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Long Short-Term Memory Model Experiments for Tropical Cyclone Rapid Intensification Prediction in the Western Pacifc from Wind Structure Evolution

Capstone Project Presentation | MSDS 500: Fundamentals of Data Science| May 26, 2024

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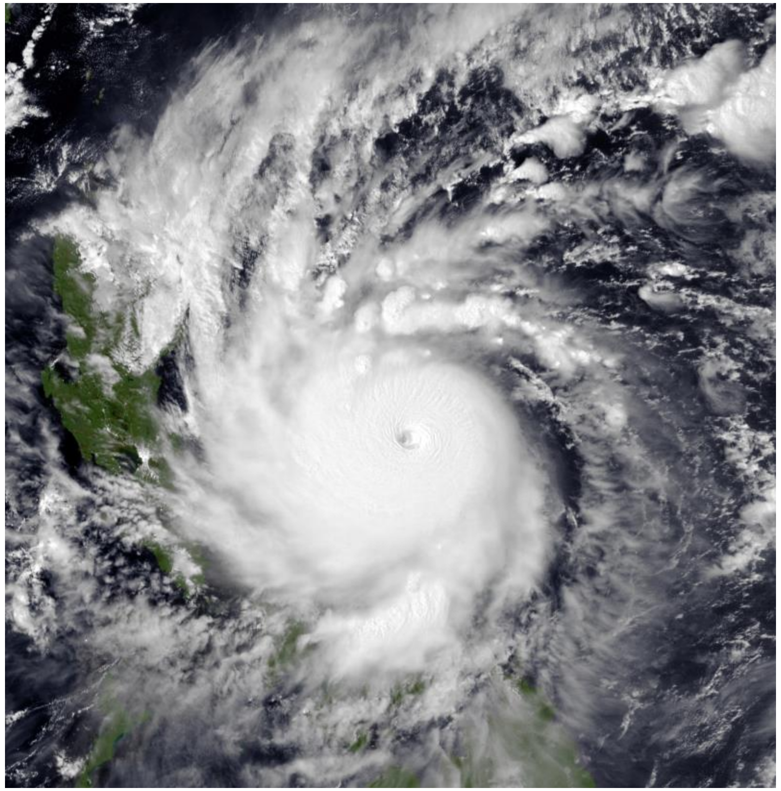
BACKGROUND — What are Tropical Cyclones?

Tropical Cyclones (Storms)
definition by the World Meteorological Organization (WMO)

- a **non-frontal** synoptic scale low-pressure system over tropical or subtropical waters with **organized convection** and **definite cyclonic surface wind circulation**



Super Typhoon Goni (Rolly, 2020) making landfall over PH (as seen from visible satellite)

Tropical Cyclones (Storms); (In PH, *Bagyo*)
audience-friendly definition

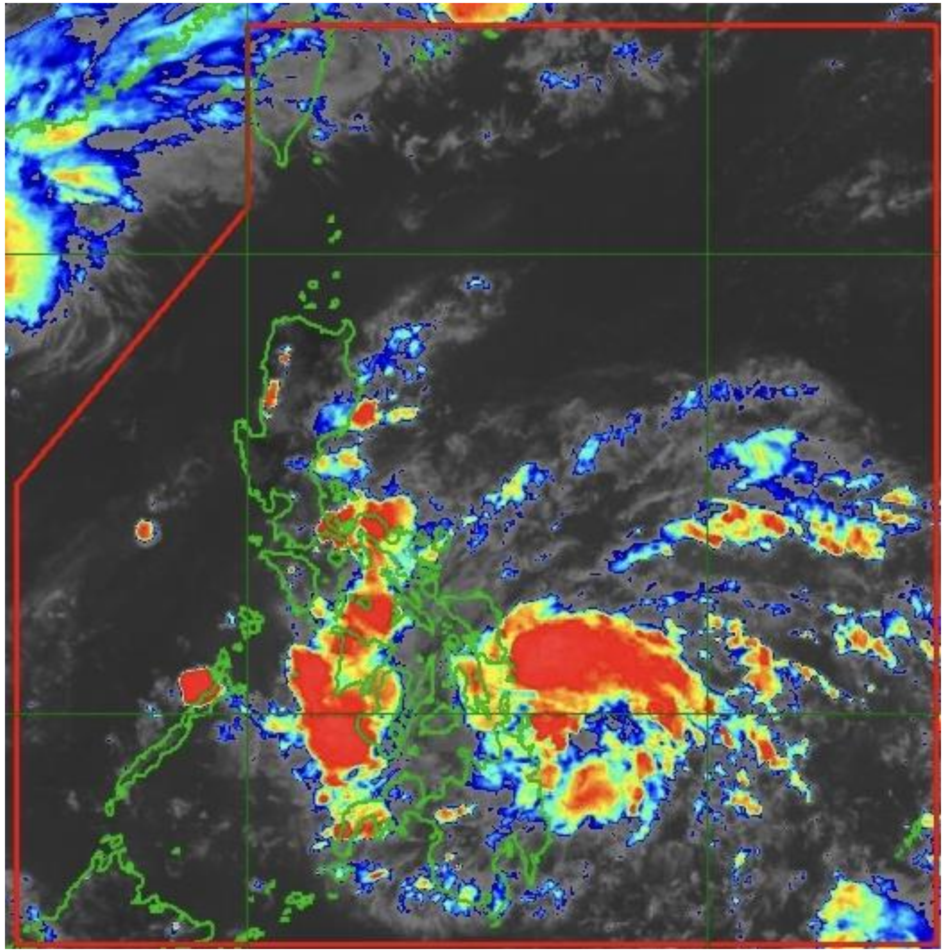
- a meteorological phenomenon with a circular wind pattern and accompanying cloud systems and rainfall

BACKGROUND What are Tropical Cyclones?

Why do meteorologists / atmospheric scientists study Tropical Cyclones?

It brings intense winds, heavy rainfall, storm surges, and flooding, upon landfall.

By understanding the characteristics of tropical cyclones, we can minimize the risks. In other words, to save lives and businesses.



TD Aghon as seen from the Himawari Satellite (05 /24 / 24)

BACKGROUND The Challenge in Rapid Intensification

Rapid Intensification (RI)
When a Tropical Cyclone's wind speed increases by equal to or greater than 30 kt (56 kph) in 1 day

The 95th percentile of all intensity changes of Tropical Cyclones globally (Kaplan et al., 2010)

In order to mitigate the disastrous effects of tropical cyclones that underwent rapid intensification, we need to identify the two main factors that influence it.

[1] Environmental Conditions

- ❑ Sea Surface Temperature
- ❑ Vertical Wind Shear
- ❑ Relative Humidity
- ❑ Outflow

[2] Internal Dynamics

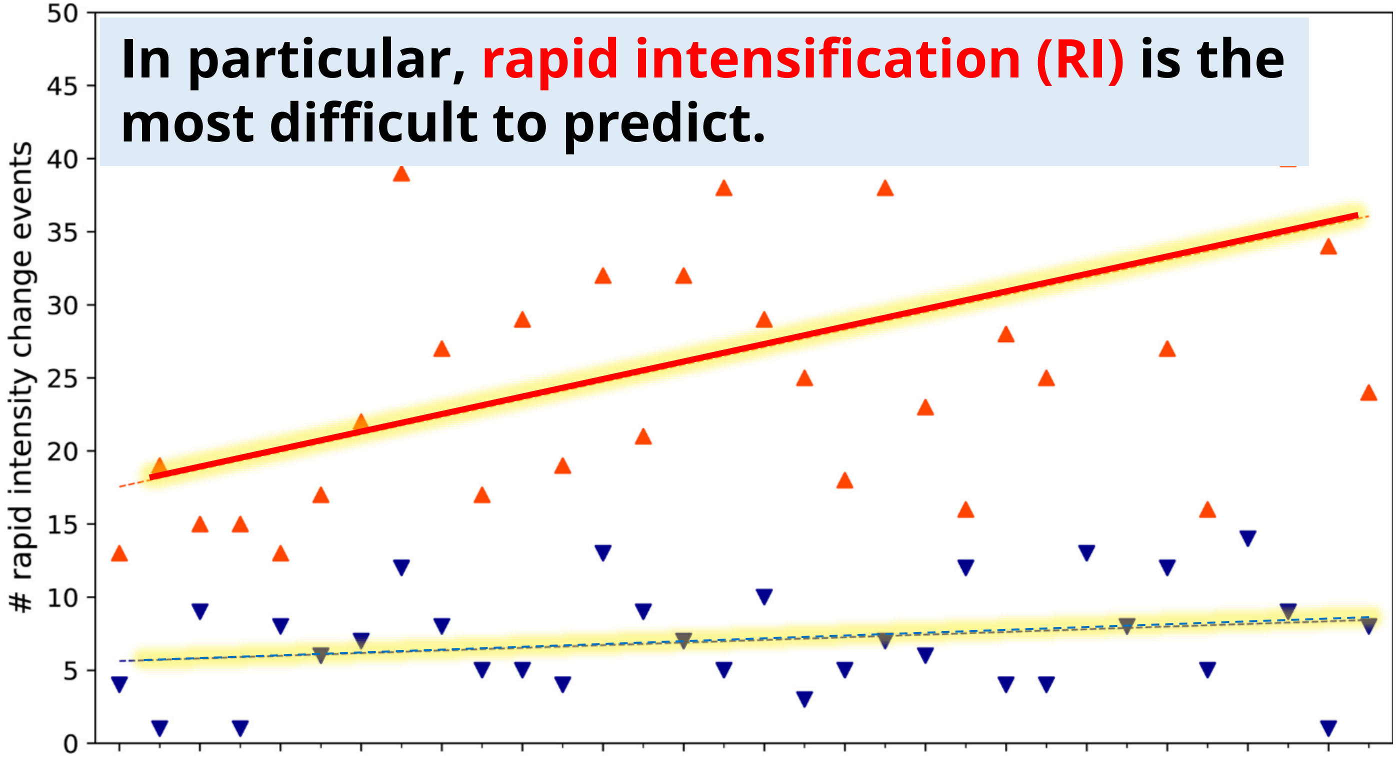
- ❑ Deep Convective Clouds
- ❑ Precipitation
- ❑ Cloud Microphysical Properties
- ❑ Wind Structure

Hendricks et al. (2012), Ruan and Wu (2016), Guo and Tan (2022)

BACKGROUND

The problem in TC rapid intensification forecasts

Problem!!! Forecasting or predicting intensification has barely improved over the past few decades.



More TCs are attaining RI over the years!

Kishtawal et al., 2012; Balaguru et al., 2018; Bhatia et al., 2019; Song et al., 2020; Shimada et al., 2020; S. Wang et al., 2020; Klotzback et al., 2022

BACKGROUND

The problem in TC rapid intensification forecasts

- ❑ Most **Super Typhoons (>185 kph)** underwent RI
- ❑ RI can have different durations (**Super Typhoons usually have long RI durations**)

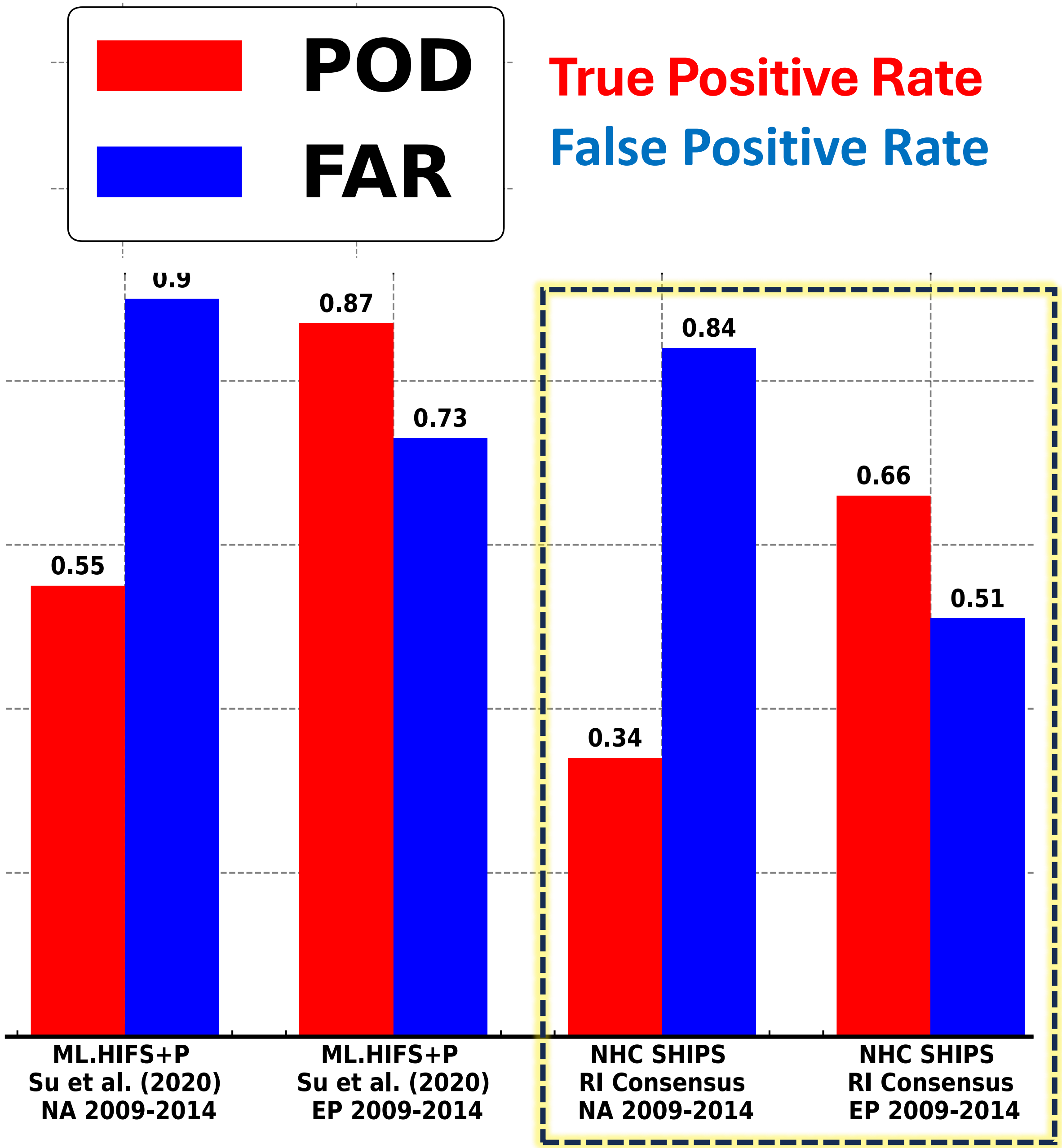
IBTrACS

Poor forecast of RI can lead to:

- ❑ False alarm
- ❑ Distrust of community to authorities
- ❑ Complacency / Panic of LGUs

BACKGROUND Rapid Intensification Prediction with ML

One solution to improve RI forecasts is to utilize numerical models and statistical methods (Wang et al., 2023).



