Typhoon Intensity Forecast Based on Multi Source Data Fusion using ConvLSTM

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***Abstract*—Typhoons pose significant threats to coastal communities, making accurate intensity prediction crucial for disaster preparedness and mitigation. In this study, we explore deep learning-based approaches for typhoon intensity forecasting, comparing three models: ConvLSTM, ConvLSTM with Cross-Channel Attention (ConvLSTM_CCA), and a Convolutional Neural Network (CNN). These models utilize satellite image sequences and auxiliary meteorological features to predict the maximum sustained wind speed of typhoons.**

Our experiments, conducted on historical typhoon data, demonstrate that incorporating spatiotemporal dependencies through ConvLSTM improves prediction accuracy compared to CNN-based methods. Furthermore, the inclusion of cross-channel attention in ConvLSTM_CCA further refines feature extraction, leading to more precise forecasts. The experimental results highlight that ConvLSTM_CCA achieves the best performance among the three models, closely aligning with actual intensity values.

***Index Terms*—typhoon intensity, ConvLSTM_CCA, CNN.**

I. Introduction

A. Background

Typhoons are among the most devastating natural disasters, causing severe damage to infrastructure, economic losses, and human casualties. Accurate typhoon intensity prediction is crucial for disaster preparedness, early warnings, and risk mitigation. However, predicting typhoon intensity remains a challenging task due to the complex interactions between atmospheric, oceanic, and environmental factors. Traditional numerical weather prediction (NWP) models often struggle with the inherent uncertainties and high computational costs associated with forecasting typhoon intensity.

With the rapid advancement of artificial intelligence, deep learning techniques have shown great promise in various meteorological applications, including typhoon tracking and intensity prediction. Convolutional Neural Networks (CNNs) and recurrent models such as ConvLSTM can capture spatial and temporal dependencies in satellite images and meteorological data. In this study, we explore the use of deep learning models, including **CNN, ConvLSTM, and ConvLSTM_CCA**, for typhoon intensity prediction based on satellite imagery and environmental features.

B. Problem Statement

The goal of this research is to predict **typhoon intensity (maximum wind speed, Vmax)** at a given timestamp using satellite images and meteorological features. Specifically, given a sequence of satellite images and corresponding environmental data, the task is to predict the typhoon's maximum wind speed in a supervised learning setting.

The dataset used in this study, **TCIR-CPAC_IO_SH**, contains satellite images, environmental features, and typhoon intensity labels. The input data consists of:

- **image_sequences**: Satellite images (originally 4 channels, processed into 1 channel) with shape `(50, 1, 201, 201, 1)`.
- **features**: Meteorological data including `land distance, region, local time (sin & cos), and R35` with shape `(50, 15)`.
- **labels**: Maximum wind speed (**Vmax**) with shape `(50,)`.

Despite the availability of these data sources, predicting typhoon intensity remains challenging due to:

1) **High variability** in typhoon structures across different regions.
2) **Complex temporal dependencies**, requiring models that capture both spatial and sequential patterns.
3) **Discrepancies between actual and predicted values**, where models may underestimate or overestimate typhoon intensity.

C. Research Objectives

The primary objective of this study is to develop and compare deep learning models for typhoon intensity prediction. Specifically, the study aims to:

1) Investigate the effectiveness of different deep learning architectures (CNN, ConvLSTM, and ConvLSTM_CCA) in predicting typhoon intensity.
2) Analyze model performance by comparing predicted and actual typhoon intensity values.
3) Identify key challenges and potential improvements for deep learning-based typhoon forecasting.

By achieving these objectives, this study contributes to the ongoing efforts in applying AI to meteorology, with the potential to improve early warning systems and disaster preparedness strategies.

II. Related Work

Typhoon intensity prediction has been extensively studied using various methodologies, ranging from numerical forecasting to statistical and hybrid approaches. These methods can be broadly categorized into the following three types:

1) **Numerical Forecast Methods:** Also known as dynamical methods, these rely on complex mathematical models to simulate typhoon movement using fundamental physical equations. However, such models require

significant computational resources and are dependent on supercomputers to obtain approximate solutions.

