

Dual-Branched Spatio-temporal Fusion Network for Multi-horizon Tropical Cyclone Track Forecast

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Abstract—A tropical cyclone (TC) is a typical extreme tropical weather system, which could cause serious disasters in transit areas. Accurate TC track forecasting is the key to reducing casualties and damages, however, long-term forecasting of TCs is a challenging problem due to their extremely high dynamics and uncertainty. Existing TC track forecasting methods mainly focus on utilizing a single modality of source data, meanwhile, suffer from limited long-term forecasting capability and high computational complexity. In this paper, we propose to address the above challenges from a new perspective - by utilizing large-scale spatio-temporal multimodal historical data and advanced deep learning techniques. A novel multi-horizon tropical cyclone track forecasting model named Dual-Branched spatio-temporal Fusion Network (DBF-Net) is proposed and evaluated. DBF-Net contains a TC features branch that extracts temporal features from 2D state vectors and a pressure field branch that extracts spatio-temporal features from reanalysis 3D pressure field. We show that with the above design, DBF-Net can fully exploit the implicit associations of multimodal data, achieving advantages that unimodal data-based method does not have. Extensive experiments on 39 years of historical TCs track data in the Northwest Pacific show that our DBF-Net achieves significant accuracy improvement compared with previous TCs track forecast methods.

Index Terms—Tropical cyclones, tracking forecast, spatio-temporal data, multimodal data fusion

I. INTRODUCTION

TROPICAL cyclones (TCs, a.k.a, typhoons or hurricanes) are low-pressure vortexes occurring over the tropical or subtropical oceans. TCs are one of the major meteorological disasters facing mankind. Accurate forecasting for the TCs trajectory can greatly reduce the casualties and property damages caused.

The research on TCs track forecast has gone through four stages since the 1960s - empirical methods, statistical methods, numerical methods and deep learning methods. Early methods of TCs track forecast were limited by observation techniques and computational devices and could rely only on the subjective experience for achieving forecast. Thus, some traditional methods such as extrapolation and similar path

methods were developed [1]. From the 1980s, with the rapid development of statistical models, forecasting models based on statistical regression methods such as Climatology and Persistence (CLIPER) [2] were proposed. However, limited representation capabilities of manual feature selection make it difficult to produce accurate forecast results. Since the 1990s, with the improvement of observation techniques and computer performance, Numerical Weather Prediction (NWP) systems (e.g. American National Hurricane Center Track and Intensity Model) gradually become the mainstream choice for official meteorological forecasting agencies. NWP achieves forecasting by solving complex partial differential equations of weather dynamics. However, NWP is very computationally expensive and requires the support of supercomputer platforms. In recent years, machine learning especially deep learning has developed rapidly. Various Deep Neural Networks (DNNs) based on deep learning have revolutionized real-world applications such as computer vision [3], natural language processing [4], time series forecasting [5], etc. Since the computational complexity of DNNs is much smaller than that of traditional NWP models, many DNN variants have been proposed recently to predict TCs track [6]–[14]. In this paper, we also focus on deep learning-based TC track forecasting.

Long-term forecasting of TCs is a challenging problem due to their extremely high dynamics and uncertainty. The trajectory of a TC could be affected by various physical quantities in the atmosphere and ocean, such as pressure field, wind field, sea surface temperature, etc. Existing deep learning-based TC track forecasting methods mainly focus on utilizing a single modality of source data [7]–[11], [14], meanwhile, suffer from limited long-term forecasting capability and high computational complexity. In this paper, we propose to address the above challenges from a new perspective - by utilizing large-scale spatio-temporal multimodal historical data and advanced deep learning techniques. We define the source data into three categories: *inherent features of TCs*, *remote sensing images* and *meteorological fields*. The key to deep learning-based forecasting methods is the full exploitation of different types of data.

The *inherent features of TCs* at a particular time are always represented by a column vector or tensor, which contains information such as the latitude, longitude and intensity of the center of TCs at that time. Infantile deep learning-based TCs track forecast model mainly utilizes historical inherent features of TCs to predict the future locations of the TCs. The classical Multi-Layer Perceptions (MLP) [7], [8] and various time series prediction models, such as Recurrent Neural Networks (RNNs) [9], [10], Long Short Term Memory (LSTM) model [11]

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and Bi-direction Gate Recurrent Unit model [14], are used to learn the time-series pattern of the data. However, the time series models based only on inherent features of TCs usually have limited accuracy of track forecast due to the lack of consideration of factors affecting TCs' trajectory.

Compared with the two-dimensional (2D) *inherent features of TCs* vector, the 3D *remote sensing images* and *meteorological fields* can describe the relevant information around the TCs. As for the TCs track forecasting using remote sensing images, it can be treated as a special kind of video frame prediction task. M. Rüttgers et al. used a Generative Adversarial Network (GAN) to predict the TCs track images and the corresponding location of TCs center [15]. Wu et al. proposed a multitask machine learning framework based on an improved GAN to predict the track and intensity of TCs simultaneously [16]. The track forecast methods above take full advantage of the powerful performance of GANs in the field of computer vision. However, the remote sensing images used in such methods need to be acquired from geostationary satellites to ensure high temporal resolution, and the images can not represent the physical factors affecting the TCs trajectory.

meteorological fields, such as pressure fields and wind fields, are the main factors affecting the trajectory of TCs. In 2017, M. Mudigonda et al. [17] proposed the CNN-LSTM model for segmenting and tracking TCs and verified the direct high correlation of TC tracks in meteorological fields. S. Kim proposed a Convolutional LSTM (ConvLSTM)-based spatio-temporal model that predicts the trajectory map based on the density map sequence generated from the wind velocity and precipitation fields [12]. But the predicted trajectory map can not reflect the exact location of the TCs precisely. Therefore, how to efficiently fuse the *meteorological fields* data into the TCs track forecast model to improve the forecast accuracy has gradually become the mainstream research direction in recent years [13], [18]. Due to the large variation in the distribution of different meteorological fields, S. Giffard-Roisin et al. [13] used different CNN models to encode the reanalysis data of wind and pressure field respectively and fuse them with past track data of TCs. However, multiple CNN models increase the number of parameters and computational complexity of the forecast model, and the model is difficult to train. In addition, the inclusion of excessive use of meteorological field data weakens the role of the inherent features data of TCs and does not adequately learn the time-series features of the data. Therefore, how to efficiently utilize the meteorological field data and fully exploit the intrinsic time-series information of the inherent features of TCs still needs further research.