True Positive Rate

False Positive Rate

National Hurricane Center Statistical Hurricane Intensity Prediction Scheme Rapid Intensification Consensys (NHC SHIPS RI Con)

SHIPS RI Consensus utilizes environmental predictors and some satellite-derived infrared features

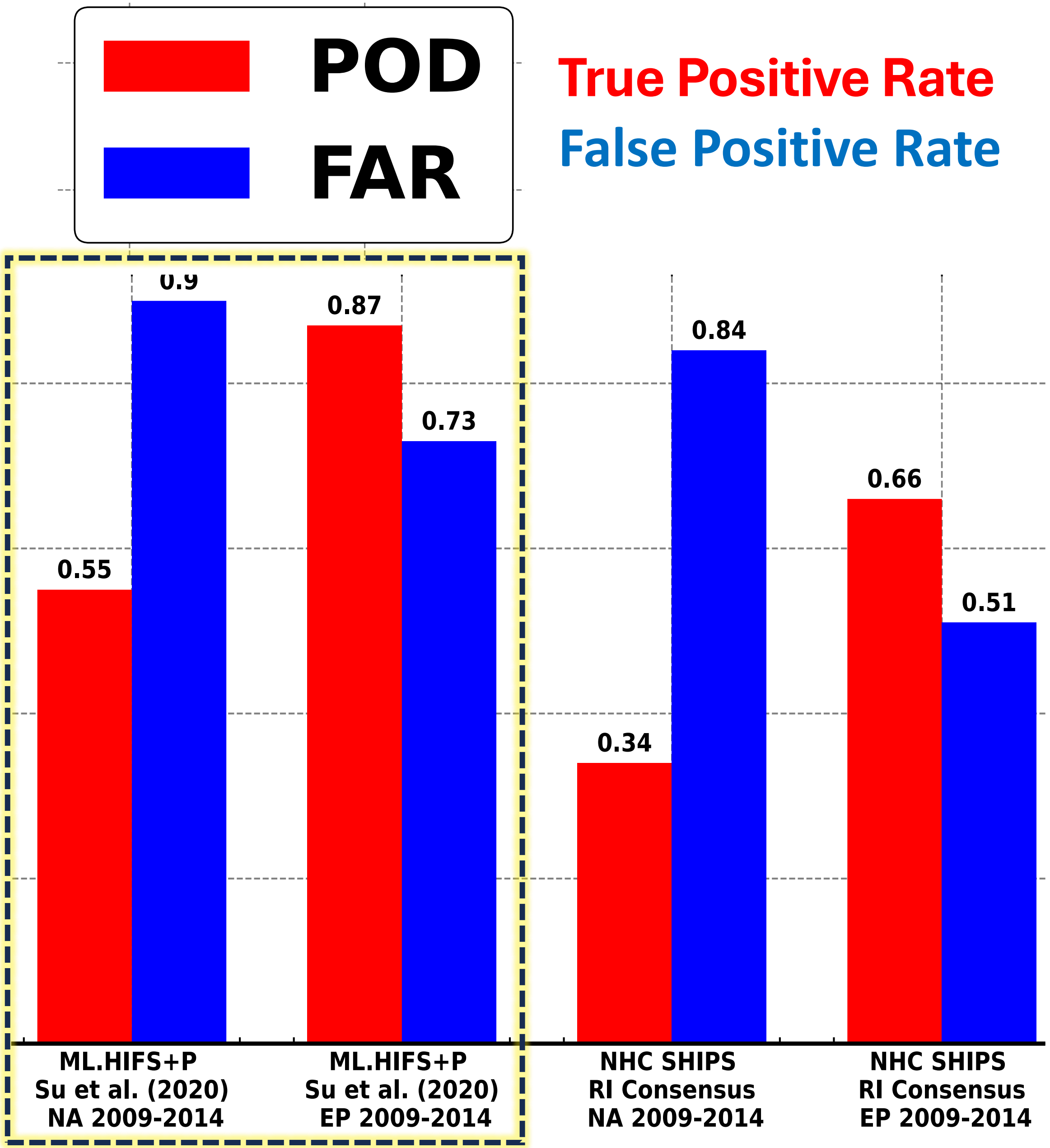
Uses an ensemble of Logistic Regression and Bayesian models

BACKGROUND Rapid Intensification Prediction with ML

Machine Learning Hurricane Intensity Forecasting Scheme plus Precipitation (ML.HIFS+P)

ML.HIFS+P **integrates satellite observed TC internal structures** such as inner-core cloud ice water path and content, outflow temperature, and surplus precipitation, along with environmental predictors from the SHIPS dataset

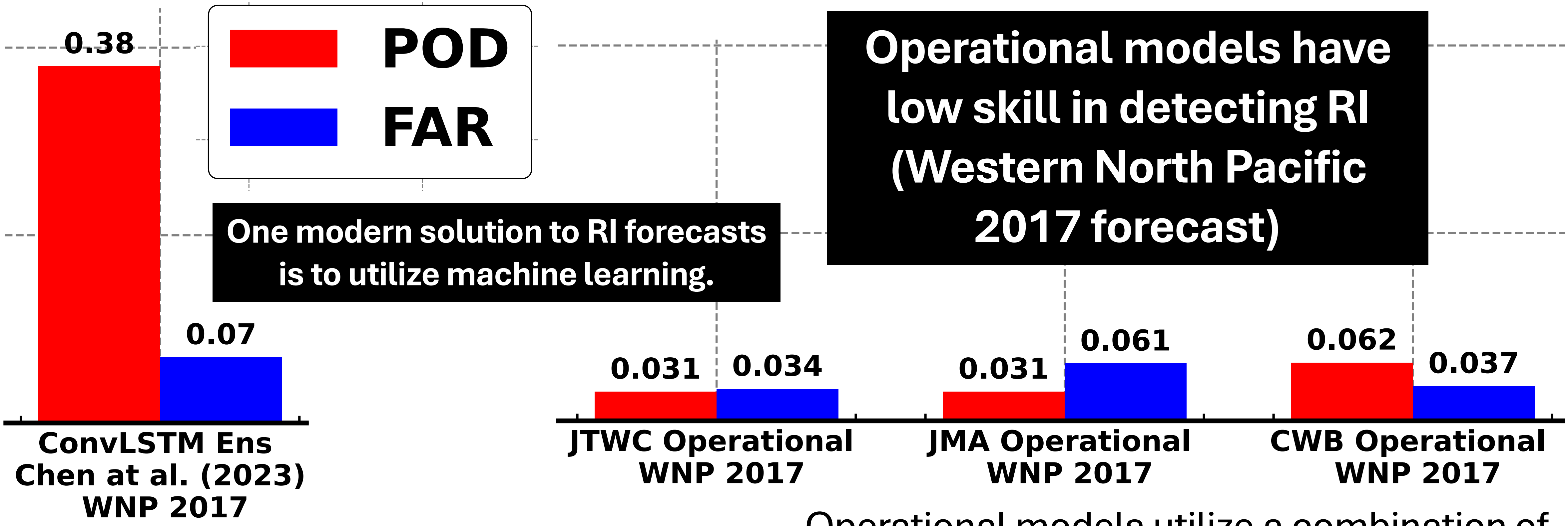
Uses a weighted ensemble of Logistic Regression, Random Forest, Extra Trees, etc.



How did the ML.HIFS+P outperform the best operational model?

- ML techniques instead of statistical techniques
- Internal structures was integrated alongside environmental predictors
- More sophisticated representation of the RI process

BACKGROUND Rapid Intensification Prediction with ML



One modern solution to RI forecasts is to utilize machine learning.

Operational models have low skill in detecting RI (Western North Pacific 2017 forecast)

Ensemble of Convolutional Long-Short Term Memory (ConvLSTM) utilized satellite images of infrared and water vapor (which are internal dynamical processes), and scalar environmental conditions *(Chen et al., 2023)*.

Operational models utilize a combination of numerical models, ensemble forecasting techniques, and statistical methods to predict RI *(Wang et al., 2023)*.

Objectives

To demonstrate the **predictive capability of the wind structure or fullness parameters for TC RI forecasting in the Western Pacific basin** by incorporating it as the features of a ***Long Short-Term Memory (LSTM)*** Model and then evaluating it in various experimental configurations.

- Synthetic Minority Oversampling Technique
- 12 and 24-hour sequences
- Dropouts and Regularization

BACKGROUND | Objectives

Why Western Pacific basin?

- significant to the Philippines
- lack of ML-RI studies in the Western Pacific

Why Wind Structure?

- rapidly intensifying TCs can exhibit a unique wind structure (e.g., high fullness / size, moderate strength)
- wind structure features can be easily derived from best-track datasets (good for quick case studies)
- majority of ML-RI studies utilize environmental predictors and satellite data, which are hard to process and computationally expensive (file format in NetCDF and HDF5)

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METHODOLOGY Dataset (IBTrACS)

Understanding the Dataset – International Best Track Archive for Climate Stewardship (IBTrACS)

A global archive of tropical cyclone data that contains the most accurate and complete information about the tracks and intensity of these storms around the world.

It combines recent and historical tropical cyclone data from multiple agencies to create a consistent, publicly accessible best-track dataset that facilitates agency comparisons.

Reference:

https://www.ncei.noaa.gov/products/international-best-track-archive

METHODOLOGY — Dataset (IBTrACS)

ORIGINAL DATASET:
rows: 243,483 instances of storms in the Western Pacific *(1884 – 2023)*
columns: 163 features / observed storm characteristics by weather stations around the world

CLEANED / TREATED DATASET: (using python pandas)
rows: 5784 instances of storms *(2001-2022)*
columns: 7 (6 as features; 1 target)

Domain knowledge-guided filtering: (backed by literature)

- recent storms (yr 2001+) – climatological characteristics
- intensifying cases (no weakening) – we are focused on intensification
- negative fullness values are omitted – to reduce noise and better data quality

Guo & Tan 2017; 2022

METHODOLOGY Wind Structure Features

Features	Description
Vmax	1-min. Maximum Sustained Winds; the intensity or strength of a TC. *(units: kt)*
RMW	Radius of Maximum Wind; distance from TC center to its band of strongest winds. *(units: nmile)*
R34	Radius of the 34 kt Wnds; distance from the TC center to the gale-force winds. *(units: nmile)*
Derived Features	
TCF	Tropical Cyclone Fullness; the size of the outer annular wind ring (R34-RMW) relative to the outer-core size (R34), and the size part of fullness *(unitless)* Mathematically equivalent to: *1 – RMW/R34*
TCF0	Tropical Cyclone Critical Fullness; the intensity part of fullness. *(unitless)* Mathematically equivalent to: *1 – 33 kt / Vmax*
RF	The ratio of fullness; simply the ratio between TCF and TCF0. *(unitless)*

```
df['TCF'] = 1 - (df['USA_RMW']/df['USA_R34_NE'])
df['TCF0'] = 1 - (33/df['USA_WIND'])
df['Rf'] = df['TCF']/df['TCF0']
```

