and LSTM which uses Time Distributed layers. Since time distributed layers look at individual time steps, I thought this would lead to improvements in the model since we are predicting a time series. I have three layers that have depths of 32, 64 and 128 followed by an LSTM, dropout, and dense layer.

V. Evaluation Method

A. Baseline Model

The baseline model uses the Adam optimizer, a mean squared error loss function, and accuracy metric.

B. CNN Model

The model was trained over 20 epochs using the Adam optimizer and a batch size of 512. We used a mean squared error loss function which accurately assesses the prediction for continuous ONI time series data. Then to evaluate the model, we have a validation set which consists of one ensemble member from the CESM. Additionally, we use accuracy as a performance metric since it can tell us how closely the CNN's output aligns with the target trend.

C. CNN + LSTM with Time Distributed Layers

This model was evaluated similar to the CNN model, using Adam optimizer with a learning rate of 1e-3 and gradient clipping. I used a mean squared error once again, and accuracy too to make a comparison to the CNN model.

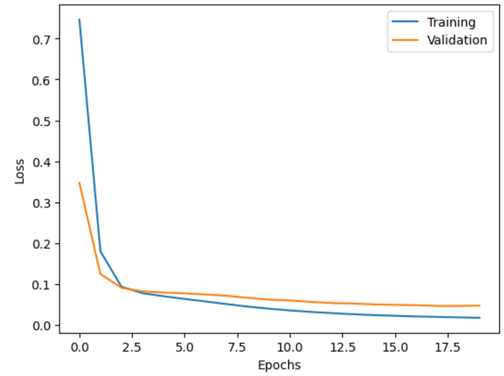

Fig. 1. Baseline Loss

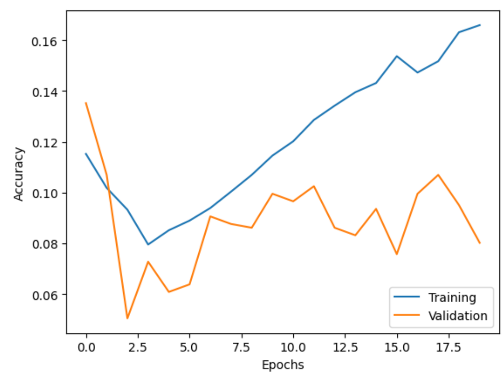

Fig. 2. Baseline Accuracy

VI. Results

A. Baseline Model

In the baseline model, both the training and validation loss approaches zero in Figure 1. In Figure 2, we see that training accuracy decreases slightly till epoch 3, and then increases. Validation accuracy is quite low and variable, suggesting that the model struggles to learn from the given input. In Figure 3, we see that the prediction is relatively accurate until time step reaches 100, and then the predicted ONI starts to desynchronize from the true ONI. The mean absolute error