To solve the problems above, this paper tries to exploit the temporal information in the inherent features data of TCs and the spatio-temporal information in reanalysis 3D pressure field data, and proposes a *Dual-Branched spatio-temporal Fusion Network* (DBF-Net) for multi-horizon tropical cyclone track forecast (i.e. predicting the TCs' track at multiple future time steps [19]). Specifically, as shown in Fig. 1, the time-series features of the input TC features are extract by a LSTM-based [20] network in the *TC features branch* efficiently. Meanwhile, the spatio-temporal features of the geopotential height (GPH) around TCs are encoded by the 3D-CNN-based [21] network

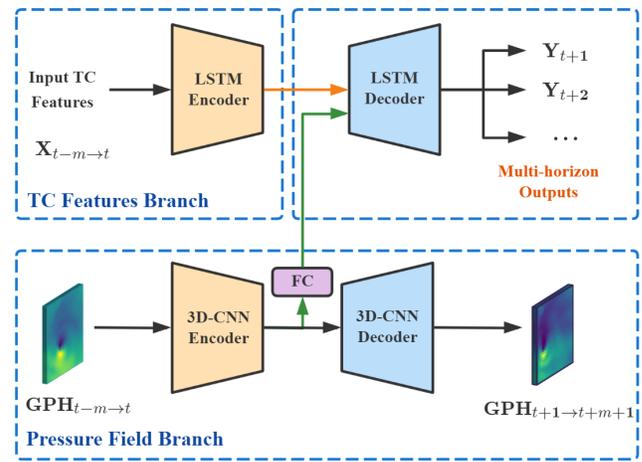


Fig. 1. An overview of the proposed DBF-Net for multi-horizon TC track forecast.

in the *Pressure field branch*, and fused into the first branch to complement the track forecasting information by predicting the GPH at multiple future time steps, and provide the multi-horizon TCs trajectory forecasting outputs.

Through efficient spatio-temporal feature extraction and fusion of the two types of data, the 24h forecast accuracy of DBF-Net on historical TC tracks data in the Northwest Pacific (WNP) is 119km which is much better compared with other deep learning-based methods [13], [14]. Besides, we also compare our method with other traditional methods, such as extrapolation [1], CLIPER model [2] and NWP methods [22]–[25]. Finally, we exhibit the forecast results for several individual cases of TC events for further analysis and verification.

II. METHODOLOGY

In this section, we will introduce the proposed Dual-Branched spatio-temporal Fusion Network (DBF-Net) in detail. The overall architecture of the DBF-Net is shown in Fig. 1. The two branches contained in DBF-Net are split into three sub-modules and will be introduced separately. Before that, the basic LSTM and 3D-CNN modules used in DBF-Net will be briefly introduced.

A. Preliminaries

We formally introduce symbols and notations in this subsection. In DBF-Net, there are two types of data as the input, where $\mathcal{X}_t = \{\mathbf{X}_j \in \mathbb{R}^p \mid j \in [t - m, t], j \in \mathbb{Z}\}$ represents the input historical inherent features sequence of TC and $\mathcal{G}_t = \{\mathbf{GPH}_j \in \mathbb{R}^{q \times q} \mid j \in [t - m, t], j \in \mathbb{Z}\}$ represents the input historical reanalysis 3D geopotential height data. Given the initial forecast time t and the corresponding input data \mathcal{X}_t and \mathcal{G}_t , the output multi-horizon TC track prediction can be computed by:

$$\mathcal{Y}_\tau = \mathbb{M}(\mathcal{X}_t, \mathcal{G}_t) \quad (1)$$

where, $\mathcal{Y}_\tau = \{\mathbf{Y}_j = (Lat_{t+j} - Lat_t, Lon_{t+j} - Lon_t) \mid j \in [1, \tau], j \in \mathbb{Z}\}$, Lat_t and Lon_t are the Latitude and Longitude of TC center at time t . $\mathbb{M}(\cdot)$ represents the end-to-end DBF-Net. It should be noted that, we use the relative change in

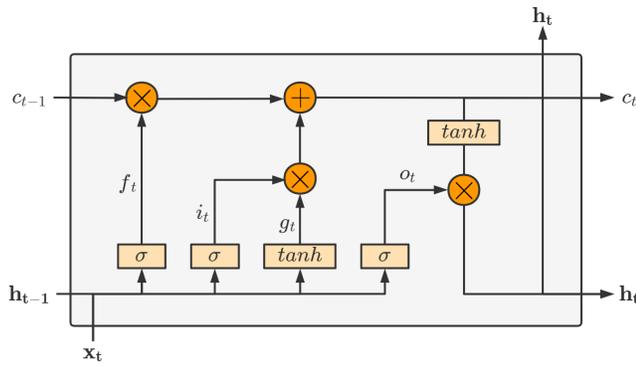


Fig. 2. The structure of LSTM module.

latitude and longitude \mathbf{Y}_j as the output of DBF-Net instead of the direct location. The reason for this is that the pressure field data is cropped from the center of TCs and the local information is more suitable for digging the relative changes in TCs motion.