$$TCF = 1 - \frac{RMW}{R34}$$

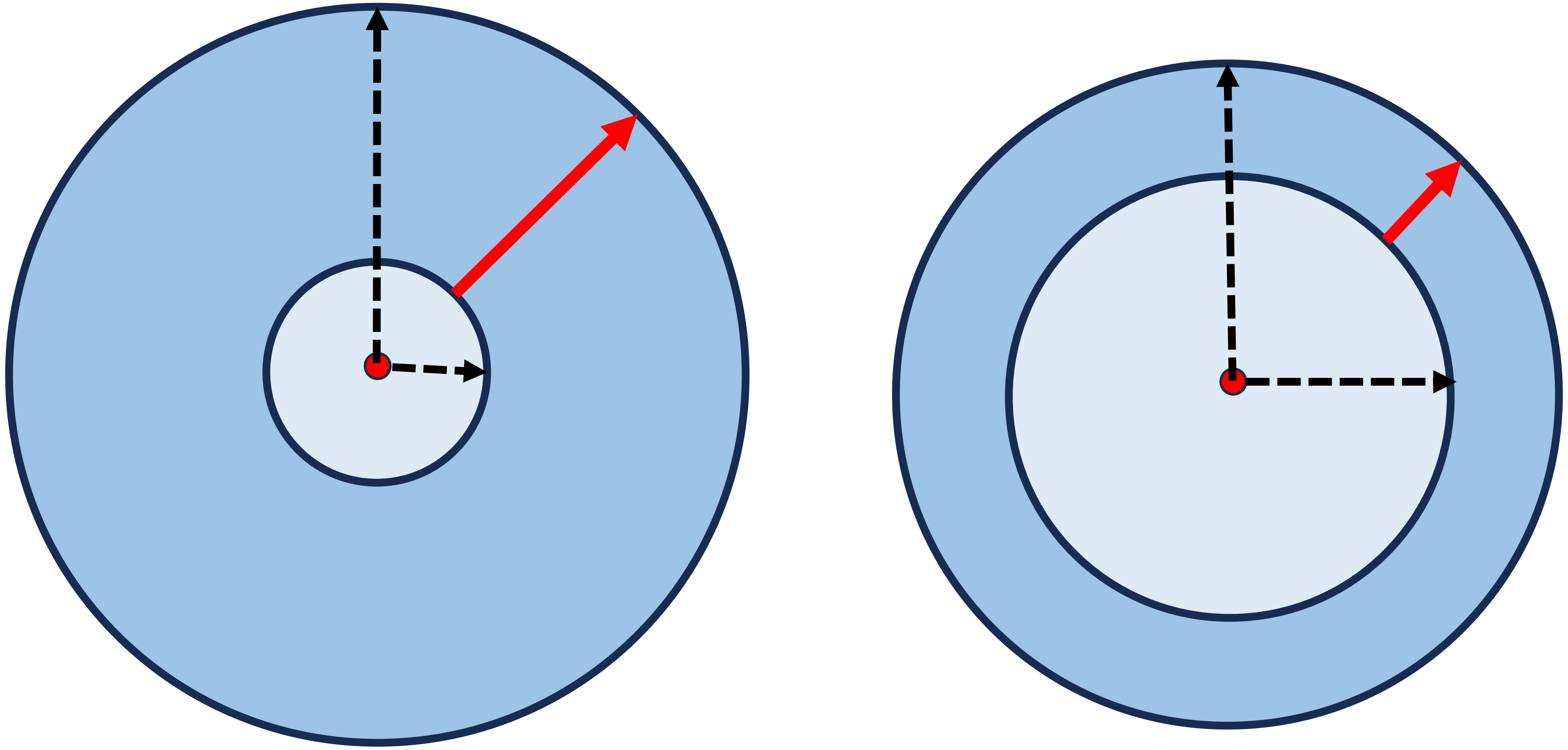
$$TCF0 = 1 - \frac{V34}{Vmax}$$

$$\mathrm{RF} = \frac{TCF}{TCF0}$$

BACKGROUND — TC Wind Structure

Features (2)
Storm Size / TC Fullness
Storm Strength / Critical Fullness

Red Arrow = difference of the dotted black lines / difference of the two radii



“LARGE” Storm

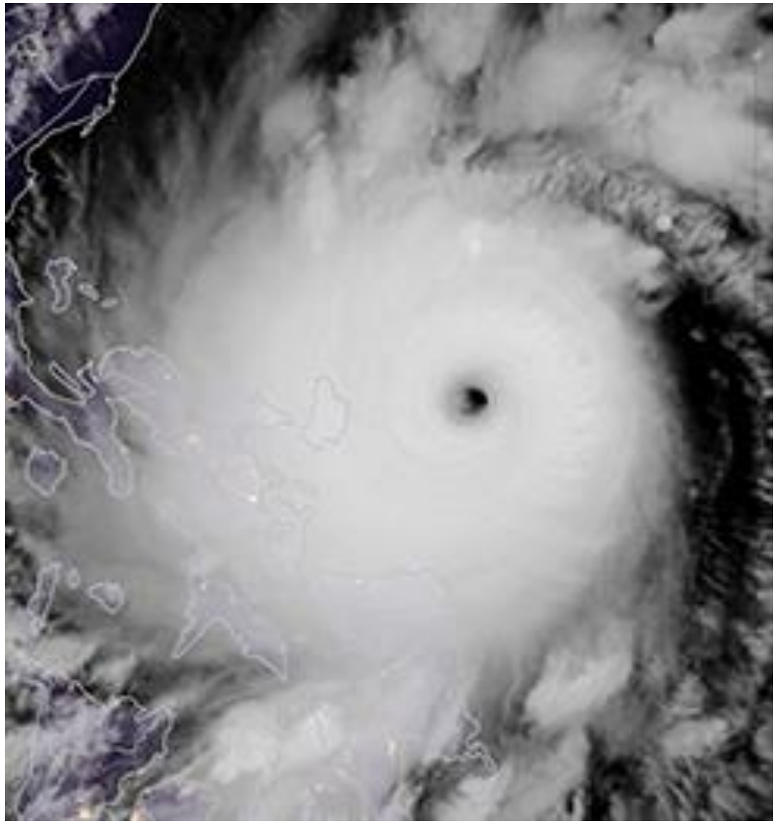
LARGE RED ARROW

“Small” Storm

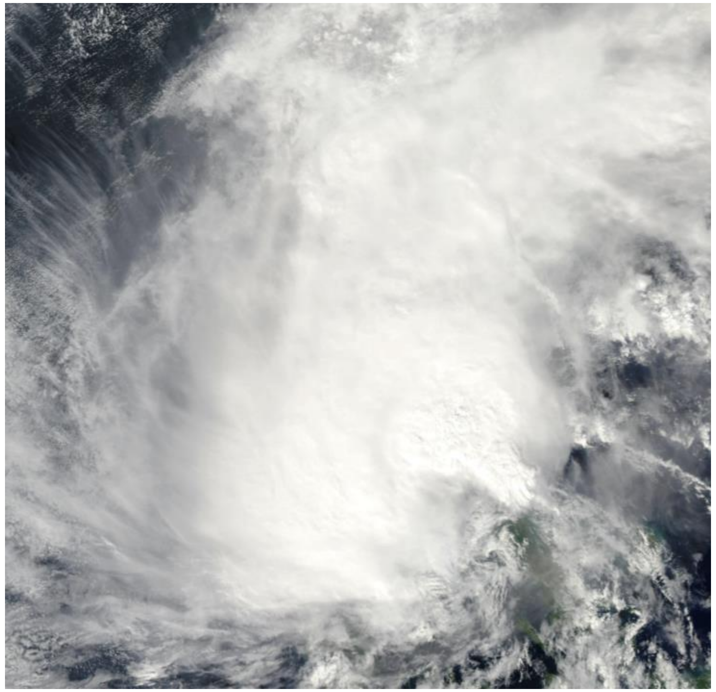
Small Red Arrow

BACKGROUND — TC Wind Structure

Features (2)
Storm Size / TC Fullness
Storm Strength / Critical Fullness



Super Typhoon Goni (2020)
Large Storm

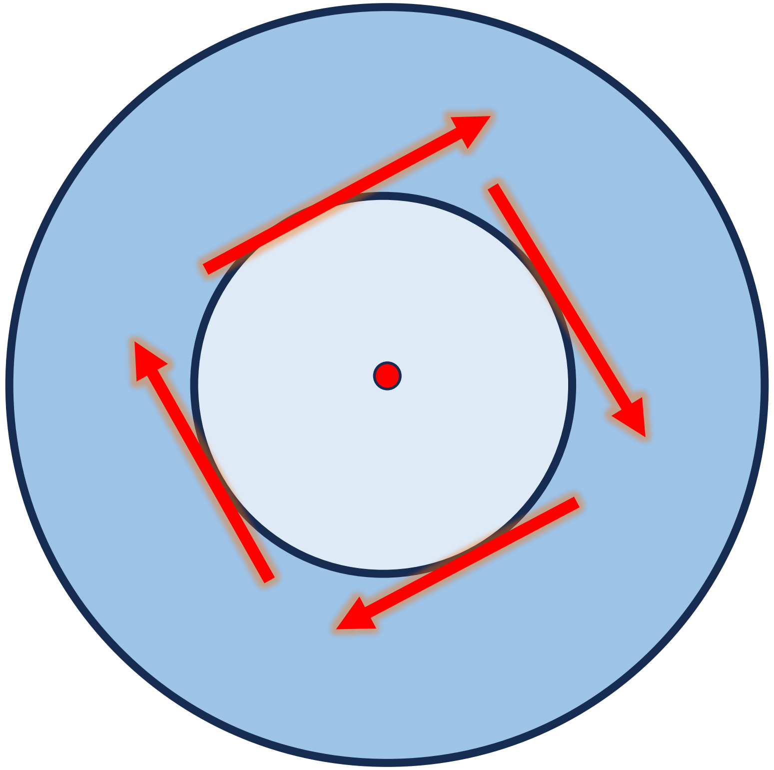


Tropical Depression Winnie (2004)
Small Storm

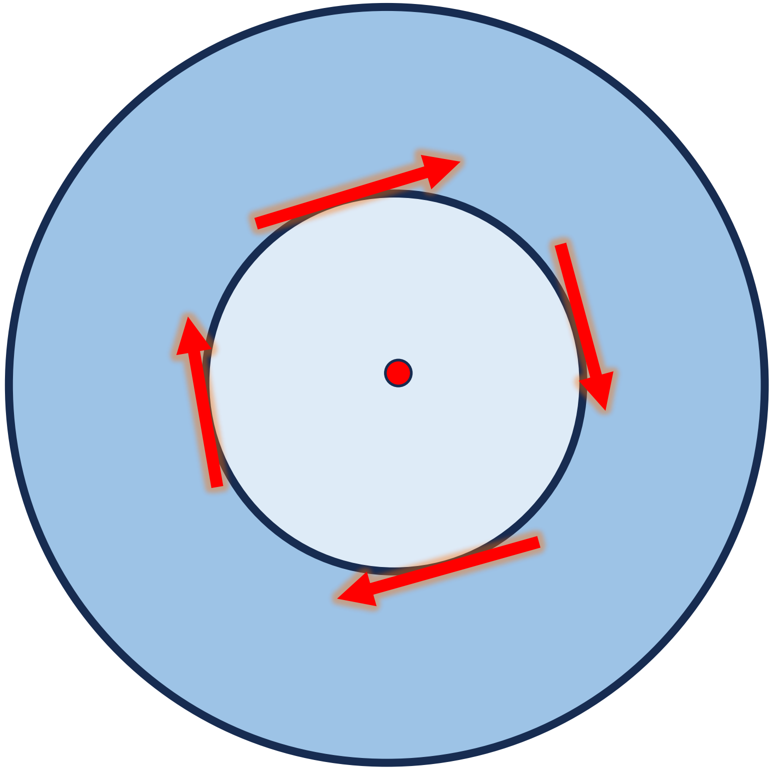
BACKGROUND — TC Wind Structure

Red Arrow = **tangential winds**

Features (2)
Storm Size / TC Fullness
Storm Strength / Critical Fullness



"Intense" Storm
Strong (Fast) Winds



"Weak" Storm
Weak (Slow) Winds

METHODOLOGY | Rolling Window Data Sampling

*one time step means six hours

Time*	Environment features	Storm features	Intensity
0			v_0
1			v_1
2	...	...	v_2
3			v_3
4			v_4
5			v_5
6	...	...	v_6
7			v_7
8			v_8
9			v_9
10	...	...	v_{10}
11			v_{11}
12			v_{12}
...			...

A Long Short-Term Memory Model for Global Rapid Intensification Prediction

Qidong Yang, Chia-Ying Lee, and Michael K. Tippett

Online Publication: 05 Jun 2020

Print Publication: 01 Aug 2020

DOI: https://doi.org/10.1175/WAF-D-19-0199.1

Page(s): 1203–1220

Do rolling window sampling with overlapping to create more instances of sequences.

(Our data has 3 hr per step)

- 12-hr sequence: 5 data points
- 24-hr sequence: 9 data points

one extra time step is due to the inclusion of the current observation

METHODOLOGY Rolling Window Data Sampling

TC Name	Time	Vmax	RMW	R34	TCF	TCF0	RF	Intensification Category
Goni	1							Slow Intensification (0)
Goni	2							Slow Intensification (0)
Goni	3							Slow Intensification (0)
Goni	4							Slow Intensification (0)
Goni	5							Rapid Intensification (1)
Goni	6							Rapid Intensification (1)
Goni	7							Rapid Intensification (1)
Goni	8							Rapid Intensification (1)
Haiyan	1							Slow Intensification (0)
Haiyan								
Haiyan								
Haiyan								
Haiyan								
Haiyan								

For example, with **8 time steps**,
we can create **4 sequences of data with 5 time steps**

Group by TC Name and Season for temporal consistency

METHODOLOGY Rolling Window Data Sampling

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METHODOLOGY

Rolling Window Data Sampling

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METHODOLOGY

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For example, with **8 time steps**,
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Group by TC Name and Season for temporal consistency

METHODOLOGY — Experiment Setup

Train Test Split: ***(Yang et al. 2020; Su et al. 2020)***

- **train (2001-2018), test (2019-2022)**
- **reason for this split:** temporal consistency (train on past, predict on future)

Number of Samples:

- **train: 4836** (NRI - 3605 & RI - 1231)
- **test: 948** (NRI – 699, RI – 249)

Resolve Class imbalance in the training set with SMOTE

- multiple TC RI studies have shown that resolving the class imbalance leads to better model performance ***(Yang 2017; Chandhra 2017; Yang et al. 2020)***
- model tends to biased toward the majority class and hence, the cost function ***(binary cross-entropy)*** will prioritize minimizing errors on the majority class

$$-\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1-p(y_i))$$

METHODOLOGY Experiment Setup

Model:

- Long-Short Term Memory (LSTM) Classifier

Hyperparameters:

- units = 50
- learning rate = 0.001
- batch size = 32
- epochs = 100
- validation split = 0.20
- optimizer = Adam

Evaluation (straightforward evaluation for interpretability)

- Probability of Detection **(POD; True Positive Rate) &** False Alarm Ratio **(FAR; False Positive Rate)**

METHODOLOGY

Experiment Setup

EXP 1: Base Model

No oversampling

Hyperparameters:

- units = 50, learning rate = 0.001, batch size = 32, epochs = 100, optimizer = Adam, val_split = 0.20

EXP 2: W/ SMOTE

SMOTE (oversampling)

Hyperparameters:

- units = 50, learning rate = 0.001, batch size = 32, epochs = 100, optimizer = Adam , val_split = 0.20

EXP 3: W/ SMOTE & Regularization

SMOTE (oversampling)

Hyperparameters:

- units = 50, learning rate = 0.001, batch size = 32, epochs = 100, optimizer = Adam , val_split = 0.20
- kernel regularizer = 0.01, recurrent regularizer = 0.01, dropout = 0.20

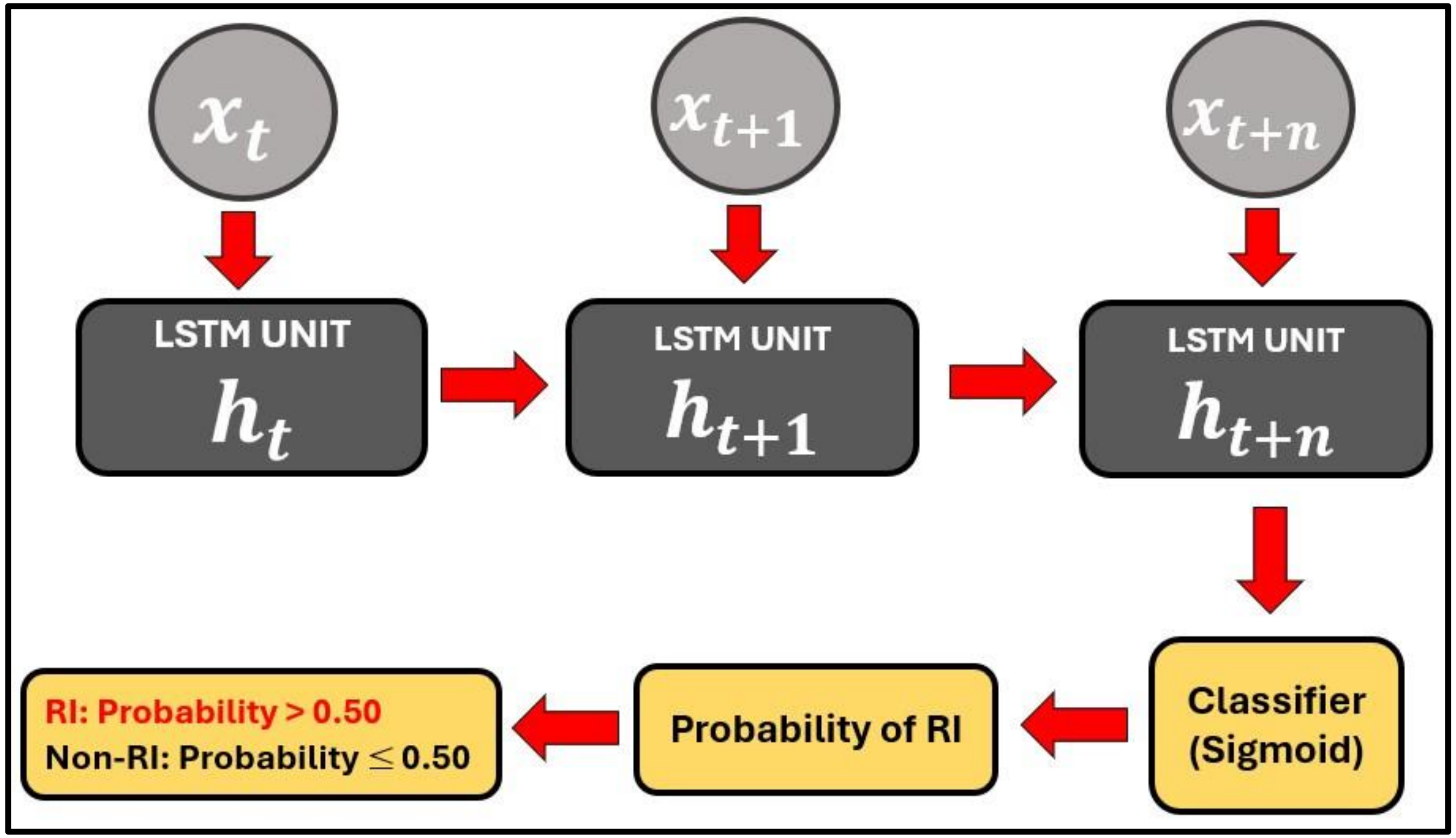
EXP 4: W/ SMOTE & Stronger Regularization

SMOTE (oversampling)

Hyperparameters:

- units = 50, learning rate = 0.001, batch size = 32, epochs = 100, optimizer = Adam , val_split = 0.20
- kernel regularizer = 0.001, recurrent regularizer = 0.001, dropout = 0.20

METHODOLOGY Long-Short Term Memory (LSTM)



The model in this study is composed of an **LSTM unit** and a **classifier unit**.