2) **Statistical Methods:** These approaches focus on leveraging historical meteorological data rather than simulating physical dynamics. Statistical models require lower computational costs compared to numerical models and have been widely adopted due to their efficiency and applicability across different regions.
3) **Statistical-Dynamical Methods:** These methods combine statistical approaches with dynamical models, where statistical techniques are employed to estimate key initial conditions for numerical simulations. The accuracy of these hybrid models largely depends on the performance of the dynamical component.

In recent years, statistical methods have gained attention due to their objectivity and relatively low computational demands. A crucial challenge in statistical modeling is the availability of large-scale historical data and the design of robust predictive models.

A. Datasets for Typhoon Intensity Prediction

Several publicly available datasets provide valuable historical typhoon data for model training and evaluation. Commonly used datasets include:

- **CMA Typhoon Dataset:** Maintained by the China Meteorological Administration (CMA), this dataset provides six-hourly records of tropical cyclone positions and intensity in the Western North Pacific (WNP) basin since 1949. It includes variables such as time, longitude, latitude, wind speed, and central pressure.
- **ERA-5 Reanalysis Data:** Provided by the European Centre for Medium-Range Weather Forecasts (ECMWF), ERA-5 is a global atmospheric reanalysis dataset available since 1979. It offers meteorological parameters such as temperature, humidity, wind speed, and pressure with a spatial resolution of approximately 31 km and an hourly temporal resolution.
- **TCIR Dataset:** The Tropical Cyclone Image Regression (TCIR) dataset compiles global tropical cyclone images from 2003 to 2017. It includes three-hourly infrared (IR), water vapor (WV), and passive microwave (PMW) satellite imagery, with a spatial resolution of 0.07° latitude/longitude.

B. Deep Learning for Typhoon Prediction

The application of deep learning in typhoon prediction has gained momentum, with various studies proposing models to capture nonlinear features in typhoon dynamics.

In 2016, Moradi et al. [1] introduced a sparse Recurrent Neural Network (RNN) for extracting nonlinear features from two-dimensional typhoon data. They also employed Dynamic Time Warping (DTW) to identify similar typhoon trajectories. However, DTW assumes monotonic typhoon motion, limiting its applicability. To address this, Alemany et al. [2] proposed a fully connected Long Short-Term Memory (LSTM) network that encodes typhoon center positions into a grid-based representation, reducing error propagation.

For modeling the three-dimensional structure of typhoons, Liu et al. [3] developed a Convolutional Neural Network (CNN) to analyze reanalysis data and predict extreme weather events, including tropical cyclones. Subsequently, Kim et al. [4] extended this work using a Convolutional LSTM (ConvLSTM) model, which integrates spatial and temporal dependencies, making it more suitable for sequential data.

C. Our Approach

While prior research has explored both typhoon trajectory and intensity prediction, our study focuses solely on intensity forecasting. We explore and compare the performance of three deep learning-based models: CNN, ConvLSTM, and ConvLSTM_CCA, to analyze traditional predictors and satellite observations. The goal is to predict the maximum wind speed (**Vmax**) of typhoons 24 hours in advance, using spatial and temporal patterns in the input data.

III. Methodology

A. Data Collection and Preprocessing

1) Dataset: In this study, we utilize the publicly available TCIR (Tropical Cyclone Image-to-Intensity Regression) dataset [5], which is specifically designed for the task of tropical cyclone intensity prediction. The dataset is divided into two main components: *Matrix* and *Info*. These components together provide both satellite observation images and cyclone metadata, which serve as inputs for the intensity regression task.