B. LSTM

Recurrent Neural Networks (RNNs) [26] are one of the popular models for capturing the temporal features of sequence data. RNNs consist of multiple neural networks stacked in the time dimension, and the temporal features could be extracted by utilizing both input data \mathbf{x}_t at time t and the extracted latent features \mathbf{h}_{t-1} at time $t-1$. However, vanilla RNNs suffer from gradient disappearance and gradient explosion when using long term sequence data for training [27]. Therefore, numerous variants have been proposed to solve the problems above [28], [29], including the well-known Long Short-Term Memory (LSTM) model [28].

As shown in Fig. 2, the LSTM improves the vanilla RNNs by replacing the traditional ANN module in RNNs with a complex LSTM module. In order to maintain the latent information for both long and short term, namely *cell state*, three different gates in LSTM module are proposed for different motivations: forget gate, input gate and output gate.

Among them, the forget gate controls the remaining information proportion of the cell state c_{t-1} and the proportion can be computed by

$$f_t = \sigma(W_f \cdot [\mathbf{x}_t, \mathbf{h}_{t-1}] + b_f), \quad (2)$$

where W_f and b_f are the weight and bias value in a fully connected layer. σ represents the Sigmoid function.

As for the input gate, it determines the amount of the candidate information feeding into the cell state by controlling the proportion index. The candidate information g_t and proportion index i_t can be computed by:

$$\begin{aligned} i_t &= \sigma(W_i \cdot [\mathbf{x}_t, \mathbf{h}_{t-1}] + b_i) \\ g_t &= \tanh(W_g \cdot [\mathbf{x}_t, \mathbf{h}_{t-1}] + b_g) \end{aligned} \quad (3)$$

Then, the cell state can be updated from time $t-1$ to time t by:

$$c_t = f_t \times c_{t-1} + i_t \times g_t \quad (4)$$

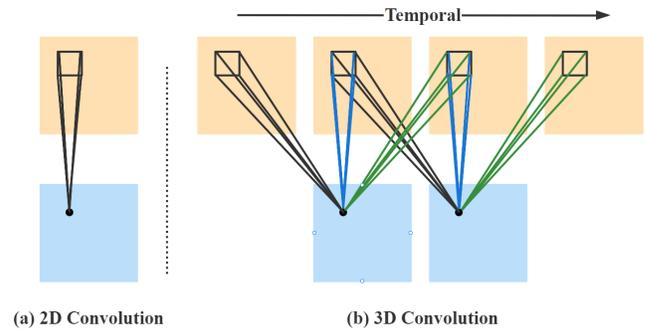


Fig. 3. The difference between (a) 2D convolution and (b) 3D convolution. The black boxes represent the convolution kernel and the lines with same color represent the same kernel weight value.

Lastly, the output gate updates the latent variable by controlling the proportion index of cell state at time t , that is:

$$\begin{aligned} o_t &= \sigma(W_o \cdot [\mathbf{x}_t, \mathbf{h}_{t-1}] + b_o) \\ \mathbf{h}_t &= o_t \times \tanh(c_t) \end{aligned} \quad (5)$$

Through the operations above, LSTM could efficiently extract the temporal features by controlling the proportions of different information flow and the cell state to ensure the gradient is always within a proper range which avoids the gradient disappearance and gradient explosion to some extent.

C. 3D-CNN

Convolutional Neural Networks (CNNs) have achieved remarkable progress in extracting spatial features from image-like 2D data. The local receptive field and shared weights make it possible for CNNs to learn the local spatial relevance of the 2D data with fewer parameters compared with the traditional fully connected layer. However, for video-like 3D data, the traditional 2D convolution can not capture the relevance of the 2D images at different time steps. Therefore, Ji et al [21] proposed the 3D-CNN for human action recognition and 3D-CNN has become a popular model for extracting spatio-temporal features from video-like 3D data.

Fig. 3 illustrates the difference between 2D and 3D convolutions. As can be seen in 3(b) the convolution kernel matrix in 3D-CNN not only slides on a single 2D feature map but also moves in the temporal dimension (same color lines in different feature maps in temporal dimension), thus both spatial and temporal features could be extracted from 3D data simultaneously.

D. TC Features Encoder Module

The TC features encoder module in the first branch of DBF-Net plays the role of encoding the inherent features of TCs $\mathbf{X}_t = (x_1, x_2, x_3, x_4, x_5, x_6)$ at multiple historical times. Each x_j in \mathbf{X}_t represents the latitude at time t , longitude at time t , maximum wind speed near the center at the bottom at time t , latitude difference between time t and $t-1$, longitude difference between time t and $t-1$ and wind speed difference between time t and $t-4$ respectively. The features above are also the classical persistence factors in statistical forecasting

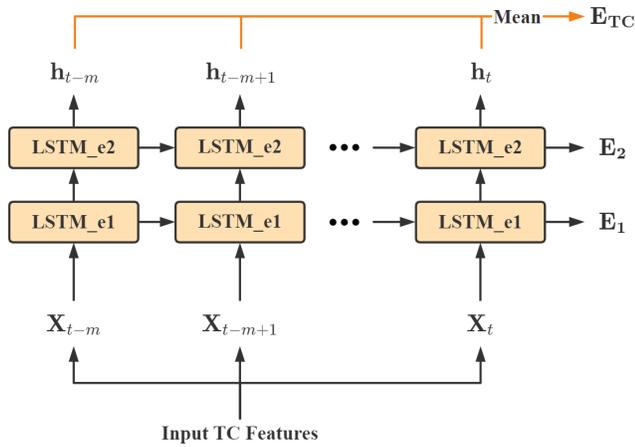


Fig. 4. The LSTM-encoder module in TC Features Branch.

methods. As a result, the purpose of the TC features encoder module is to encode time series features of the persistence factors.