The **LSTM is used as a feature extractor**. A sample, which consists of the features with n length of sequence and it is fed to the LSTM one by one in time sequence.

After inputting, the LSTM's current state is generated, denoted by h.

As samples are fed into the LSTM in time sequence, the state of the LSTM unit is updated, allowing the LSTM to capture the temporal characteristics of the sequence.

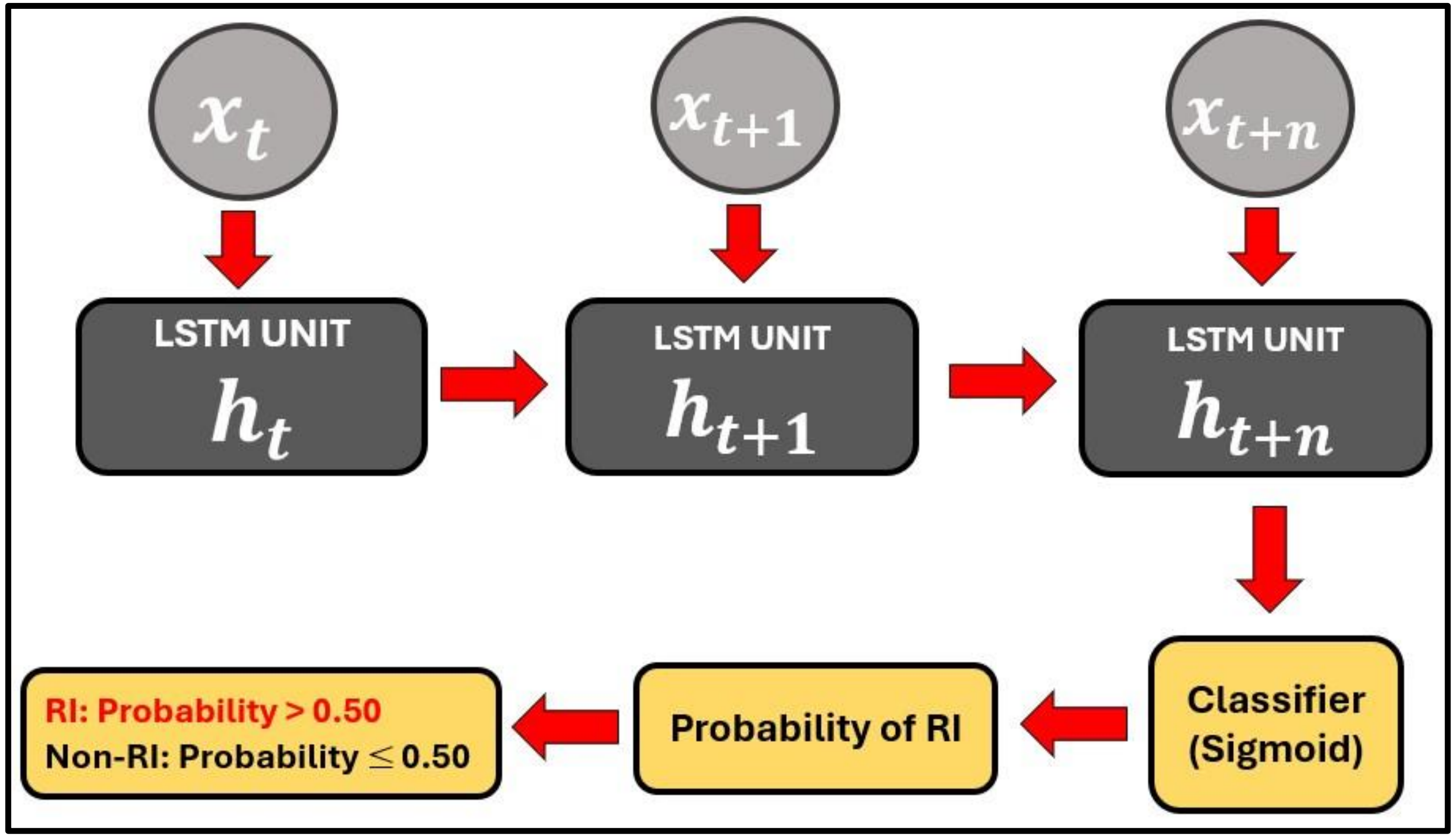
Yang et al. 2020

METHODOLOGY Long-Short Term Memory (LSTM)

The final state ht+n is now a condensed representation of the samples.

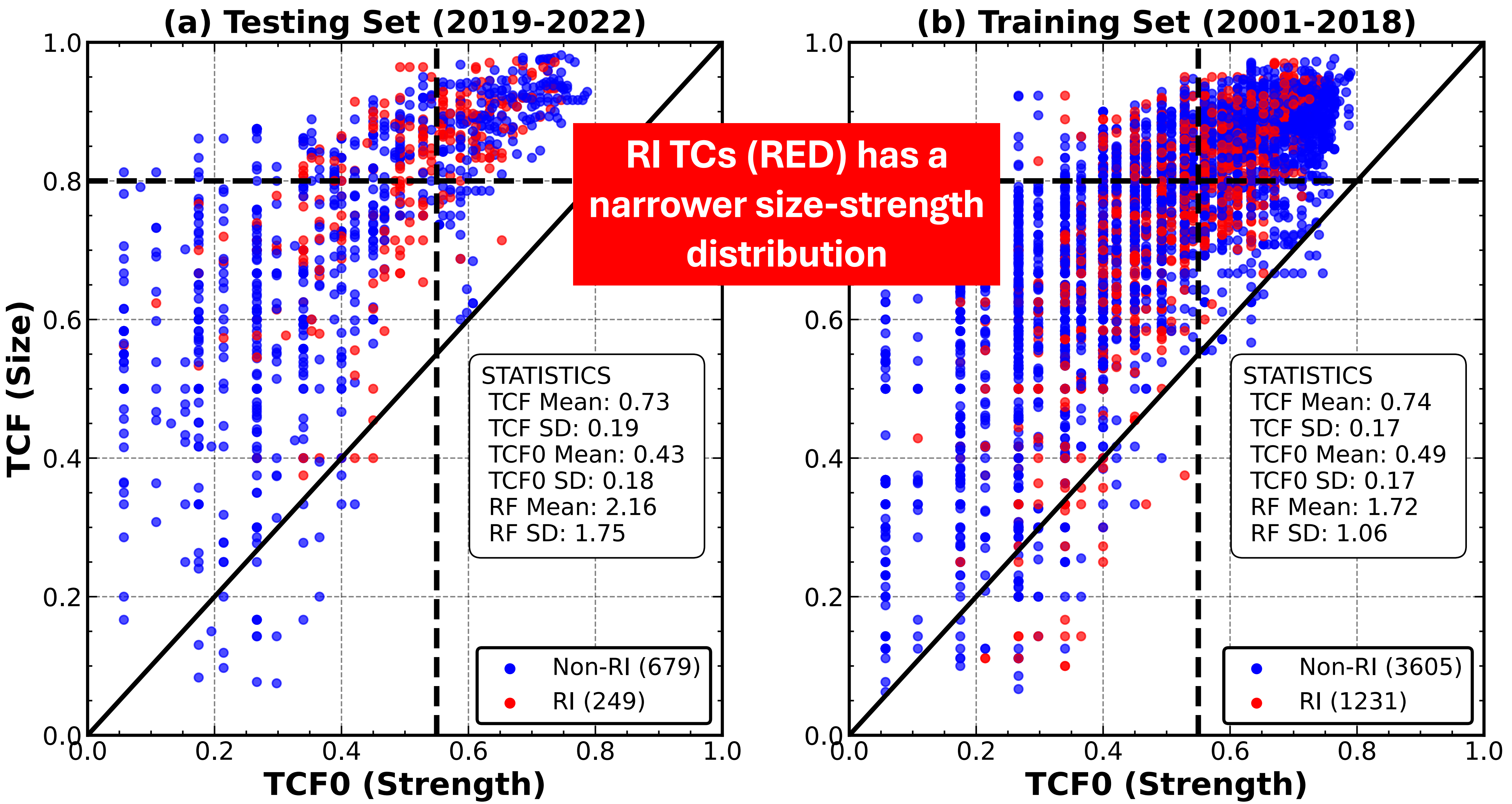
This will then be fed into a **classifier** unit with a sigmoid activation function that outputs the **probability of RI**.

For outputs above **0.50 probability, the LSTM model classifies the prediction as RI**, and Non-RI if otherwise.



Yang et al. 2020

Wind Structure — Exploratory Data Analysis



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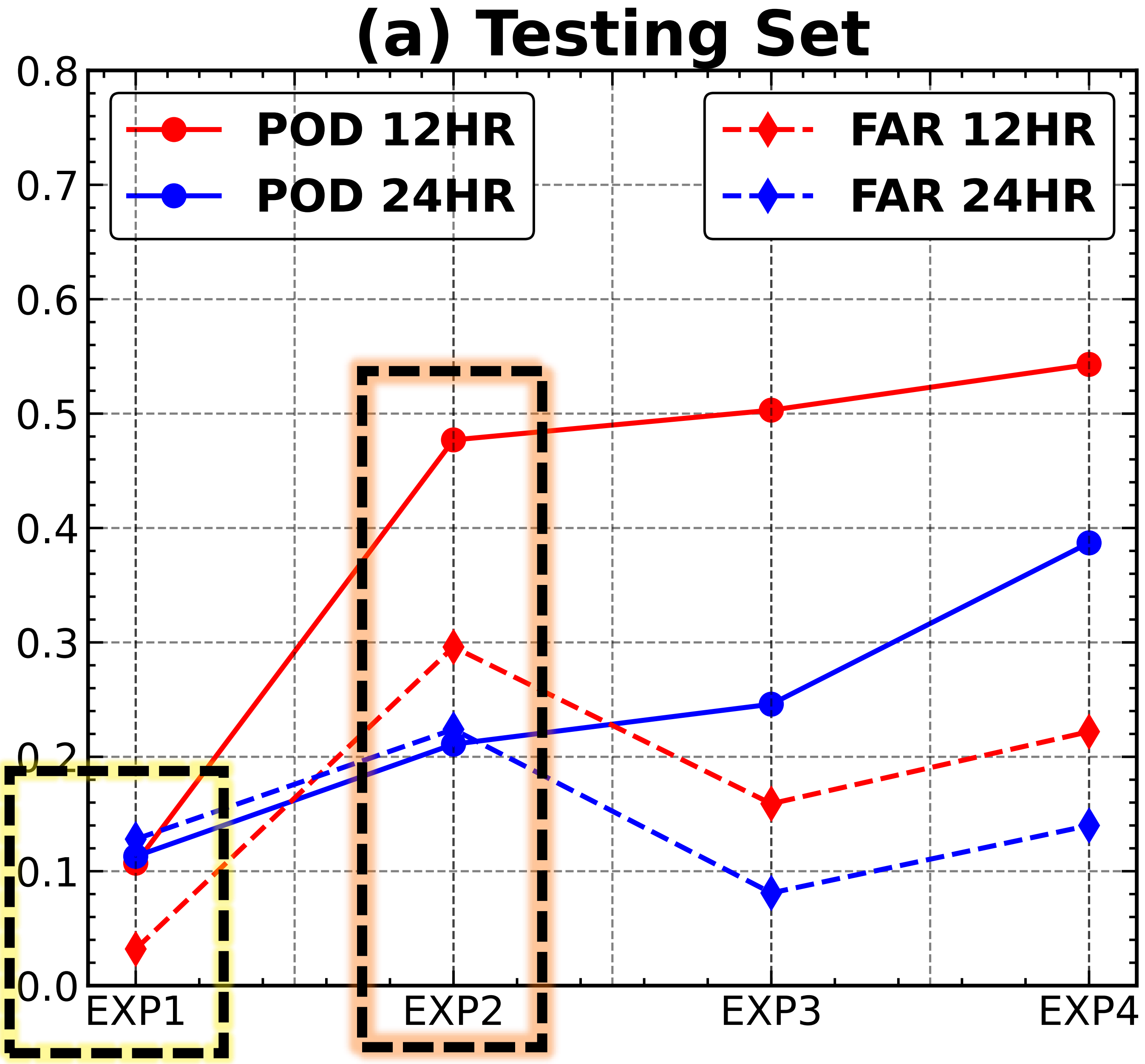
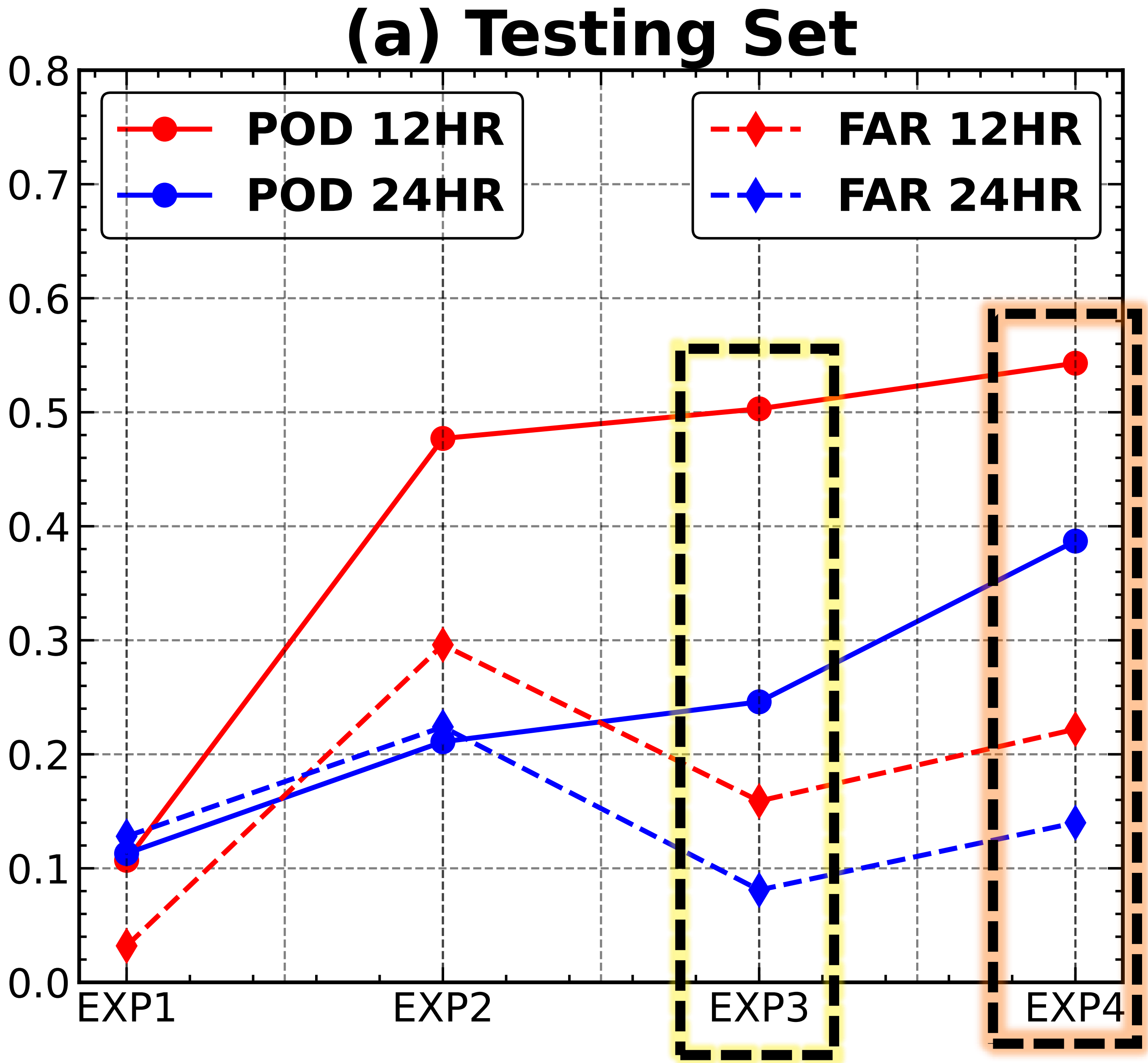
INITIAL RESULTS — POD and FAR for each experiment