The *Matrix* data is stored in a grid format, where each grid point contains multiple channels representing different physical properties, such as wind speed, pressure, and temperature. These channels capture the spatial distribution and intensity characteristics of the cyclone. The *Info* data, on the other hand, includes cyclone metadata such as the unique cyclone ID, observation time, location (longitude and latitude), maximum wind speed (Vmax), and sea-level pressure (MSLP). This information describes the basic state and characteristics of the cyclone at different time points and locations.

The Matrix dataset consists four channels: channel_1, channel_2, channel_3, and channel_4. Channel_1 and channel_2 display relatively stable data, with values ranging from 281.83 to 295.68 and 237.17 to 253.06, respectively. Channel_3 exhibits greater variability, with values ranging from 0.013 to 0.405, indicating potential anomalies or specific events. Channel_4 contains all zero values, suggesting that the channel is either not enabled or not recording valid data. Overall, channels 1 and 2 provide stable measurements, while the fluctuations in channel 3 warrant further investigation, and channel 4 may require a review of its configuration or sensor status.

The Info dataset contains observation records for 623 tropical cyclones, with each record corresponding to a specific time and location for the cyclone's status. Key fields in the dataset include the dataset name (*data_set*, always labeled as CPAC), cyclone ID (*ID*), longitude (*lon*), latitude (*lat*), observation time (*time*, in YYYYMMDDHH format), maximum sustained wind speed (*Vmax*, in knots), the four-quadrant average radius of the 35-knot wind speed (*R35_4qAVG*, in nautical miles), and the sea-level pressure (*MSLP*, in hectopascals). These fields comprehensively document the time, location, intensity, and affected areas of each cyclone.

The following cyclone IDs are included in the dataset, with the number of corresponding frames (observations) listed for each ID:

Cyclone ID	Number of Frames
200301C	62
200401C	29
200501C	29
200601C	149
200801C	82
200901C	139
201001C	91
201301C	106
201302C	90
201303C	92

TABLE I: Cyclone IDs and the corresponding number of frames in the TCIR dataset

Each set of records with the same cyclone ID corresponds to observations of the same cyclone at different time points, documenting the evolution of its position (longitude and latitude), wind speed (Vmax), and pressure (MSLP). By analyzing these data, the path and intensity changes of each cyclone can be tracked, providing essential information for meteorological research and tropical cyclone disaster forecasting. This dataset also offers valuable resources for validating and improving climate models used to simulate tropical cyclones.

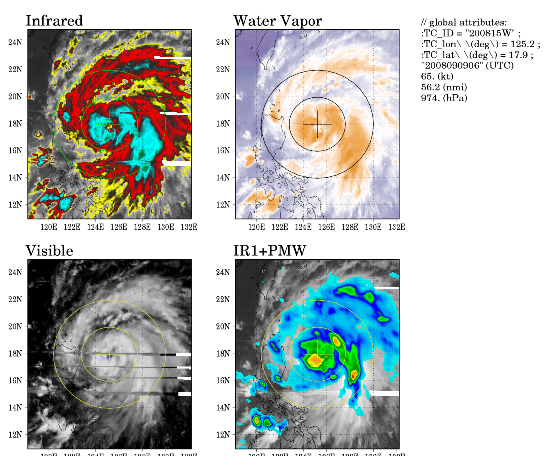

Fig. 1: Example of a dataset image used for tropical cyclone intensity prediction. The figure illustrates different satellite observation channels: Infrared (IR), Water Vapor (WV), Visible (VIS), and IR1+PMW. These channels provide crucial information on the structure and intensity of tropical cyclones.

2) Preprocessing: In this section, we describe the preprocessing steps applied to the dataset to prepare it for model training. The dataset used in this study is stored in the file `TCSA.h5`, which consists of two main components: `matrix` (containing typhoon satellite images with 4 channels) and `info` (containing post-season typhoon analysis data).

Data Cleaning First, we remove typhoon records with missing or `NaN` values to ensure data consistency. This is achieved using the function:

```
data_cleaning_and_organizing(image_matrix,
    info_df)
```

which filters out incomplete records from the dataset.