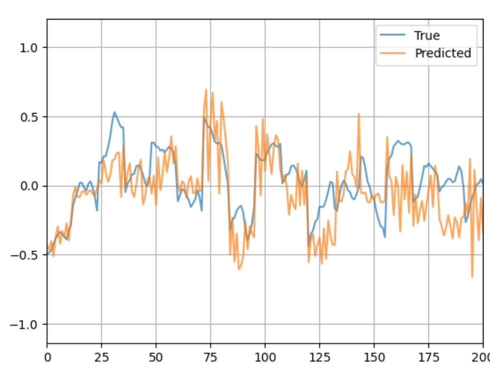

Fig. 3. Baseline Comparison

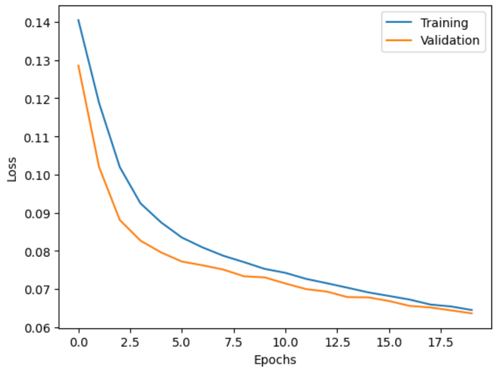

Fig. 4. CNN Loss

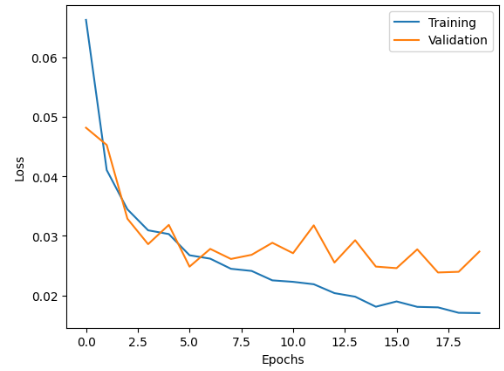

Fig. 7. CNN+LSTM Loss

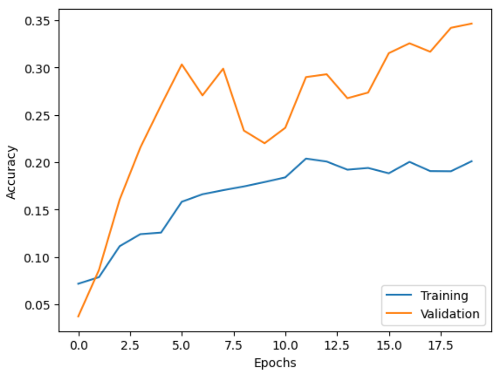

Fig. 5. CNN Accuracy

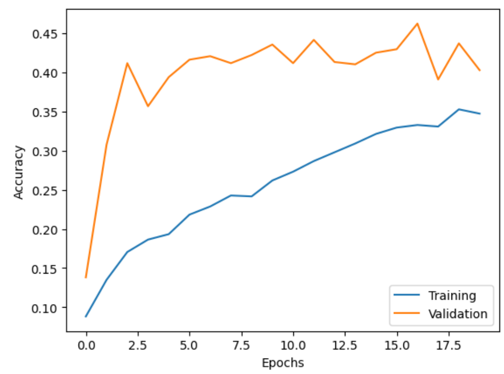

Fig. 8. CNN+LSTM Accuracy

(MAE) also increases as prediction goes more months in advance.

B. CNN Model

In the loss plot (Figure 4), both the training and validation decrease with more epochs, which indicates that the model incrementally learns and improves with data. Since both curves are close to each other, this also means there is no significant overfitting. Additionally, the losses reach 0.06 so there is not much improvement left in the model. In the accuracy plot (Figure 5), training accuracy plateaus around 20 percent while validation accuracy plateaus around 35 percent. The final accuracy on the test set is 23 percent. There is much less variablity in the predicted ONI values compared to the baseline model in Figure 6, resulting in lower error. While still not perfect, this more developed CNN predicts ONI values better. We can see how the predicted values are closely aligned to the phases of El Nino and La Nina with troughs and peaks.

C. CNN + LSTM

Both the training and validation loss decreases again in Figure 7, but the validation loss starts to fluctuate after 5

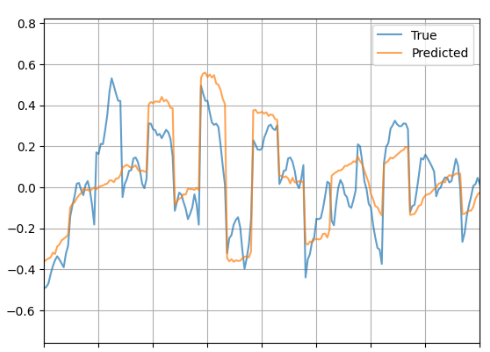

Fig. 6. CNN Comparison

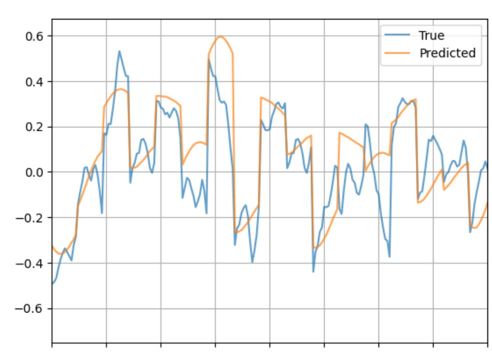

Fig. 9. CNN+LSTM Comparison

epochs which suggests overfitting. There is a stark difference between the training and validation accuracy shown in Figure 8. The training accuracy increases linearly while the validation accuracy quickly increases and plateaus around 40 percent. The final accuracy on the test set is 21 percent. In Figure 9, we now see good agreement between the predicted and true values, where the model is able to accurately detect both the phases of El Nino and La Nina, as well as their magnitude. The RMSE of the first month is 0.01 and at month 12, it is 0.05.

VII. Discussion

While the performance of the CNN and CNN + LSTM models do not produce the highest accuracy, they still show how neural networks can extract patterns from climate data and provide ENSO predictions. This is clearly shown in the loss curves from both of the models, where training and validation loss steadily decreases with more epochs. Additionally, the CNN + LSTM model has a validation accuracy that increases faster than that of the CNN model, which indicates that the LSTM is able to learn patterns in the data more efficiently than the CNN alone. Nevertheless, both of the models have relatively low accuracies: 23 percent for the CNN and 21 percent for the CNN + LSTM.

While there are improvements to be made in the model, it should be noted that historic time lags of SST alone may not be enough to produce accurate ENSO predictions. ENSO is dependent on a multitude of factors as well as being a part of a chaotic climate system. For example, El Nino deepens the thermocline, a certain depth of the ocean, and can raise sea surface height and the reverse during La Nina. So, including sea surface height as an input to the neural networks can lead to increased accuracy since they act as a proxy for internal wave dynamics that sea surface temperature alone cannot pick up. Even though these models were not successful in ENSO prediction, with more complex architectures and inputs, they still hold great potential for climate modeling compared to more computationally expensive methods.

VIII. Conclusion

In this work, we applied deep learning methods to predict the El Nino-Southern Oscillation. We developed two models: a CNN and a combined CNN and LSTM. They achieved accuracies of 23 percent and 21 percent respectively. While the accuracies are not high, they still show the potential of deep learning for climate prediction and that SST anomalies alone may not be sufficient for ENSO prediction. Future work should include increasing variables and adding more channels to the models, and to increase the complexity of the models.

References

[1] 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

[2] 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.