For both 12 and 24-hr LSTM models in the testing set EXP 1 exhibited the worst performance in detecting RI due to the class imbalance. The models might prioritize optimizing accuracy for the majority class at the expense of misclassifying instances for the minority class.

When SMOTE was employed in EXP 2, the POD increased, as the model learned in balance class instances. However, FAR also increased as the LSTM models made errors in misclassifying Non-RI instances as RI.

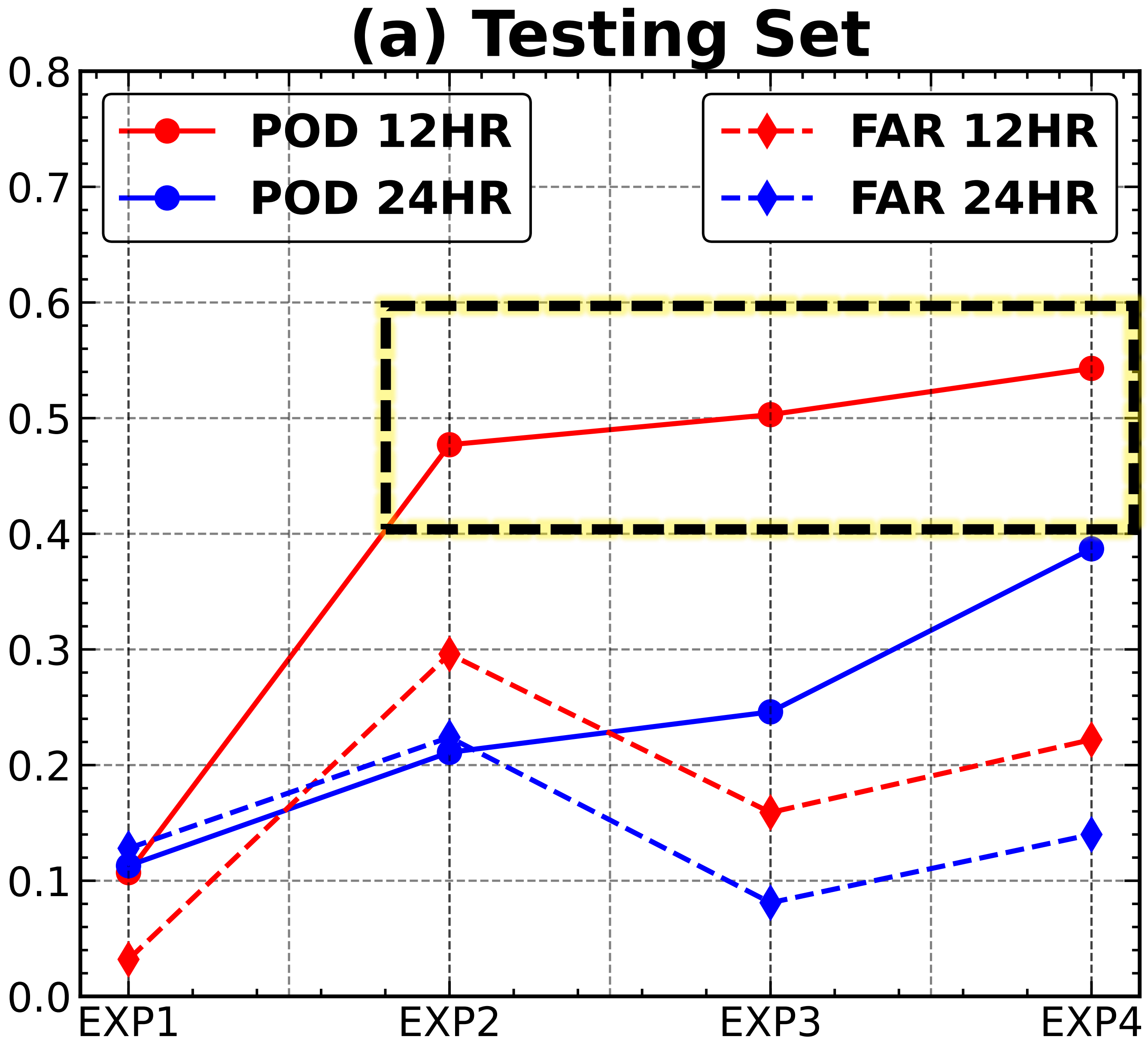
INITIAL RESULTS — POD and FAR for each experiment



The introduction of dropout and regularization in EXP 3 addressed the overfitting issue that resulted in an increased POD with a corresponding decrease in FAR. This indicates that the models improved at detecting RI while keeping false alarms low.

However, in EXP 4, stronger regularization has been detrimental to the overall model performance. Although the POD increased for both models, the FAR also increased.

INITIAL RESULTS POD and FAR for each experiment

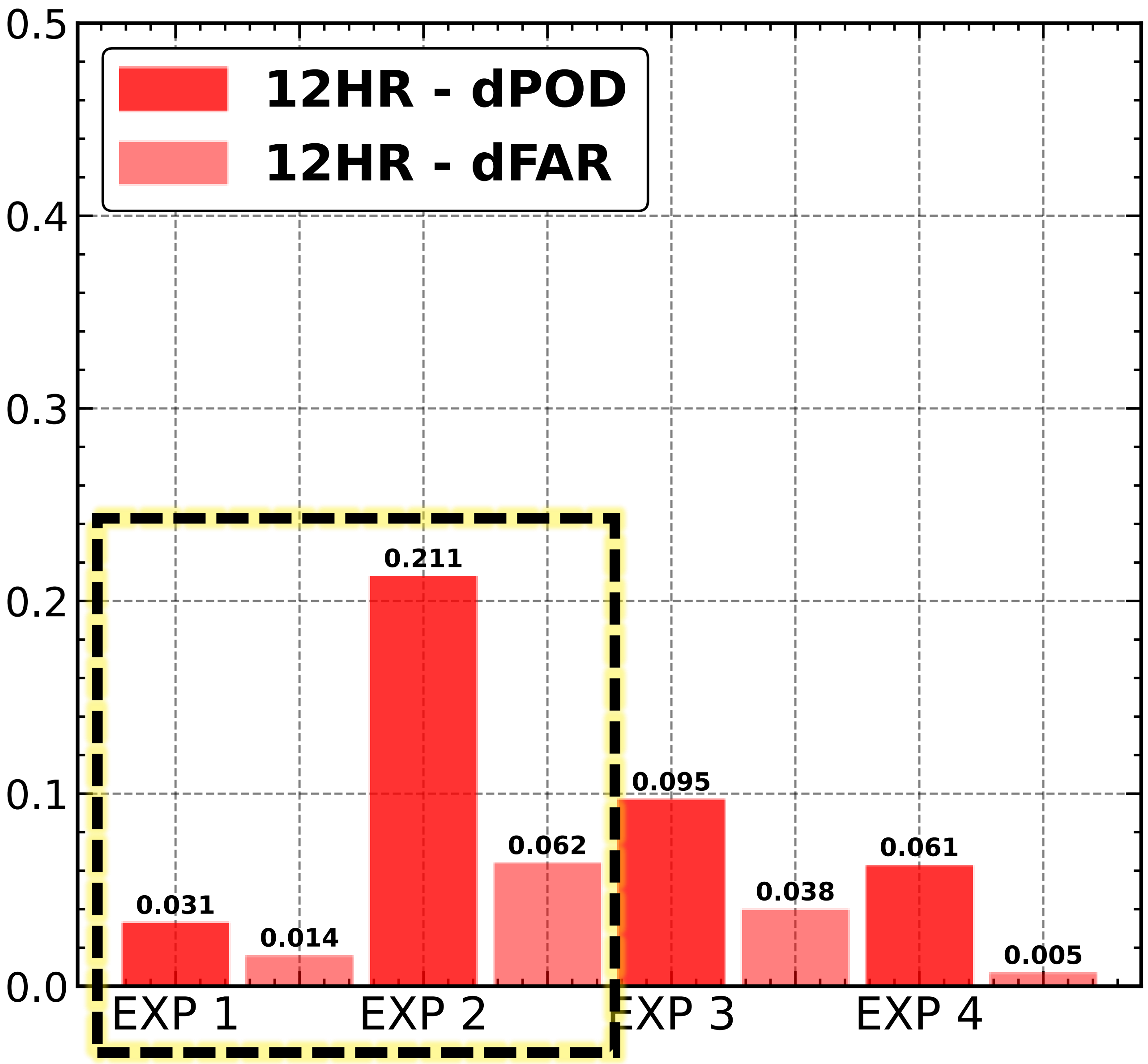


It is important to note that the **12-hr LSTM model has consistently outperformed the 24-hr LSTM model across 3 experiments**, indicating that shorter sequences are more effective for RI prediction than longer sequences.

shorter sequences captured the most relevant and recent information, leading to better model generalization

the results indicate that applying the right blend of regularization can achieve optimal model performance on the testing set.

INITIAL RESULTS POD and FAR for each experiment



To better assess model generalization, the absolute differences of both POD (dPod) and FAR (dFAR) between the training and testing sets for the LSTM model across all experiments are shown.

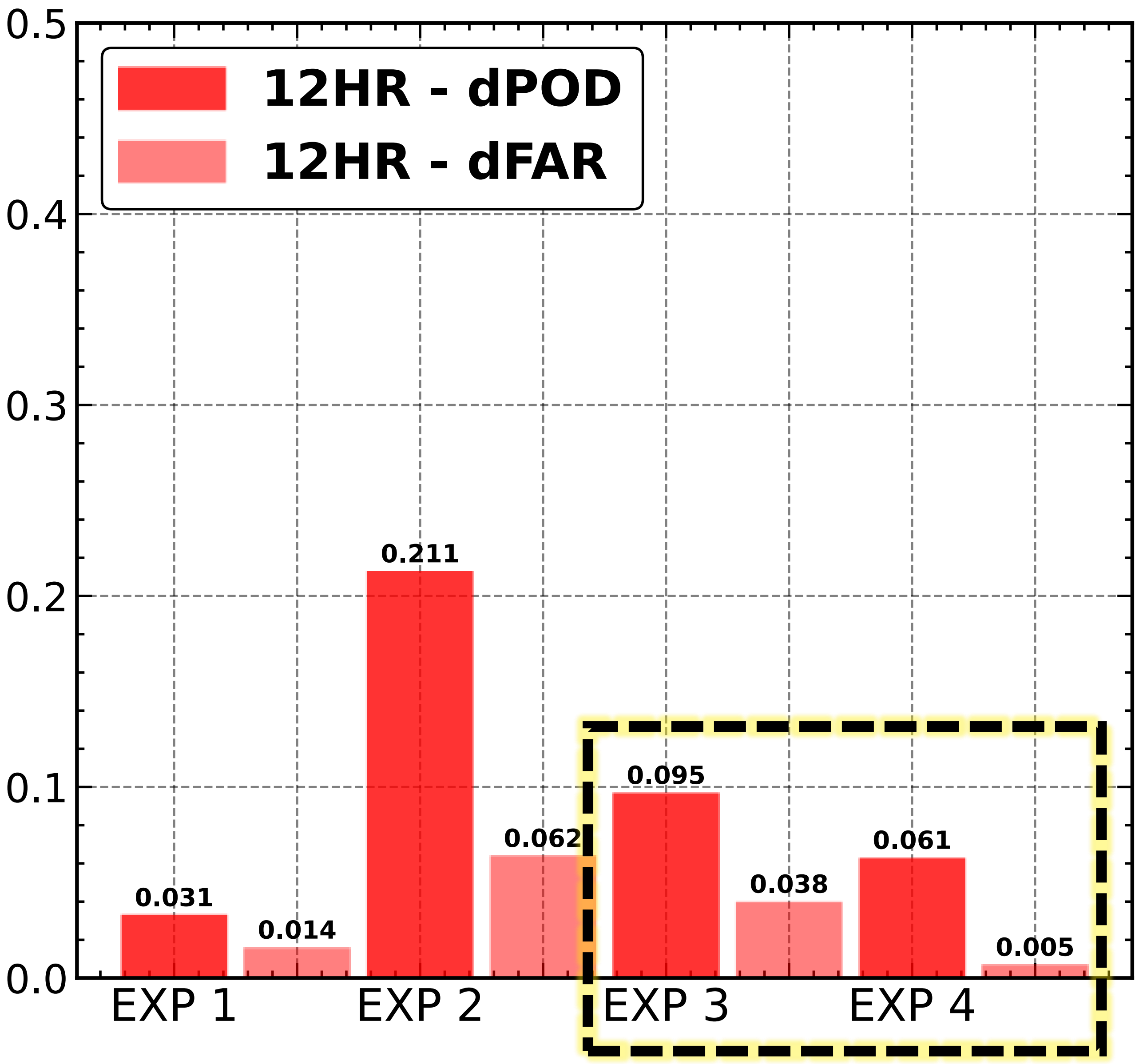
For the 12HR model, the initial experiment shows the lowest dPOD and dFAR, indicating minimal difference between the two sets, suggesting a stable but potentially underfitted model.