Data Splitting After cleaning, the dataset is split into training, validation, and test sets with the following proportions:

```
train ratio = 0.7, valid ratio = 0.2, test
    ratio = 0.1
```

This is implemented via the function:

```
data_split_by_ratio(image_matrix, info_df,
    phase, train_ratio=0.7, valid_ratio=0.2,
    test_ratio=0.1)
```

where `phase` indicates whether the data belongs to the training, validation, or test set.

Grouping by Typhoon ID Typhoon records are then grouped based on their unique Typhoon ID to organize data efficiently:

```
image_matrix, info_df =
    group_by_id(image_matrix, info_df)
```

This ensures that all records corresponding to the same typhoon event are properly aggregated.

Normalization of Typhoon Intensity Labels To ensure consistency across different typhoon IDs, the intensity labels are normalized using MinMax scaling. This transformation standardizes the intensity values to a range between 0 and 1, which helps stabilize the training process. The normalization is applied as follows:

```
vmax_scaler = MinMaxScaler()
intensity =
    vmax_scaler.fit_transform(intensity.reshape(-1,
    1)).flatten()
vmax_scaler_dict[single_TC_info.ID.values[0]] =
    vmax_scaler
```

The fitted scalers for each typhoon ID are stored in a dictionary and saved to a file for later use. This ensures that the same scaling parameters can be applied during the inverse transformation after prediction:

```
with open('vmax_scaler_dict.pkl', 'wb') as f:
    pickle.dump(vmax_scaler_dict, f)
```

This step guarantees that predicted intensities can be accurately converted back to their original scale for meaningful interpretation.

Temporary Data Storage To facilitate further processing, the cleaned and organized data is stored temporarily in a file:

```
phase_path = Path(data_folder,
    TCSA.tfrecord.{phase})
```

where `phase` represents one of `train`, `valid`, or `test`.

Typhoon Data Processing and Formatting For each typhoon record, we integrate satellite image data with post-season analysis data. The image data is reshaped as follows:

```
images =
    tf.reshape(tf.io.decode_raw(example['images'],
    tf.float32), [history_len, 201, 201, 4])
```