As shown in Fig. 4, the TC features encoder module consists of a two-layer stacked LSTM encoder. Each \mathbf{X}_t in sequence \mathcal{X}_t is passed sequentially into the two-layer LSTM encoding module and produces the latent variable \mathbf{h}_t . The output of each LSTM encoding layer is fed into the corresponding layer at next time step. The specific operation procedure in each LSTM encoding layer is as follows:

$$i_t = \sigma(W_{ii}\mathbf{X}_t + b_{ii} + W_{hi}\mathbf{h}_{t-1} + b_{hi}) \quad (6)$$

$$f_t = \sigma(W_{if}\mathbf{X}_t + b_{if} + W_{hf}\mathbf{h}_{t-1} + b_{hf}) \quad (7)$$

$$g_t = \tanh(W_{ig}\mathbf{X}_t + b_{ig} + W_{hg}\mathbf{h}_{t-1} + b_{hg}) \quad (8)$$

$$c_t = f_t \times c_{t-1} + i_t \times g_t \quad (9)$$

$$o_t = \sigma(W_{io}\mathbf{X}_t + b_{io} + W_{ho}\mathbf{h}_{t-1} + b_{ho}) \quad (10)$$

$$\mathbf{h}_t = o_t \times \tanh(c_t) \quad (11)$$

where the i_t , f_t and o_t represent the output of the input gate, forget gate, and output gate in LSTM model. $W_{ii}(W_{hi})$, $W_{if}(W_{hf})$ and $W_{io}(W_{ho})$ are the corresponding weight matrix related to the $\mathbf{X}_t(\mathbf{h}_{t-1})$. c_t is the cell state fed into the next time step together with the latent variable \mathbf{h}_t . $\sigma(\cdot)$ is the Sigmoid function.

Given the input sequence \mathcal{X}_t of length $m+1$ and the corresponding latent variable sequence $\{\mathbf{h}_{t-m}, \mathbf{h}_{t-m+1}, \dots, \mathbf{h}_t\}$, t is the initial forecast time, we can compute the final time series code of the TC features by:

$$\mathbf{E}_{TC} = \frac{1}{m+1} \sum_{i=0}^m \mathbf{h}_{t-i} \quad (12)$$

E. Pressure Field Branch

To efficiently use the meteorological fields in the vicinity of TCs and improve the forecast accuracy, a 3D-CNN-based encoder-decoder networks are utilized to generate high-level spatio-temporal features from the reanalysis 3D geopotential height (GPH) data at multiple time steps (as shown in Fig. 5).

As shown in Table I, the encoder of the pressure field branch contains three convolutional layers, the first two of which

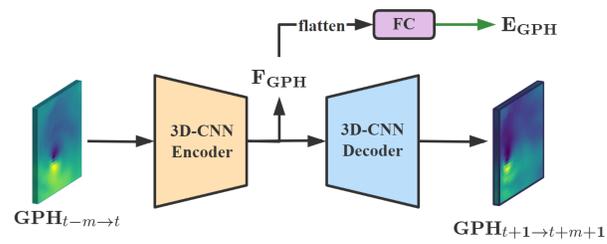


Fig. 5. The pressure field branch architecture.

TABLE I
THE 3D-CNN-BASED ENCODER ARCHITECTURE OF THE PRESSURE FIELD BRANCH

Layers	Kernel Size	Stride	In Channel
Conv_1	$3 \times 3 \times 3$	$1 \times 1 \times 1$	1
MaxPool_1	$1 \times 2 \times 2$	$1 \times 2 \times 2$	16
Conv_2	$3 \times 3 \times 3$	$1 \times 1 \times 1$	16
MaxPool_2	$1 \times 2 \times 2$	$1 \times 2 \times 2$	32
Conv_3	3×3	1×1	32
MaxPool_3	2×2	2×2	64

are 3D-CNN with kernel size $3 \times 3 \times 3$. To ensure that the GPH field data cover the full spatial extent that may affect the TC tracks, the window size at each historical time step \mathbf{GPH}_t of input 3D field \mathcal{G}_t is set to 51×51 values, which is approximately a radius of 1400km (the resolution of the reanalysis GPH data is 0.5 degrees). We choose LeakyReLU as the activation function of the encoder to enhance the nonlinear representation of the model. The output high-level spatio-temporal features can be computed by:

$$\begin{aligned} \mathbf{E}_{GPH} &= FC(\text{flatten}(\mathbf{F}_{GPH})) \\ &= FC(\text{flatten}(\text{Encoder}(\mathcal{G}_t))) \end{aligned} \quad (13)$$

where $FC(\cdot)$ is a fully connected layer. $\text{flatten}(\cdot)$ is the flatten operation that flattening output feature map of the 3D-CNN encoder.

As for the decoder in the pressure field branch, its structure is symmetrical with the 3D-CNN encoder and the transpose convolution is used to recover the spatio-temporal information from high-level features. It predicts the future $m+1$ time steps of the GPH, which is same length of time as the input \mathcal{G}_t . The loss function of the pressure field branch is computed by:

$$\begin{aligned} L_{GPH} &= \sum_{i=t+1}^{t+m+1} \|\text{Decoder}(\mathbf{F}_{GPH}) - \mathbf{TGPH}_i\|_1 \\ &= \sum_{i=t+1}^{t+m+1} \|\mathbf{GPH}_i - \mathbf{TGPH}_i\|_1 \end{aligned} \quad (14)$$

where \mathbf{TGPH}_i is the target value of the future GPH data. $\|\cdot\|_1$ is the l_1 -norm function.