As expected, introducing SMOTE leads to the highest dPOD and dFAR, suggesting a potentially overfitting model.

Adding dropout and regularization to the model reduced dPOD and dFAR, suggesting that the model is now generalizing better. Further strengthening regularization (EXP 4) further reduced both dPOD and dFAR.

INITIAL RESULTS

POD and FAR for each experiment



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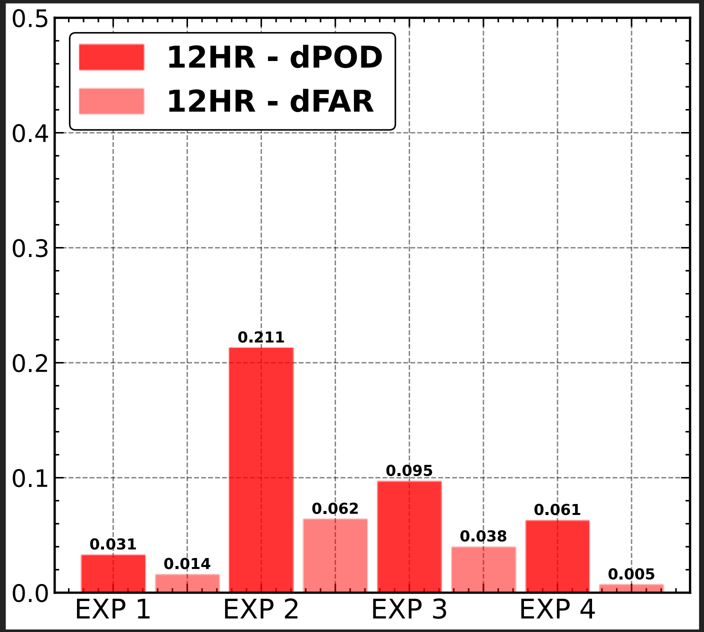
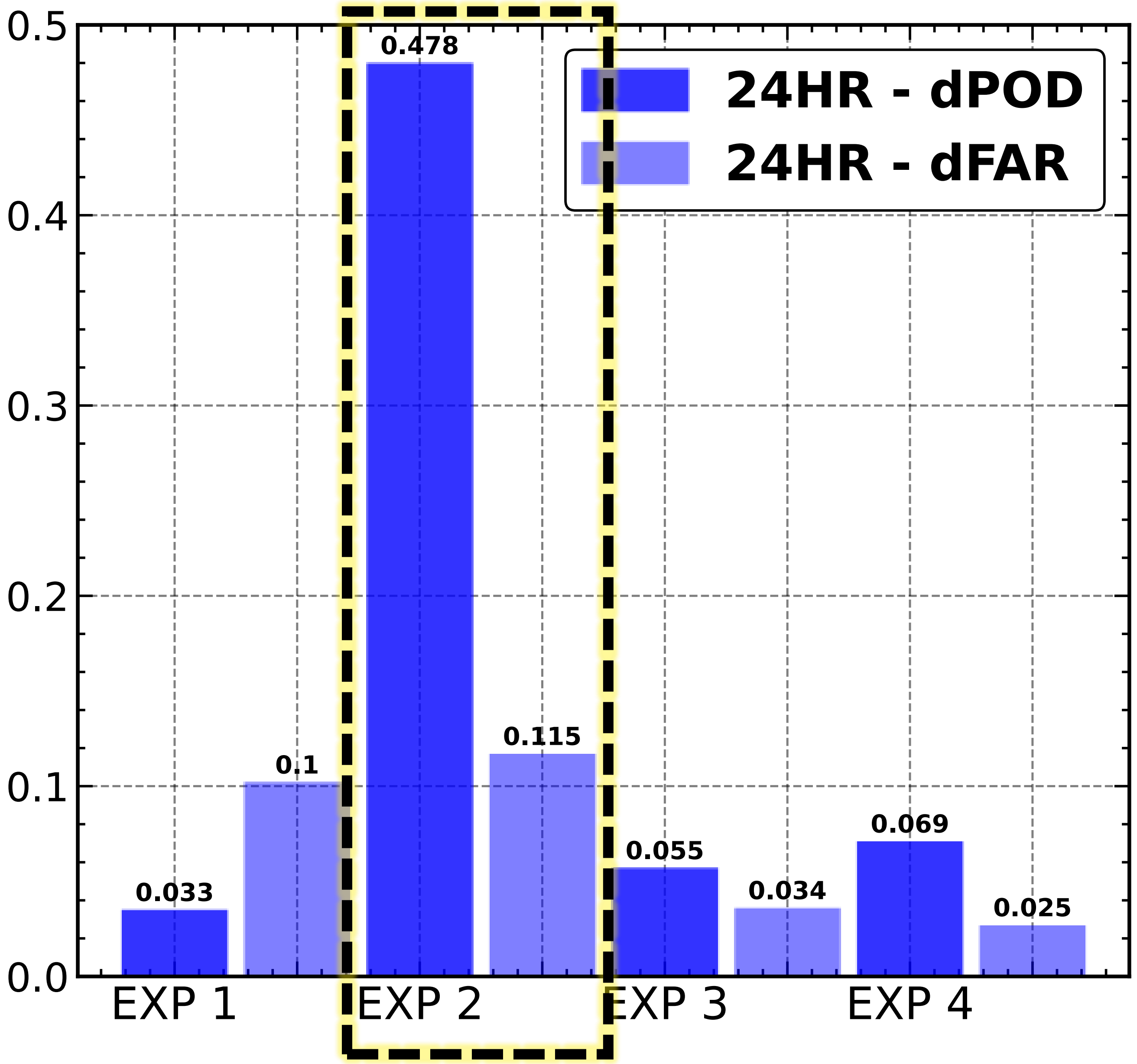
INITIAL RESULTS

POD and FAR for each experiment



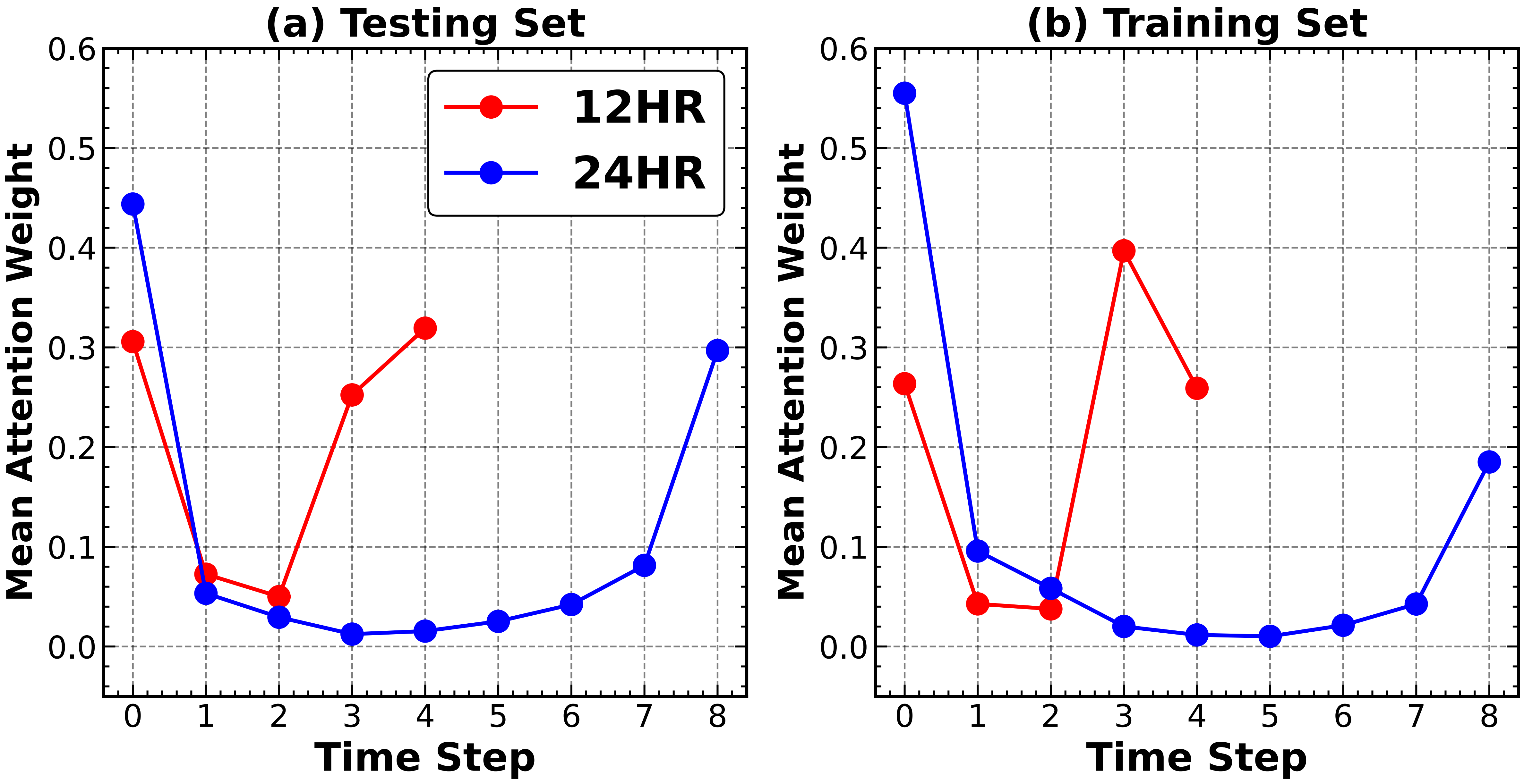
dPOD and dFAR of the 24HR model are generally higher than that of the 12HR model (EXP 1, EXP 2, EXP 4), especially in EXP 2.

This indicates that the 24HR model overfits more than the 12HR model, as expected since the shorter sequence can learn with less complexity, potentially reducing overfitting.