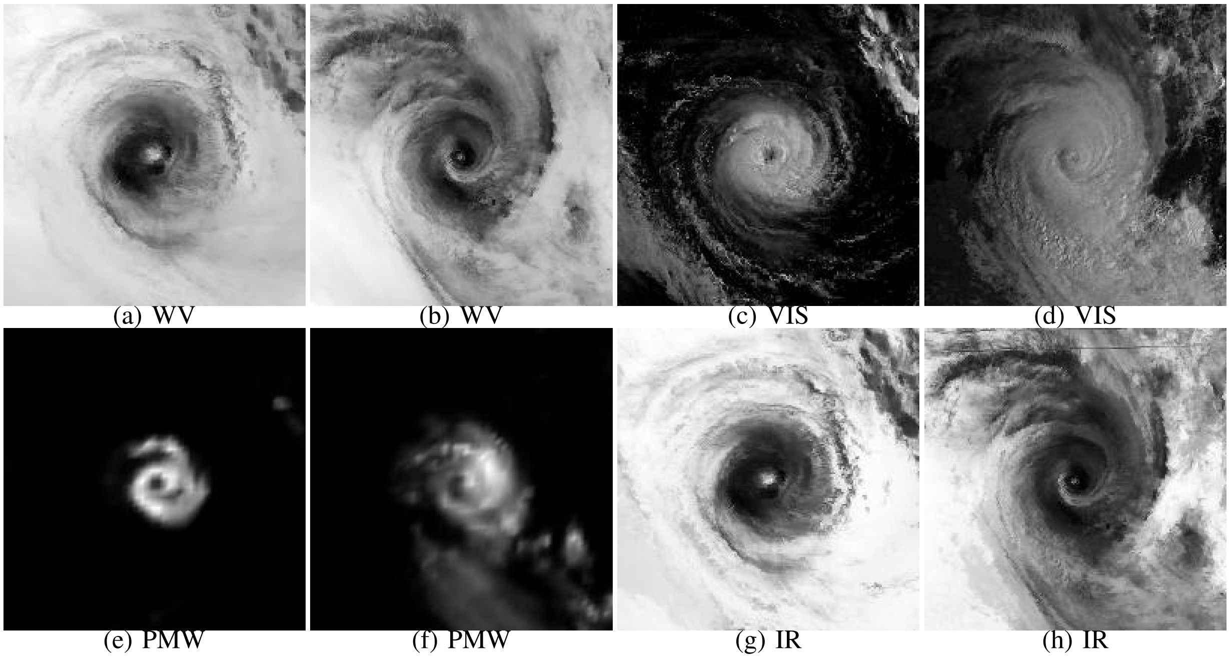

Fig. 2: Example of 4 channels dataset image

This ensures that images are formatted correctly for ConvLSTM model input.

Filtering by Minimum History Length A minimum history length constraint is applied, defined as:

```
min_history_len = encode_length +
    estimate_distance + 2
```

Only typhoon sequences meeting this criterion are retained in the dataset.

Sequence Breakdown for Model Input The data is then segmented into smaller sequences to match the input requirements of the ConvLSTM model. Each sequence is extracted as:

```
starting_frame_ID_ascii =
    frame_ID_ascii[encode_length +
    1:-estimate_distance]
```

This step ensures that each sample contains a valid historical sequence for training.

Shuffling and Batching Finally, the dataset is shuffled with a buffer size of 1000 and is batched appropriately:

```
dataset = TC_sequence.shuffle(buffer_size=1000)
```

This enhances the model's generalization by preventing the network from learning an order-dependent pattern in the training data.

B. AI Solution Selection

To predict tropical cyclone rapid intensification, we experimented with three deep learning models: Convolutional Neural Networks (CNN), Convolutional Long Short-Term Memory (ConvLSTM), and a hybrid ConvLSTM_CCA model. Each model is designed to leverage spatial and temporal features in satellite imagery and auxiliary cyclone data. In this subsection, we describe the CNN and ConvLSTM models.

1) Convolutional Neural Network (CNN): The CNN model is designed to extract spatial features from satellite imagery of cyclones. The architecture consists of multiple convolutional layers followed by fully connected layers for prediction. The key components of the model are as follows:

- **Input Normalization:** A batch normalization layer normalizes the input images to stabilize training.
- **Feature Extraction:** Several convolutional layers progressively extract high-level spatial features. The network includes:
  - Convolutional layers with 16, 32, 64, 128, 256, 512, and 1024 filters, using kernel sizes of 3x3 and 5x5.
  - Max-pooling layers to reduce spatial dimensions and retain significant features.
  - Batch normalization layers to improve convergence.
- **Feature Integration:** Flattened convolutional features are concatenated with auxiliary cyclone information, such as land distance, translation speed, and intensity.
- **Output Layers:** Fully connected dense layers with dropout regularization to prevent overfitting, followed by a final regression output layer.

The CNN model processes image sequences by reshaping and normalizing inputs before passing them through the convolutional layers. Extracted features are then flattened and combined with cyclone metadata before generating the final prediction.

2) Convolutional Long Short-Term Memory (ConvLSTM): To capture both spatial and temporal dependencies in cyclone evolution, we employ a ConvLSTM-based model. The ConvLSTM architecture integrates convolutional operations with recurrent memory, making it suitable for sequential image data. The key components of this model include:

- **Feature Extraction:** A series of convolutional layers extract spatial information from each time step in the image sequence.

- **Recurrent Processing:** A ConvLSTM2D layer with 64 filters and a kernel size of 4x4 captures temporal dependencies between image frames.
- **Feature Compression:** A convolutional layer compresses the ConvLSTM output into a lower-dimensional representation.
- **Feature Integration:** Flattened features are concatenated with auxiliary cyclone data.
- **Output Layers:** A series of dense layers with dropout regularization predict cyclone intensity changes.