F. Dual-Branched Features Fusion Decoder Module

Based on the LSTM-based encoder in TC features branch and the pressure field branch mentioned above, there are three types of intermediate variables from two branches that fed into the LSTM-based decoder module, that is the final time series

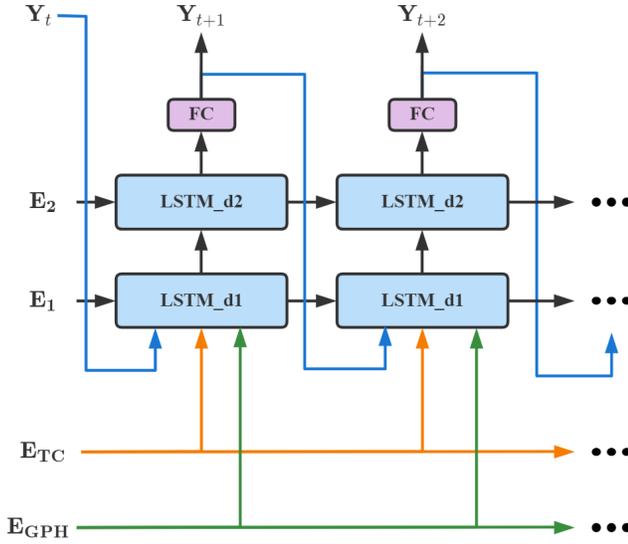


Fig. 6. The LSTM-based decoder module in TC Features Branch with dual-branched features fusion.

code of the TC features E_{TC} , the high-level spatio-temporal reanalysis 3D GPH features E_{GPH} and the output features from LSTM encoder layers E_1 and E_2 . In this subsection, we will introduce the LSTM-based decoder module for efficiently fusing the dual-branched multi-modal features and generating multi-horizon TC track forecasting results.

The proposed LSTM-based decoder module contains a two-layers stacked LSTM decoder and the subsequent two fully connected layers. The detailed decoding and feature fusion process is defined as follows:

$$i_t = \sigma(W_{Ti}E_{TC} + W_{Gi}E_{GPH} + W_{Yi}Y_{t-1} + W_{hi}h_{t-1} + b_i) \quad (15)$$

$$f_t = \sigma(W_{Tf}E_{TC} + W_{Gf}E_{GPH} + W_{Yf}Y_{t-1} + W_{hf}h_{t-1} + b_f) \quad (16)$$

$$g_t = (W_{Tg}E_{TC} + W_{Gg}E_{GPH} + W_{Yg}Y_{t-1} + W_{hg}h_{t-1} + b_g) \quad (17)$$

$$c_t = f_t \times c_{t-1} + i_t \times g_t \quad (18)$$

$$o_t = \sigma(W_{To}E_{TC} + W_{Go}E_{GPH} + W_{Yo}Y_{t-1} + W_{ho}h_{t-1} + b_o) \quad (19)$$

$$h_t = o_t \times \tanh(c_t) \quad (20)$$

$$Y_t = FC_2(ReLU(FC_1(h_t))) \quad (21)$$

where the initial state h_t and c_t are the elements of E_1 and E_2 , which are the final state of the LSTM encoder layers. The initial input of the LSTM decoder Y_t is set to zero. The loss function of the LSTM-based decoder is also l_1 -norm function, which is defined as follows:

$$\begin{aligned} L_{loc} &= \sum_{i=t+1}^{t+\tau} \|Decoder(E_{TC}, E_{GPH}, E_1, E_2, Y_t) - Y_i\|_1 \\ &= \sum_{i=t+1}^{t+\tau} \|T_i - Y_i\|_1 \end{aligned} \quad (22)$$

TABLE II
EXAMPLES OF CMA-BST DATA. **I** STANDS FOR THE INTENSITY LEVEL OF TCs. **LAT** AND **LON** ARE THE LATITUDE AND LONGITUDE OF TCs' CENTERS (UNIT: $\times 0.1^\circ$). **PRES** STANDS FOR THE CENTRAL MINIMUM PRESSURE (UNIT: hPa). **WND** AND **OWD** STAND FOR THE 2-MINUTE MAXIMUM AND AVERAGE NEAR-CENTER WIND SPEED RESPECTIVELY (UNIT: M/S).

YYYYMMDDHH	I	LAT	LON	PRES	WND	OWD
1953061506	0	125	1116	1000	10	15
1953061512	0	132	1117	1000	10	15
1953061518	0	142	1117	1000	10	15
1953061600	0	150	1117	1000	10	20
1953061606	0	159	1112	999	10	20

where, T_i is the ground-truth changes of latitude and longitude. With the operation above, the features from both inherent TC features and reanalysis 3D pressure field can be fused effectively and we can achieve the multi-horizon TC track forecasting results Y_t based on the fused multi-modal features.

G. Loss functions and multi-stages training

We trained our proposed DBF-Net in a three stages manner. First, we only train the TC features encoder module by adding a fully connected layer to directly predict the target value of the TC track and get the pre-trained LSTM encoder in the TC features branch. Then, we utilize the reanalysis 3D pressure fields GPH data to train the pressure field branch of the DBF-Net and learn the temporal dynamic changing of GPH data. Finally, we add the LSTM decoder module into the training pipeline and train the DBF-Net in an end-to-end manner. The loss function at the final step is as follows:

$$L_{final} = L_{loc} + \alpha L_{GPH} + \beta L_2 \quad (23)$$

where, the L_2 is the regularization term with l_2 penalty. α and β are hyper-parameter. The training schedule detail will be discussed in Section 3.3.

III. EXPERIMENT

In this section, we evaluate our proposed DBF-Net on the historical TC tracks data in Northwest Pacific (WNP). The forecasting performance of DBF-Net is verified by the comparison with other deep learning-based and traditional TC track forecast methods. We also analyze the forecast results for several individual cases of TC events and the specific forecasting characteristics of the DBF-Net.