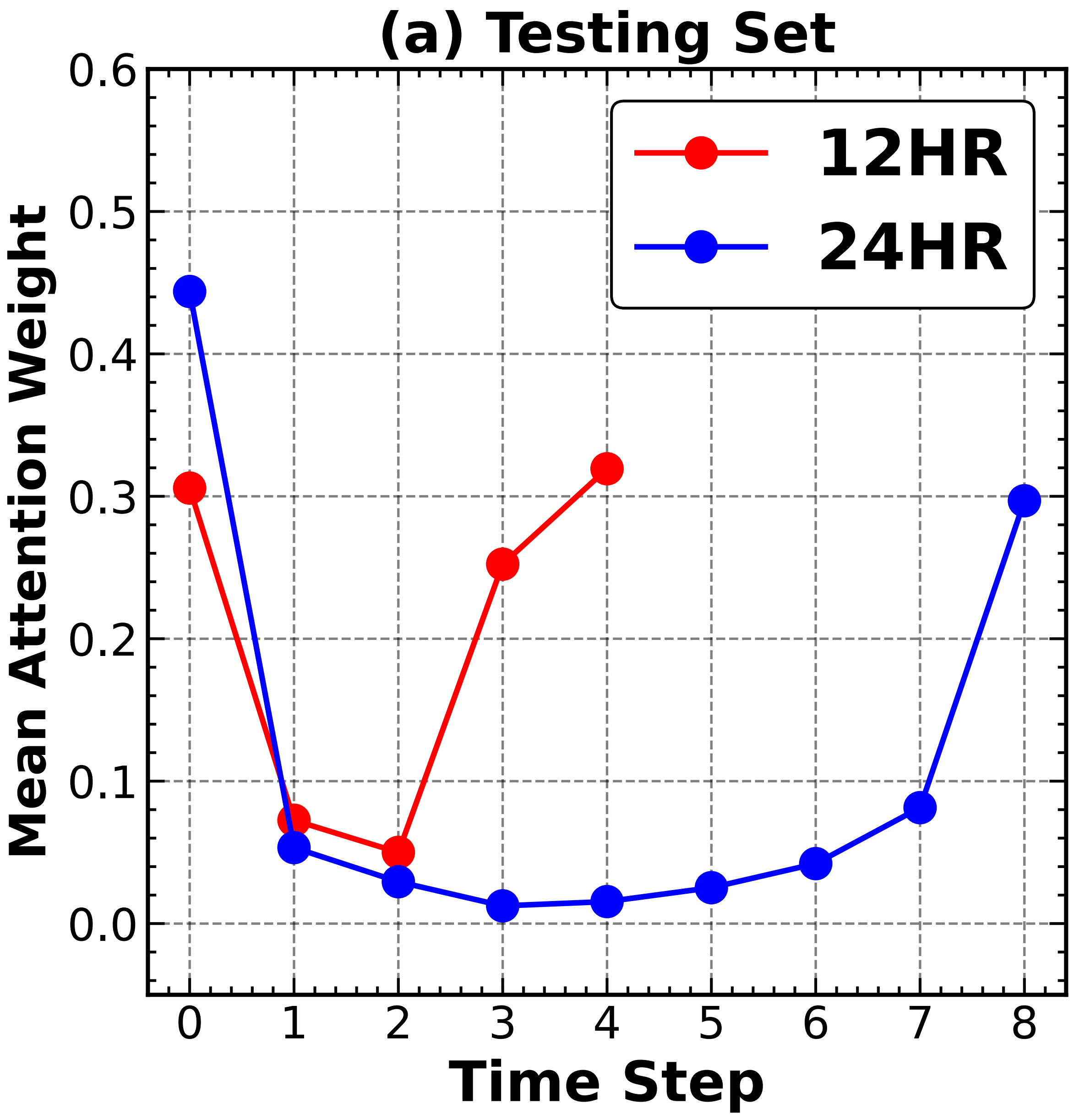


INITIAL RESULTS

Attention Weights



INITIAL RESULTS Attention Weights

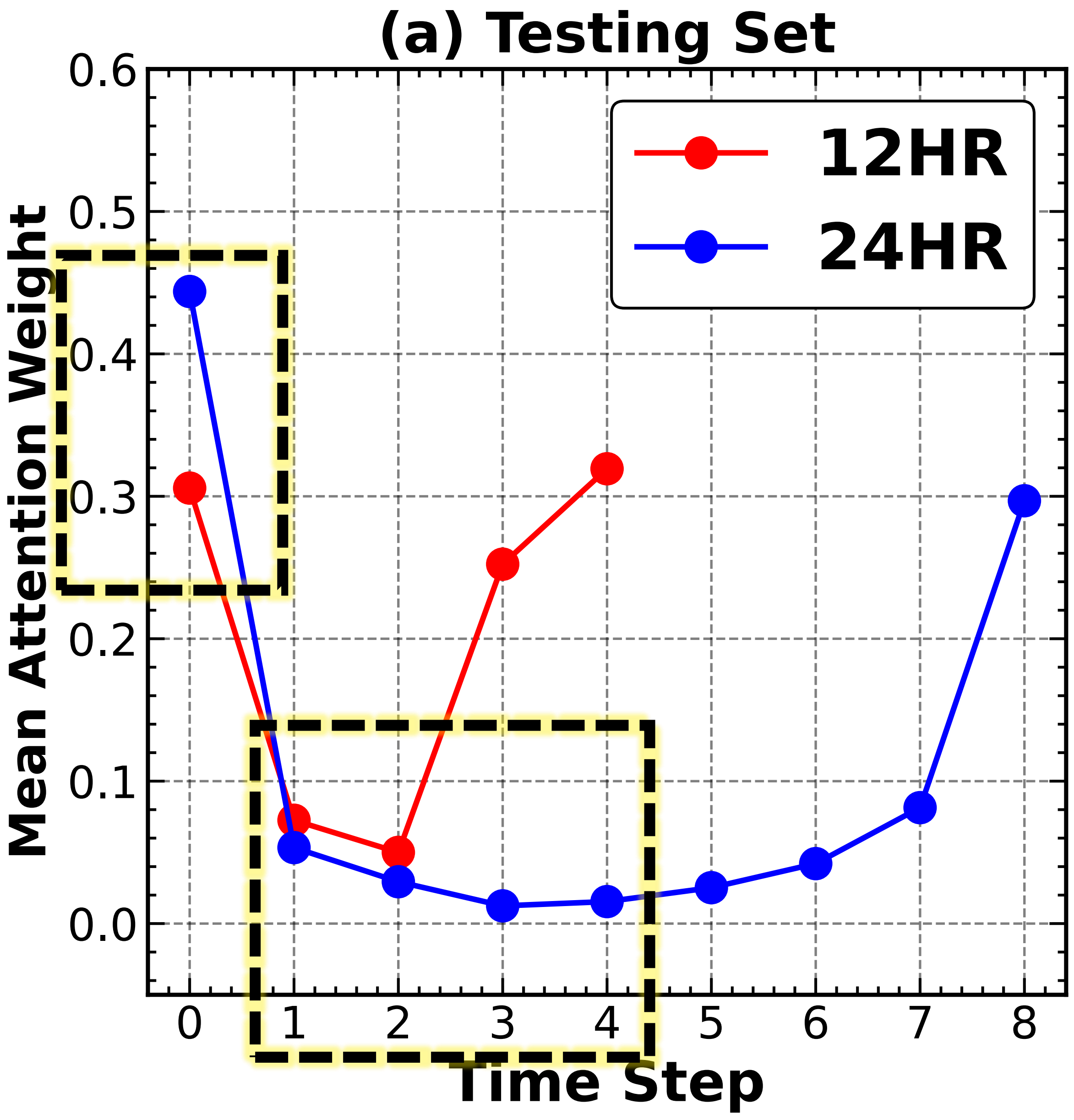


To provide insight into the temporal significance assigned by the LSTM models at different time steps, the **mean attention weights** of the two LSTM models on both testing and training sets are shown.

The EXP 2 was chosen as this experiment does not involve dropout and regularization.

INITIAL RESULTS

Attention Weights



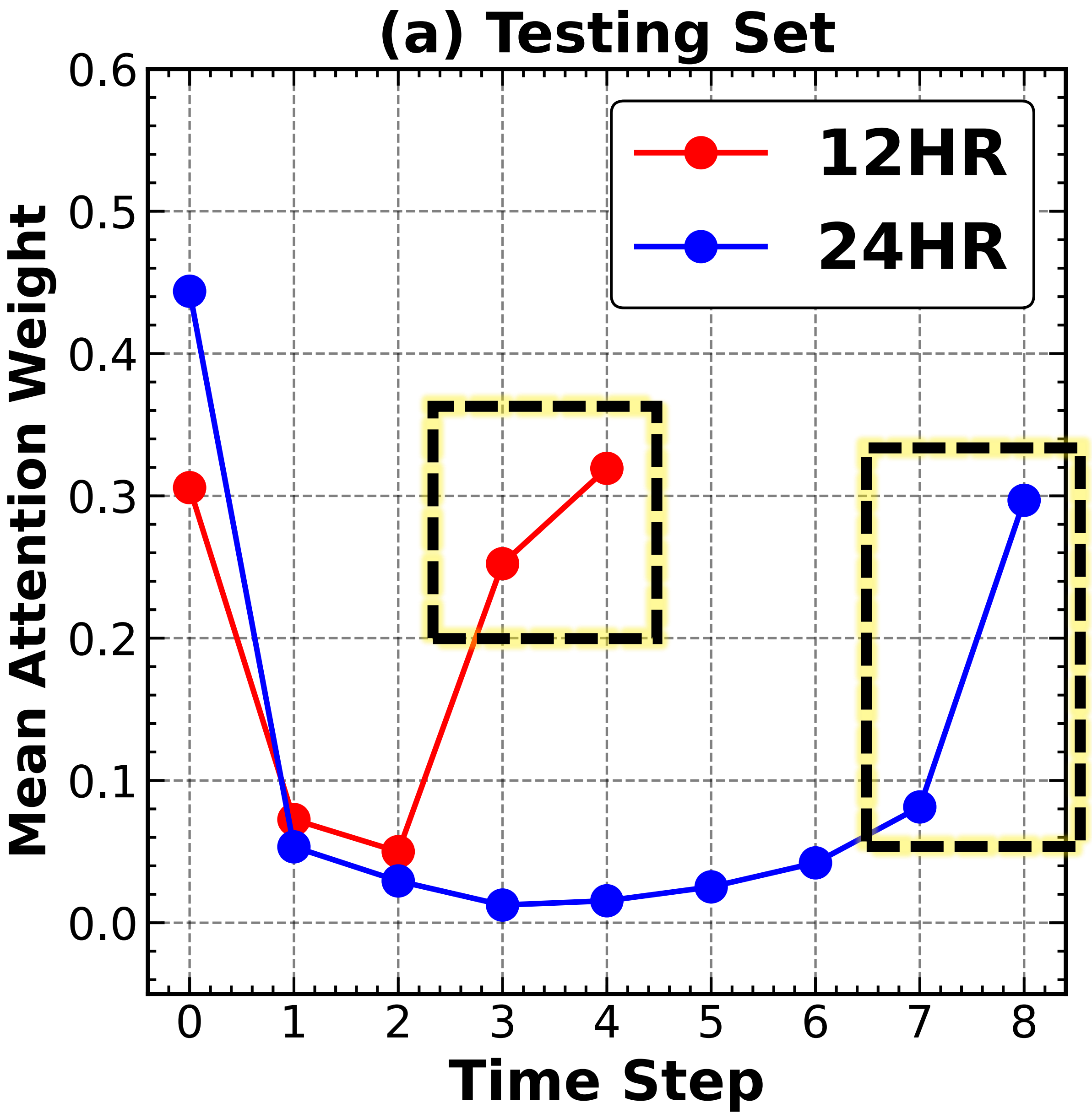
Both models have high attention weights on the initial time step. Then, both models follow similar trends on the subsequent and intermediate time steps where a sharp and then a steady decrease in attention weight occurs.

Next, the attention weight increased sharply for the 12HR model in the last two time steps, particularly in the second to the last time step.

For the 24HR model, the attention weight increased sharply at the last step.

INITIAL RESULTS

Attention Weights



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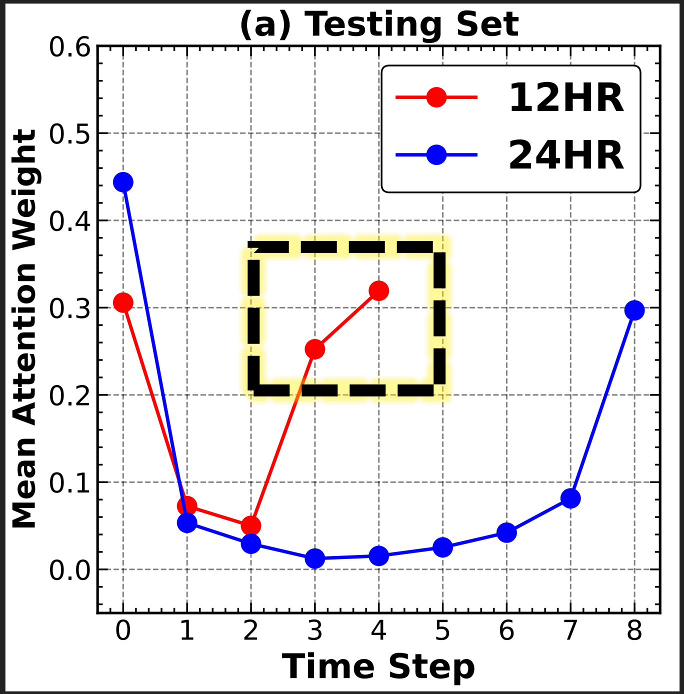
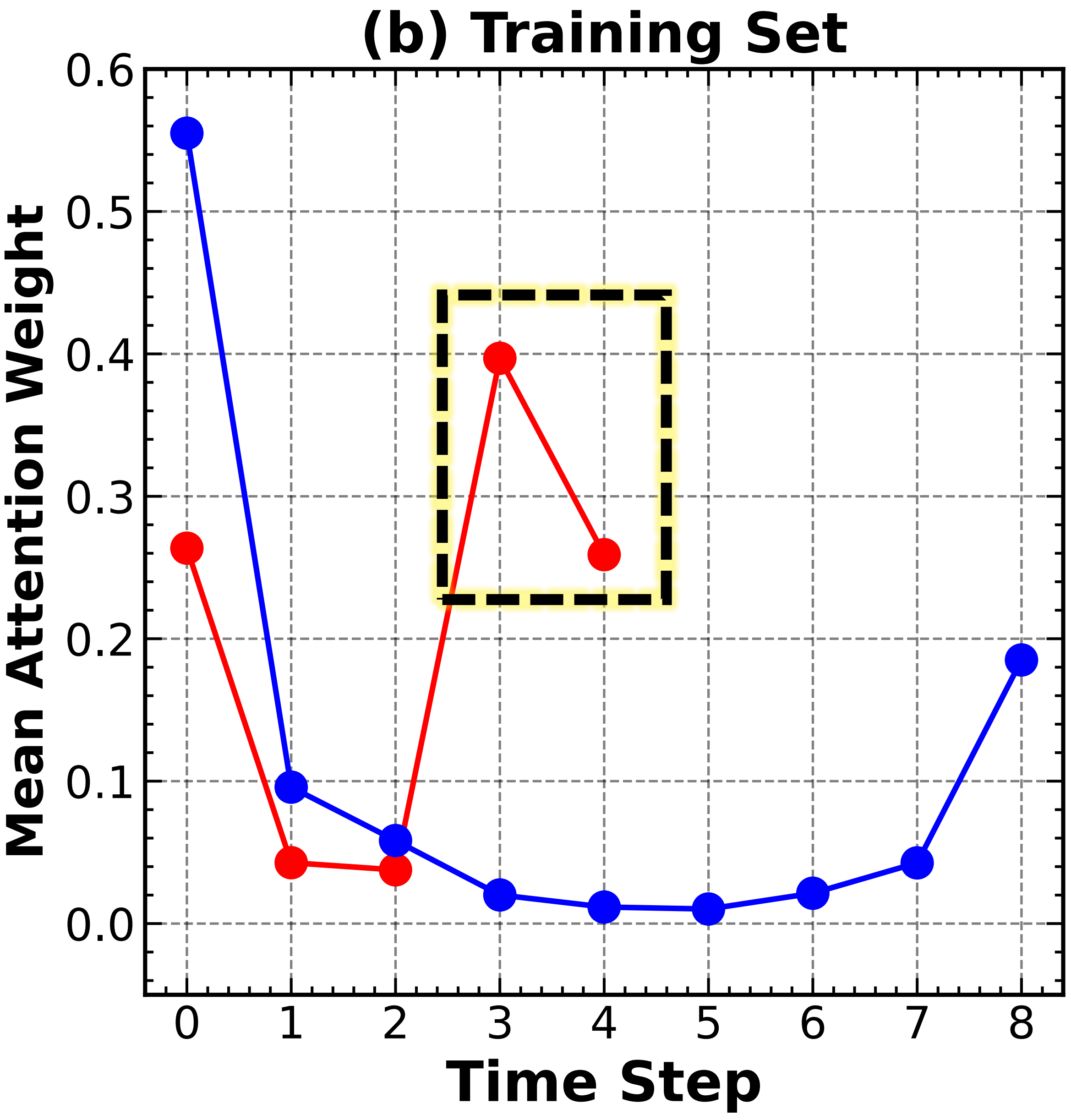
INITIAL RESULTS

Attention Weights

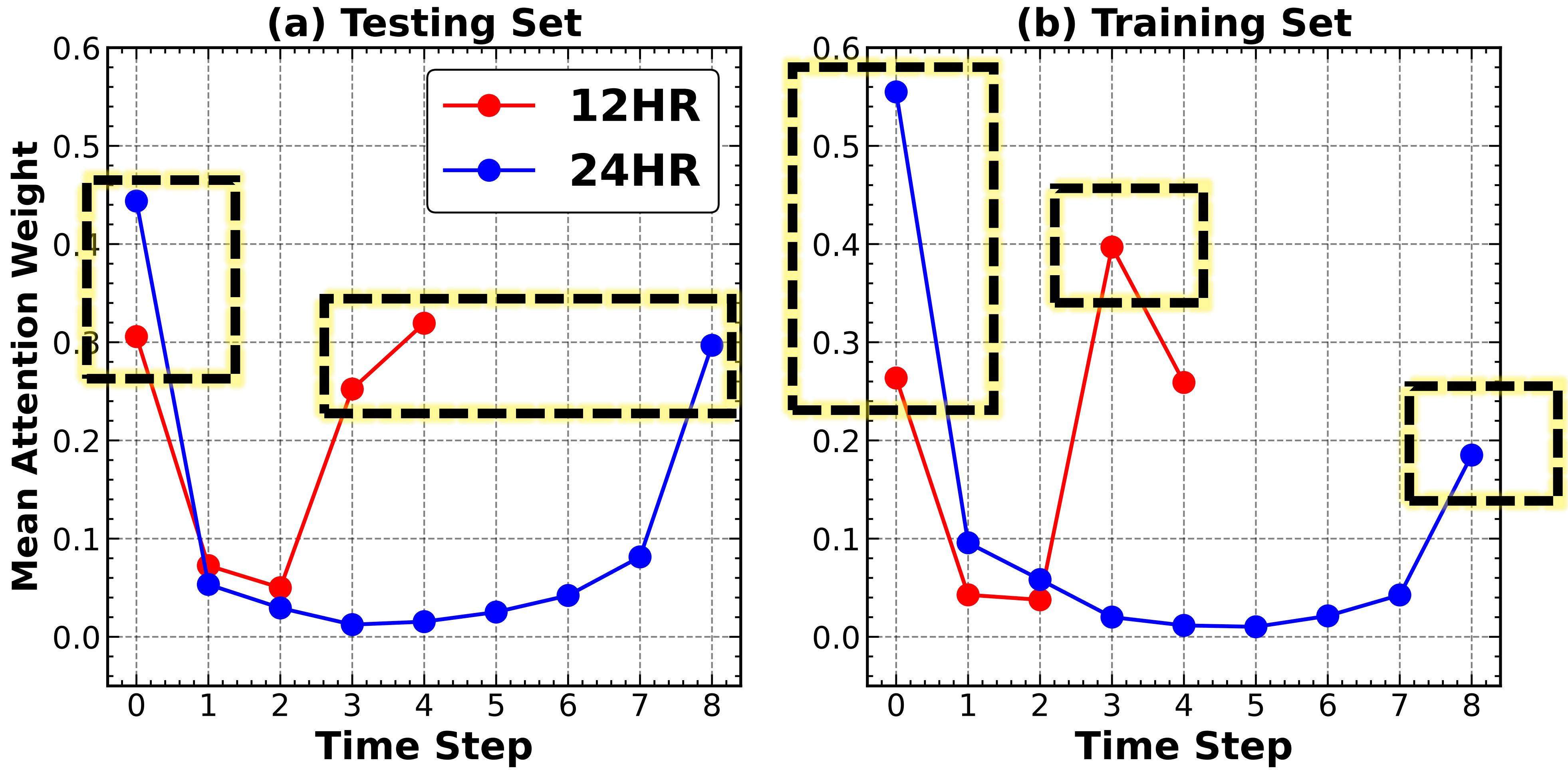


The general trend for the training set mirrored the testing set, except for the last two steps of the 12HR model.