The ConvLSTM model takes an input sequence of cyclone images, processes them through convolutional layers, and then passes the encoded features into the ConvLSTM block. The recurrent module captures temporal relationships between frames, aiding in predicting cyclone intensification trends.

In the next section, we will introduce the ConvLSTM_CCA model, which further integrates feature selection techniques to enhance prediction accuracy.

3) Convolutional Long Short-Term Memory with Canonical Correlation Analysis (ConvLSTM_CCA): The ConvLSTM_CCA model is designed for spatiotemporal sequence prediction. It integrates convolutional neural networks (CNNs) for feature extraction, cross-channel attention (CCA) for enhanced feature representation, and convolutional Long Short-Term Memory (ConvLSTM) for sequential modeling. The final regression output is obtained through fully connected layers.

The choice of the ConvLSTM_CCA model for predicting typhoon intensity is inspired by the research findings of Chen et al. [6], which propose a deep learning ensemble approach for forecasting tropical cyclone rapid intensification.

Model Architecture

The model consists of the following key components:

Input Normalization The input images are normalized using batch normalization to stabilize training and improve convergence speed:

$$x' = \frac{x - \mu}{\sigma} \tag{1}$$

where μ and σ are the mean and standard deviation of the batch.

Image Encoding The encoding block extracts hierarchical spatial features using two convolutional layers:

$$x_1 = \text{ReLU}(\text{Conv2D}(x, F = 16, K = 4, S = 2)) \tag{2}$$

$$x_2 = \text{ReLU}(\text{Conv2D}(x_1, F = 32, K = 3, S = 2)) \tag{3}$$

where F denotes the number of filters, K is the kernel size, and S is the stride.

Cross-Channel Attention (CCA) A cross-channel attention mechanism enhances important spatial features. This module consists of:

$$M = \text{ReLU}(\text{Conv2D}(x_2, F = 32, K = 3, S = 1, P = \text{same})) \tag{4}$$

$$A = \text{Conv2D}(M, F = 1, K = 2, S = 1, P = \text{same}) \tag{5}$$

where M represents the intermediate feature map, and A is the attention mask. The final attended feature is computed as:

$$x_{cca} = A \odot x_2 \tag{6}$$

where $\odot$ represents element-wise multiplication.

ConvLSTM for Temporal Encoding The attended features are fed into a ConvLSTM network to model temporal dependencies:

$$h_t = \text{ConvLSTM2D}(x_{cca}, F = 64, K = 4) \tag{7}$$

where h_t is the hidden state of the ConvLSTM.

Feature Fusion and Regression The encoded spatiotemporal features are passed through a convolutional layer followed by fully connected layers:

$$f = \text{ReLU}(\text{Conv2D}(h_t, F = 64, K = 1)) \tag{8}$$

$$v = \text{Flatten}(f) \tag{9}$$

$$v = \text{Concat}(v, \text{auxiliary\_features}) \tag{10}$$

$$y = \text{Dense}(\text{ReLU}(\text{Dense}(v, 128)), 1) \tag{11}$$

where auxiliary_features represent additional input features.

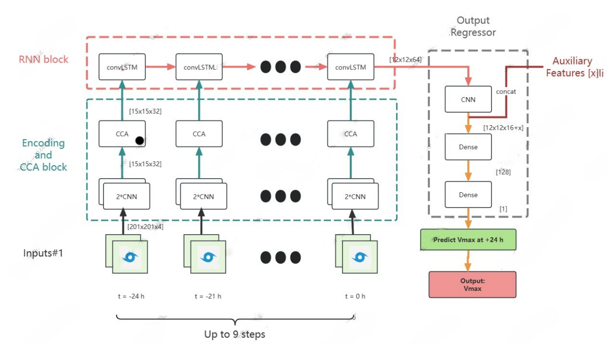

Fig. 3: Model Architecture of Convolutional Long Short-TermMemorywithCanon ical Correlation Analysis (ConvLSTM_CCA)

C. Model Training and Optimization

In this study, three machine learning models were trained for typhoon intensity prediction: CNN, ConvLSTM, and ConvLSTM_CCA. The models were trained using the same dataset, TCSA_data, under consistent training settings to ensure fair comparisons.