A. Dataset

Best track dataset (CMA-BST). The inherent features data of TCs is extracted from the Best Track (BST) data released by China Meteorological Administration (CMA) [30]. It includes the location and intensity of TCs in the Northwest Pacific (WNP) Ocean ($0^\circ N \sim 50^\circ N$, $100^\circ E \sim 210^\circ E$) at six-hour intervals from 1949 to 2018. Examples of the CMA-BST data are shown in Table II.

Geopotential Height dataset (CFSR-GPH). The reanalysis 3D geopotential height (GPH) data in pressure field branch is collected from Climate Forecast System Reanalysis (CFSR)

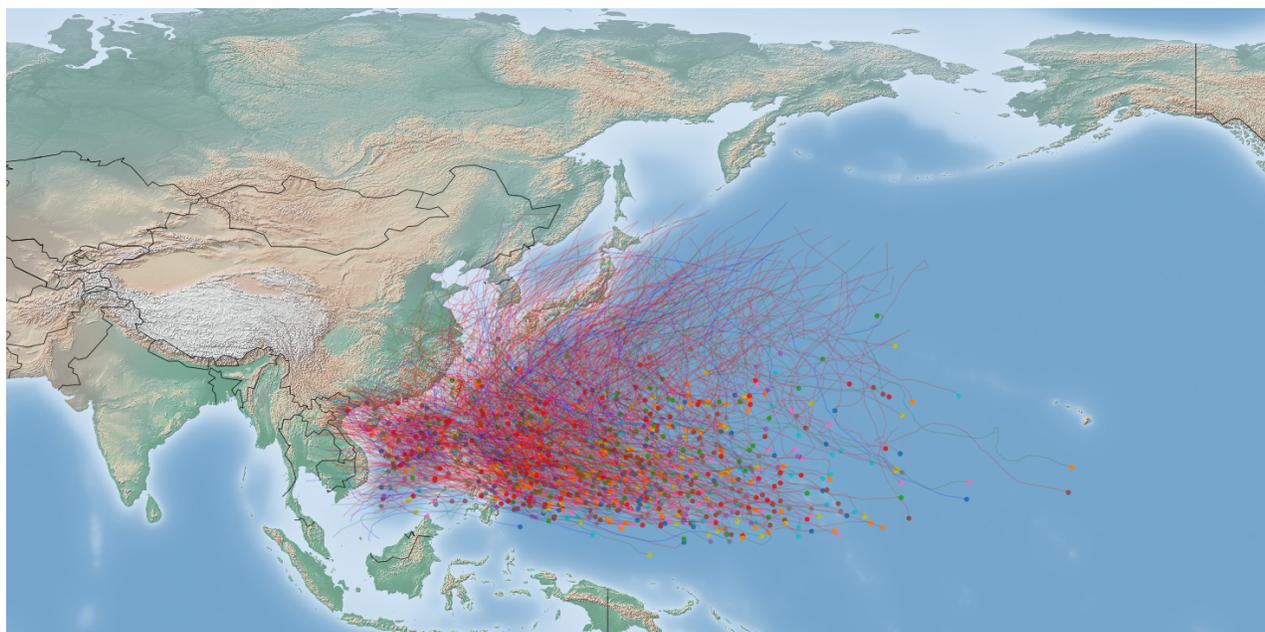


Fig. 7. All TCs track data used in the experiment. The line in red, blue and green represent the TCs for training, validating and testing. The scatters in different color represent the first locations of TCs.

TABLE III
DATASET SPLITTING BASED ON CMA-BST AND CFSR-GPH.

	Train Set	Val Set	Test Set
Years	1979~2008	2009~2013	2014~2018
#TCs	723	104	113
#Samples	13233	1847	2174

dataset released by The National Centers for Environmental Prediction (NCEP) [31]. CFSR-GPH is grid data with a spatial resolution of 0.5° and the temporal resolution is aligned with CMA-BST from 1979 to present. TCs in WNP are mostly generated at the southern edge of the subtropical high pressure and move along its periphery. Therefore, the 500hPa geopotential height data is chosen as the background pressure field to describe the activity of TCs.

Data pre-processing. For both input data from CMA-BST and CFSR-GPH, we use the maximum-minimum normalization for data pre-processing and feed them into the TC features and pressure field branch respectively.

Dataset Split. Based on the CMA-BST and CFSR-GPH dataset mentioned above. We choose overlap of the two datasets i.e. TCs from 1979 to 2018. And we only keep the TCs with a life cycle greater than four days to ensure the persistence. There are 940 TCs left in this dataset. We make 17000+ samples for model training, validating and testing based on a sliding window of length $input\ sequence\ length + prediction\ length$ (as shown in Figure 7 and Table III).

B. Metrics

We use the Mean Distance Error (MDE) to evaluate the TCs track forecast results. The MDE is a commonly used metric to

measure the average distance error between model prediction and ground truth. The MDE can be computed by:

$$MDE = 2 \times R \times \arcsin \sqrt{\sin^2\left(\frac{\varphi_{pre} - \varphi_{gt}}{2}\right) + \cos \varphi_{pre} \cos \varphi_{gt} \sin^2\left(\frac{\lambda_{pre} - \lambda_{gt}}{2}\right)} \approx \sqrt{\Delta Lat^2 + \Delta Lon^2} \times 110 \quad (24)$$

where, $R \approx 6371km$ represents the radius of earth. φ_{pre} and φ_{gt} stand for the latitude value of prediction and ground truth. λ_{pre} and λ_{gt} stand for the longitude value of prediction and ground truth.

Besides, the skill score is also the index to evaluate the practical availability of the methods, as follows:

$$skill\ score = \frac{e_A - e_B}{e_A} \times 100\% \quad (25)$$

where, e_A is the prediction error of CLIPER method and e_B is the error of proposed method.