This indicates a consistent learning pattern between testing and training sets, particularly for the 24HR model.

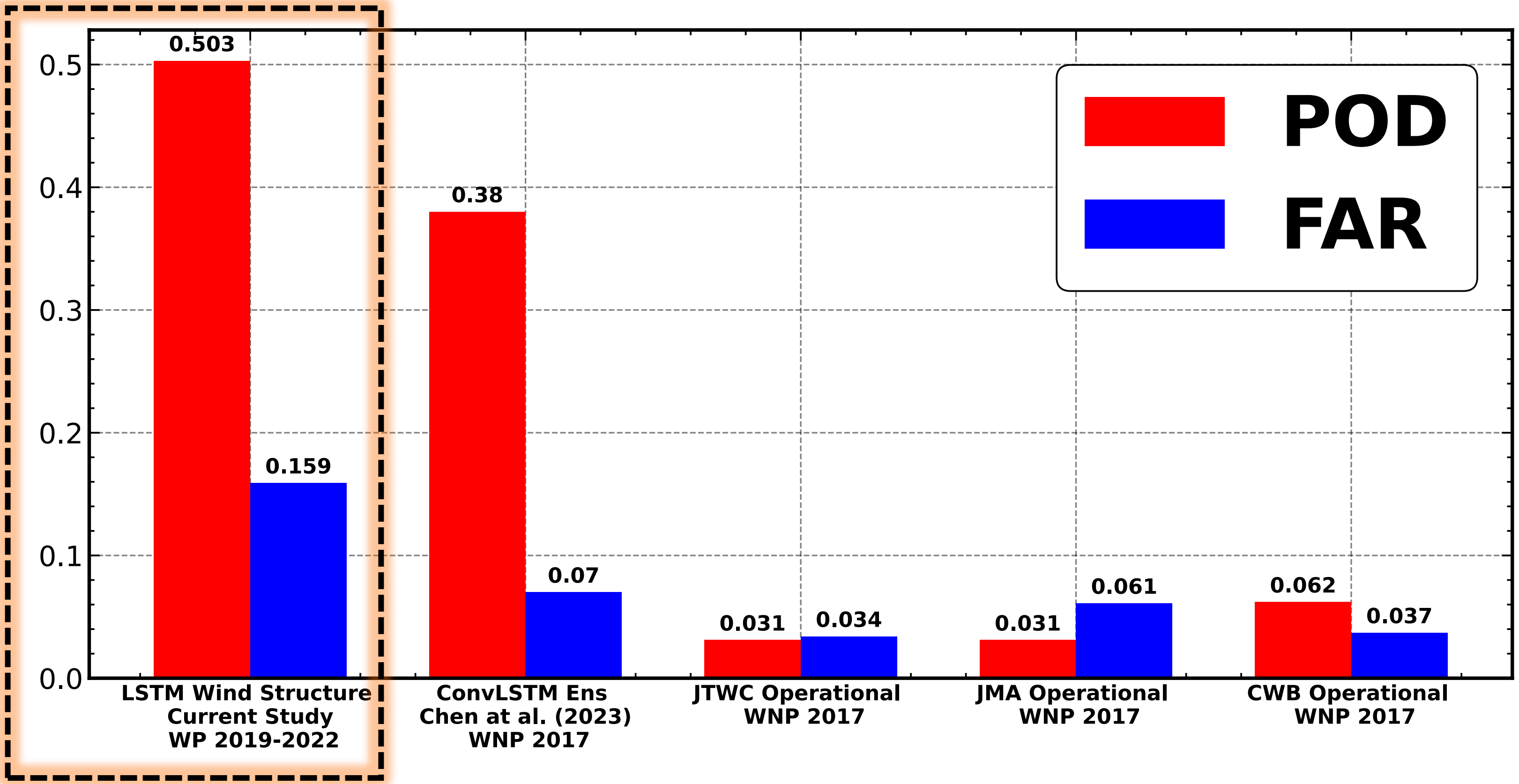


INITIAL RESULTS
Attention Weights



The **significant weight of the initial and final time steps indicates temporal bias**, where the model focuses too much on these time steps, leading to an **unbalanced training in which crucial information is undervalued in the middle time steps**. Introducing regularization could lead to a different trend of the mean attention weights.

INITIAL RESULTS Model Comparison



The best model of this study performed better than operational models in terms of detecting RI. However, the high FAR is still a concern. It is important to note that this is not a fair comparison since these models were tested on different time periods

- Different time periods can exhibit different TC climatological characteristics (Kaplan et al. 2010)
- The testing set used in this study is filtered for intensifying cases only
- To realistically compare our model with operational ones, we need to validate our model with respect to operational forecasts

TABLE OF CONTENTS

CONCLUSIONS

- The results of this study show the **potential of LSTM models for TC RI prediction** by utilizing wind structure evolution.
- The best-performing model achieved a POD of 0.503 and a FAR of 0.109, highlighting the **need for further refinement to achieve a good trade-off between POD and FAR**.
- This model should also **be validated against forecasts from operational agencies** and recent TC RI ML predictive models using the same testing set.
- Wind structure could be **integrated with conventional RI predictors** such as environmental conditions and TC internal structures from satellite observations to develop a more holistic and sophisticated TC RI forecast model.

CONCLUSIONS FUTURE WORK

Repeat the same set of experiments with Stacked LSTM, and LSTM with Attention Mechanism

- Tune Hyperparameters on a Validation Set
  - learning rate, batch size, epochs
  - dropout size, regularization
- Ensemble the results due to the randomness of the batch training and dropouts

Analyze feature importance using SHAP

Composite (Meteorological) Analysis of the Wind Structure Features

- RI vs Non-RI
- True Positives vs False Positives

Make a regression model to explicitly predict the intensification rate

CONCLUSIONS FUTURE WORK

DISCUSSION:

Hyperparameter tuning results:
- classic LSTM
- stacked LSTM
- attention-based LSTM

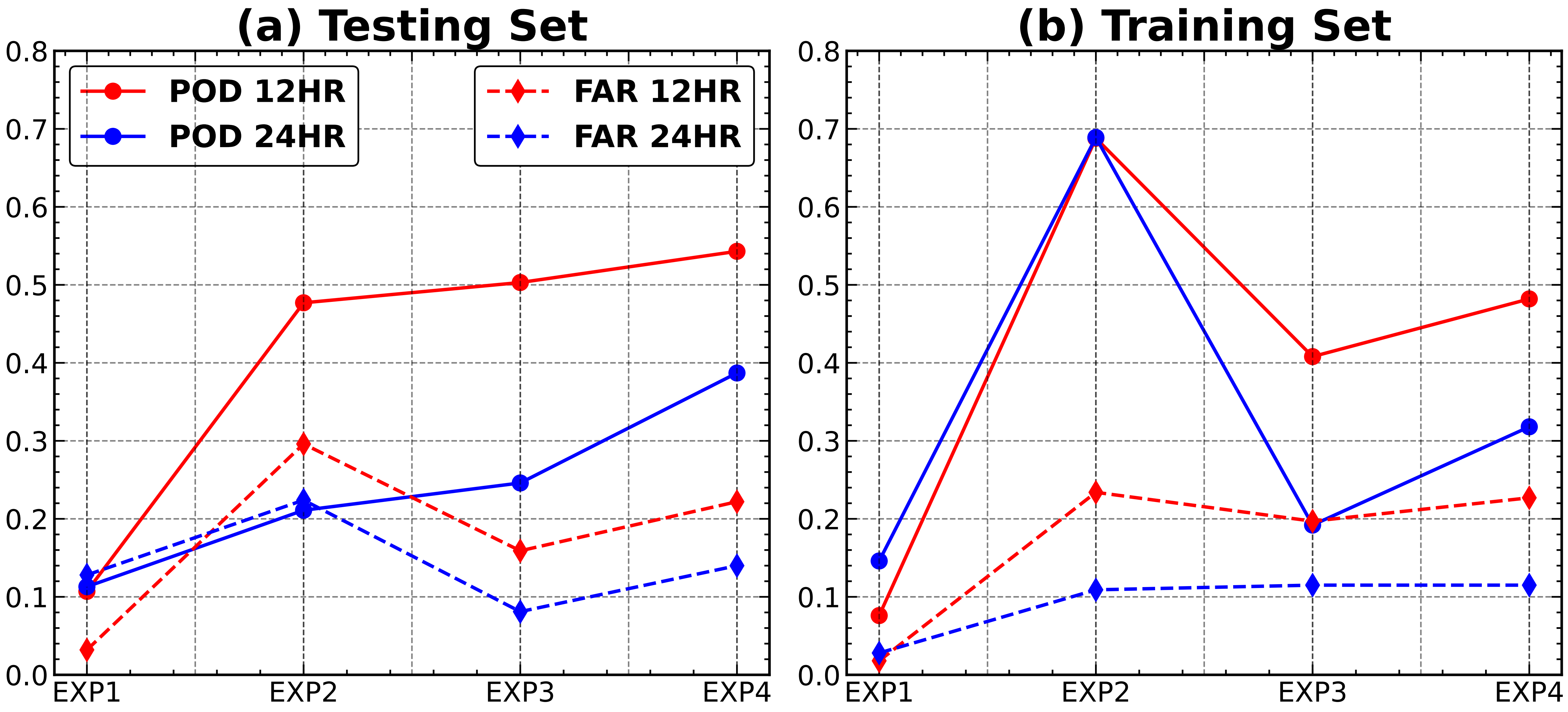
Model performance comparison
- training and testing set performance of the tuned classic, stacked, and attention-based LSTM **(POD vs FAR)**
- training and testing set performance of the tuned classic, stacked, and attention-based LSTM **(POD difference and FAR difference)**

Feature importance with SHAP

Composite (Meteorological) Analysis of the Wind Structure Features
- RI vs Non-RI (training and testing sets)
- True Positives vs False Positives

INITIAL RESULTS

Supplemental Slides



Rolling Window Sampling

SUPPLEMENTAL SLIDES

```python
# Function to create input-output pairs for 12-hour sequences
def create_12_hour_sequences(data):
    X_12 = []
    y_12 = []
    for _, group in data.groupby(['NAME', 'SEASON']):
        for i in range(len(group) - 4):  # Generate sequences of 5 time steps (current observation included)
            X_12.append(group.iloc[i:i+5][['USA_WIND', 'USA_RMW', 'USA_R34_NE', 'TCF', 'TCF0', 'Rf']].values)
            target = group.iloc[i+4]['RI Category']
            y_12.append(target) # Output value (0 for Non-RI, 1 for RI)
    return np.array(X_12), np.array(y_12)
```

```python
# Function to create input-output pairs for 24-hour sequences
def create_24_hour_sequences(data):
    X_24 = []
    y_24 = []
    for _, group in data.groupby(['NAME', 'SEASON']):
        for i in range(len(group) - 8):  # Generate sequences of 9 time steps (current observation included)
            X_24.append(group.iloc[i:i+9][['USA_WIND', 'USA_RMW', 'USA_R34_NE', 'TCF', 'TCF0', 'Rf']].values)
            target = group.iloc[i+8]['RI Category']
            y_24.append(target) # Output value (0 for Non-RI, 1 for RI)
    return np.array(X_24), np.array(y_24)
```

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EDUCATION

- Bachelor of Science in Meteorology – BICOL UNIVERSITY
  - 2019-2023

WORK EXPERIENCE

- **Part Time Lecturer** – Bicol University (Physics & Meteorology Department)
  - **Phys 134:** Waves and Optics (currently)
  - **Phys 133:** Electricity, Magnetism, & Optics
  - **Meteo108:** Computational Methods for Meteorology
  - **Meteo114:** Mesoscale Meteorology

- **External Thesis Advisor for Undergraduate**
  - **Study 1:** Flood Risk Mapping of Davao City using Ensemble Machine Learning Models
  - **Study 2:** Tropical Cyclone Fullness and its Relationship to Deep Convections and Vorticity Advection

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RESEARCH PUBLICATIONS / PROJECTS

[2023] Environmental Conditions and Internal Dynamical Processes during the Rapid Intensification of Super Typhoon Goni (2020) – LEAD AUTHOR
Proceedings of the Philippine Meteorological Society Volume 6 – Recent Advances and Applications of Meteorology and its Allied Sciences in the Philippines https://philmetsoc.com/PMS/publications, **ISSN 2599-5537**

[2023] On the Intensification of Super Typhoon Goni (2020), Part 2: Internal Dynamical Processes (ORAL PRESENTATION) – LEAD AUTHOR
7th Taiwan-Philippines Earth Sciences International Conference – National Cheng Kung University @ Tainan, Taiwan
http://www.edsrc.ncku.edu.tw/tpesic/Abstract.pdf

[TBD] On the Intensification of Super Typhoon Goni (2020): Environmental Conditions, Deep Convective Clouds, Precipitation, Cloud Microphysics, and Wind Structure – LEAD AUTHOR
To be submitted to the Asia-Pacific Journal of Atmospheric Sciences as LEAD AUTHOR