1) Training Parameters: Each model was trained using a batch size of 50 and a maximum of 30 epochs. The learning rate was set to 0.0005, and evaluation was performed after each epoch. The class weight was set to 1 for all models to maintain balanced training.

TABLE II: Training Parameters for Different Models

Parameter	CNN	ConvLSTM	ConvLSTM_CCA
Batch Size	50	50	50
Max Epoch	30	30	30
Learning Rate	0.0005	0.0005	0.0005
Encode Length	1	1	1
Estimate Distance	8	8	8
Input Image Type	[2]	[2]	[0,2]
Data Rotation	No	No	No
Class Weight	1	1	1

2) Optimization Strategy: The Adam optimizer was used to train all models, ensuring efficient gradient-based optimization. The learning rate of 0.0005 was selected based on preliminary experiments to balance convergence speed and stability. The different input image types in ConvLSTM_CCA were selected to leverage additional information for improved prediction performance.

IV. Experimental Results & Discussion

To evaluate model performance, we analyze the training loss curves for MAE and MSE across different epochs. Figure 4 presents the training loss trends for CNN, ConvLSTM, and ConvLSTM_CCA, illustrating their convergence behavior and generalization capacity.

The MAE and MSE loss curves reveal notable differences in convergence rates and final performance among the three models. CNN exhibits a relatively stable decrease in both MAE and MSE, but its convergence is slower compared to ConvLSTM and ConvLSTM_CCA. The ConvLSTM model demonstrates faster convergence, benefiting from its ability to capture temporal dependencies in typhoon intensity variations. Meanwhile, ConvLSTM_CCA further improves upon ConvLSTM by integrating additional input channels, leading to a lower overall loss and better stability in training.

These results suggest that leveraging both temporal dependencies and additional feature representations enhances the predictive capability of the model. The improved performance of ConvLSTM_CCA highlights the effectiveness of incorporating multiple input channels for a more robust prediction of the intensity of the typhoon.

Meanwhile, to evaluate the performance of the proposed ConvLSTM_CCA model in predicting typhoon intensity, we compare its predictions with two baseline models: ConvLSTM and CNN. The evaluation is carried out on typhoon 201518S, using multiple time sequences as test cases. Table III summarizes the actual versus predicted values for each model.

A. Performance Comparison

The results indicate that the ConvLSTM_CCA model outperforms the other two models in terms of prediction accuracy. The following observations can be made:

- The ConvLSTM_CCA model provides more accurate predictions, with the lowest deviation from the actual values across all test sequences. For example, in sequence 2015031618, the prediction of 53.24 is much closer to the actual value of 55.0 compared to 45.07 (ConvLSTM) and 58.57 (CNN).
- The CNN model exhibits significant deviations in some cases, such as sequence 2015032212, where it predicts 43.01 while the actual value is 82.5, highlighting its limitations in capturing temporal dependencies.
- The ConvLSTM model, while performing better than CNN, still struggles in some cases, such as sequence 2015031618, where it predicts 45.07 instead of 55.0.

B. Model Effectiveness

The superior performance of ConvLSTM_CCA can be attributed to its ability to:

- Capture both spatial and temporal dependencies effectively through the integration of ConvLSTM and the cross-channel attention mechanism.
- Enhance feature representation using attention mechanisms, leading to more refined predictions.
- Reduce overfitting and improve generalization compared to traditional ConvLSTM and CNN models.

Overall, the results validate the effectiveness of ConvLSTM_CCA in predicting typhoon intensity with higher precision than the baseline models. Future work could involve extending the evaluation to more typhoon events and exploring additional enhancements, such as transformer-based architectures, to further improve prediction accuracy.