C. Implementation Details

We train our proposed DBF-Net in a three stages manner with the Pytorch framework, which has been discussed in Section 2.5. We use the RMSProp optimizer and set the initial learning rate to 0.001. The batch size of training set is set to 64. The hyper parameter α and β in equation (19) is set to 1.2 and 0.00001 respectively.

For multi-horizon forecasting (i.e. predicting the TCs track at multiple future time steps), the output prediction sequence length of the DBF-Net is 4 and the input sequence length is 5. That is we predict the 6h, 12h, 18h and 24h TCs tracks based on the historical data from time $t - 5$ (30h prior) to time t (the current time). We train our DBF-Net on a single NVIDIA GeForce GTX 3090 GPU.

TABLE IV
COMPARISON OF THE TCs TRACK FORECASTING RESULTS OF STATISTICAL AND DEEP LEARNING METHODS.

Methods	MDE (km)			
	6h	12h	18h	24h
extrapolation	33.78	79.20	135.48	201.28
CLIPER-BP	37.53	73.31	115.13	162.62
FFN [13]	32.90	-	-	136.10
BiGRU-attn [14]	-	-	-	147.38
DBF-Net (Ours)	31.30	58.94	87.60	119.05

D. Comparison with Statistical/Deep Learning Forecast Methods

We first compare our proposed DBF-Net with other statistical and deep learning based TCs track forecast methods, including the extrapolation method [1], CLIPER method [2], feature fusion network [13] and recent BiGRU-attn [14]. The extrapolation is a simple traditional TCs track forecast method. It assumes that the direction and speed of TCs movement do not change much, and predicts based on the movement direction and velocity at previous times. CLIPER can be treated as the benchmark of other track forecast methods. It uses correlation analysis to screen climate persistence factors and constructed multivariate linear regression models. In this paper, we replace the multivariate linear model with a back propagation (BP) neural network model, which enhancing the nonlinear representation of the CLIPER model. We selected 20 factors with strong correlation from 46 climate persistence factors by Pearson correlation analysis and feed them into the BP neural network.

As shown in Table IV, our proposed DBF-Net outperforms previous works. Specifically, compared with the benchmark forecast method CLIPER, DBF-Net achieves better MDEs for all forecast time steps. That is the skill score with respect to the CLIPER is positive, which demonstrates the practical availability of our method. In addition, our DBF-Net also outperforms previous deep learning based methods. Compared with FFN [13] that utilizes the wind, pressure fields simultaneously, our DBF-Net achieves better results only based on pressure field. This also shows that our method can better encode the effective features of the input data.

E. Comparison with NWP Forecast Methods

We further compare our DBF-Net with the Numerical Weather Prediction (NWP) system that commonly used in operational forecasting. The global pattern T213/T639 released by China Meteorological Administration (CMA) and Shanghai typhoon region pattern (SHTP) released by Shanghai Typhoon Institute of the CMA [22]–[25] are chosen for comparison. Compared with our deep learning based method, the NWP methods always need a great number of computation resources and the inference time increases rapidly as input data resolution increases. However, NWP methods still can achieve better forecast accuracy compared with deep learning based

methods. As shown in Table V, DBF-Net could achieve comparable performance compared with global pattern T213/T639, especially in year 2014 and 2015, the 24h MDE of DBF-Net is much better than T213/T639. However, compared with the region pattern SHTP, the forecast of the DBF-Net still has a certain gap. The great performance of the SHTP may due to the high-resolution multi-layer nested grid input data and huge computational resource consumption. In contrast, our proposed DBF-Net achieves relatively high prediction accuracy under the premise of low-resolution input (1° spatio resolution for GPH data) and small computational resource consumption. The inference time of our DBF-Net for multi-horizon forecast is only 2.03 seconds which is about three to four orders of magnitude faster compared with the NWP methods. Besides, we believe that by using higher resolution data for model training, our DBF-Net could further improve the forecast accuracy which can be further studied in the future works.

TABLE V
COMPARISON OF THE TCs TRACK FORECASTING RESULTS OF NWP METHODS. THE RESULTS OF NWP METHODS IS RELEASED BY [22]–[25]

Year		T213/T639	SHTP	DBF-Net
2014	#Samples	411	112	330
	24h MDE (km)	121.8	64.9	107.4
2015	#Samples	46	440	671
	24h MDE (km)	150.6	67.8	107.0
2016	#Samples	412	194	332
	24h MDE (km)	114.9	88.5	118.9
2017	#Samples	301	253	319
	24h MDE (km)	98.7	89.1	130.6
AVG		121.5	77.6	116.0
Inference Time		-	-	2.03s

F. Ablation Study

Verification of model structure. In order to verify the effectiveness of our proposed Dual-Branched spatio-temporal Fusion Network (DBF-Net) architecture, we experimented with different branching structures. As can be seen in Table VI, our proposed DBF-Net with two branches encoder-decoder networks and feature fusion module, which is denoted as "DBF-Net*", achieves the best forecast MDE except with the 6h forecast result in "DBF-Net" that verified the consistency of our method. In addition, the relatively bad performance of LSTM-based and 3D-CNN-based encoder-decoder architecture alone, which is denoted as "TC-features-only" and "Pressure-fields-only", demonstrate that it is hard to obtain good forecast results for single inherent features or meteorological fields input. It makes sense to fuse these two types of data for better forecast accuracy. The results in Table VI also show the effectiveness of the 3D-CNN Decoder module for enhancing the temporal dynamic changing of GPH data.

It should be noted that the 3D-CNN decoder module in pressure fields branch only plays a role in model training. Once the DBF-Net is trained, the inference is done by just passing

TABLE VI

THE IMPACT OF DIFFERENT BRANCHES IN DBF-NET. * REPRESENTS THE MODEL WITH 3D-CNN DECODER IN PRESSURE BRANCH TO ENHANCE THE TEMPORAL DYNAMIC CHANGING OF GPH DATA.