V. Conclusion & Future Work

In this study, we developed and evaluated the ConvLSTM_CCA model for tropical cyclone intensity prediction. Our model integrates convolutional and recurrent neural network architectures with a cross-channel attention mechanism to enhance spatiotemporal feature extraction. Experimental results demonstrate that ConvLSTM_CCA achieves improved prediction accuracy compared to standard ConvLSTM and CNN models, particularly in capturing rapid intensity changes. The results validate the effectiveness of incorporating cross-channel attention in enhancing deep learning-based typhoon forecasting models.

Despite its promising performance, several limitations remain. First, the model's accuracy could be further improved by integrating additional meteorological and environmental factors beyond the currently used features. Second, while the ConvLSTM_CCA model shows strong performance for selected cases, further validation on a more diverse dataset, including different basins and typhoon seasons, is necessary to ensure robustness and generalizability.

For future work, we propose several directions to enhance the model. One possible improvement is the incorporation of physics-informed neural networks (PINNs) to integrate domain knowledge from atmospheric sciences into deep learning models. Additionally, leveraging transformer-based architectures for sequence modeling may further enhance the model's ability to capture long-term dependencies in cyclone evolution. Finally, deploying the model in an operational forecasting system and evaluating its real-time performance would provide valuable insights into its practical applicability for disaster preparedness and mitigation strategies.

Overall, this study contributes to the ongoing efforts to improve tropical cyclone intensity prediction using deep learning techniques. The proposed ConvLSTM_CCA model demonstrates the potential of integrating attention mechanisms with spatiotemporal neural architectures, paving the way for further advancements in this field.

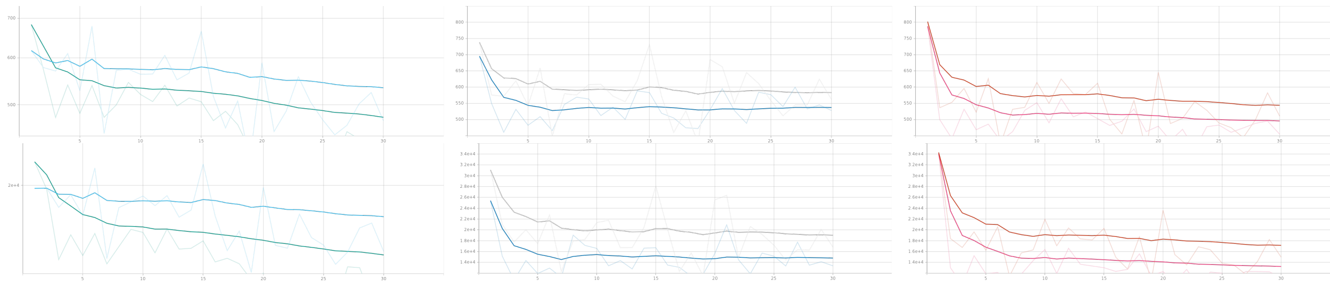

Fig. 4: Training loss curves (MAE and MSE) for different models. The top row shows MAE loss trends, while the bottom row presents MSE loss trends. From left to right: CNN, ConvLSTM, ConvLSTM_CCA.

TABLE III: Prediction Results for Typhoon 201518S

Model	Sequence ID	Actual	Predicted
env01-ConvLSTM	2015031403	45.0	43.66
	2015032212	82.5	84.97
	2015031400	96.89	90.48
	2015031618	55.0	45.07
env06-ConvLSTM_CCA	2015031403	45.0	41.07
	2015032212	82.5	80.87
	2015031400	96.89	92.77
	2015031618	55.0	53.24
env13-CNN	2015031403	45.0	46.24
	2015032212	82.5	43.01
	2015031400	96.89	50.28
	2015031618	55.0	58.57

Appendix A
Code.

Code used. The implementation of our models and experiments is available in the following GitHub repository: https://github.com/RiverLiangH/typhoonPredict/tree/normalization_version.

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