Architecture	MDE (km)			
	6h	12h	18h	24h
TC-features-only	32.87	69.08	111.08	158.11
Pressure-fields-only	34.35	64.07	95.83	130.79
Pressure-fields-only*	34.27	63.31	93.63	126.89
DBF-Net	31.18	59.13	88.82	121.79
DBF-Net*	31.30	58.94	87.60	119.05

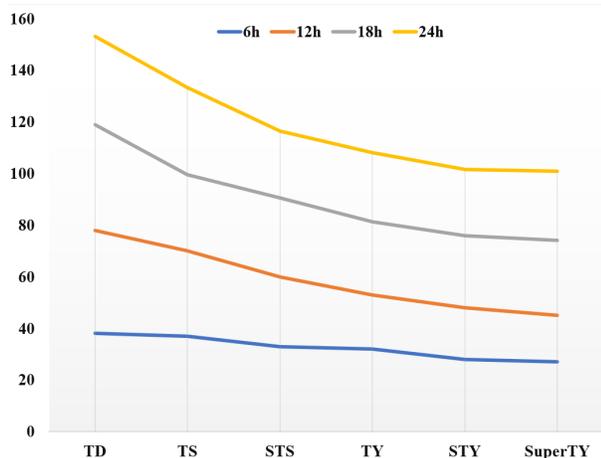


Fig. 8. The TCs track forecast result of our proposed DBF-Net of various intensity.

TC features branch and 3D-CNN encoder module. Therefore, the 3D-CNN decoder module does not increase the memory and computational cost of the DBF-Net inference.

Effectiveness of multi-stages training method. As mentioned in Section II G, we train our DBF-Net in a multi-stages manner to enhance the ability of feature extraction from different input data of each module in DBF-Net. In order to verify the effectiveness of the multi-stages training method, we also trained our DBF-Net in an end-to-end manner and the 24h track forecast accuracy is 128.61km, which is 9.56km worse compared with the one with multi-stages training.

Forecast Accuracy for TCs of Different Intensity Levels. We classify TCs according to the intensity level at the initial forecast time. That is tropical depression (TD), tropical storm (TS), severe tropical storm (STS), typhoon (TY), severe typhoon (STY) and super severe typhoon (SuperTY). Fig. 8 reports the track forecast error of various TCs' intensity. It shows that, the forecast error decrease consistently as the intensity of TCs increase. It means that the performance of DBF-Net for forecasting TCs' track with low intensity is relatively poor. The same conclusion is also reported in previous works [13].

G. Case Study

In this subsection, we select three individual cases of TC events, namely Typhoon Trami 1824, Typhoon Hagibis

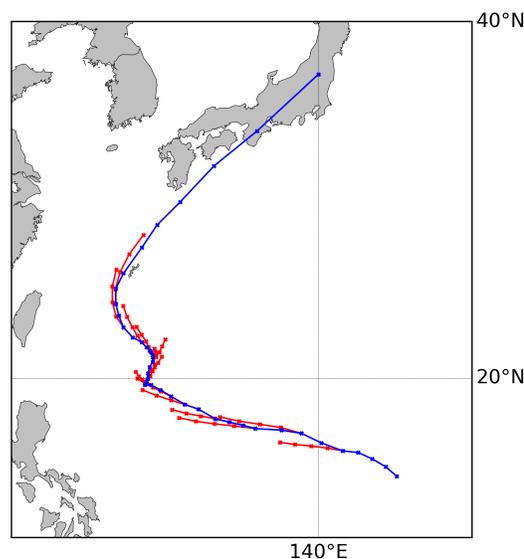


Fig. 9. TCs track forecast results for typhoon Trami 1824. The blue line represents the ground truth track. The red line represents the forecast results.

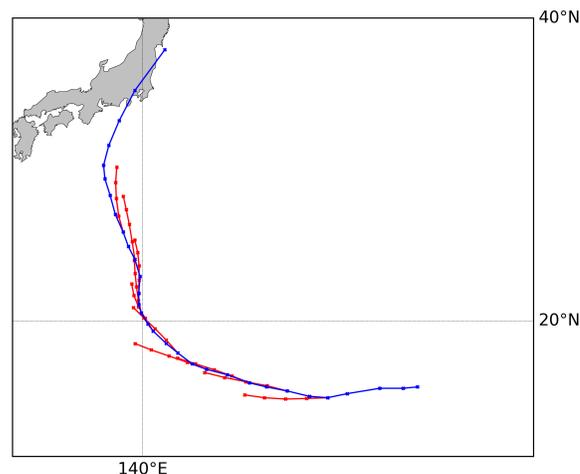


Fig. 10. TCs track forecast results for typhoon Hagibis 1919. The blue line represents the ground truth track. The red line represents the forecast results.

1919 and Typhoon Fengshen 1925 (the four digits after the typhoon name represent the typhoon number, for example, the typhoon 1919 represents the 19th typhoon of year 2019). According to the forecast results, the validity of the DBF-Net is further verified, and the forecast characteristics of DBF-Net are analyzed.

Fig. 9~11 and Table VII~ IX shows the TCs track forecast results for the three cases. In the figures, the blue line represents the ground truth track of TCs and the red line is the forecast results of the proposed DBF-Net. The intersection of the blue and red lines is the location of initial forecast time. The 4 points extending from the red line represent the forecast path in the next 24 hours (6-hour interval) from the initial forecast time.

For Typhoon Trami 1824, its path generally shows a trend of first westward and then northward. As shown in Fig. 9, the error between the forecast and the ground truth track is relatively small at the inflection point from west to north.

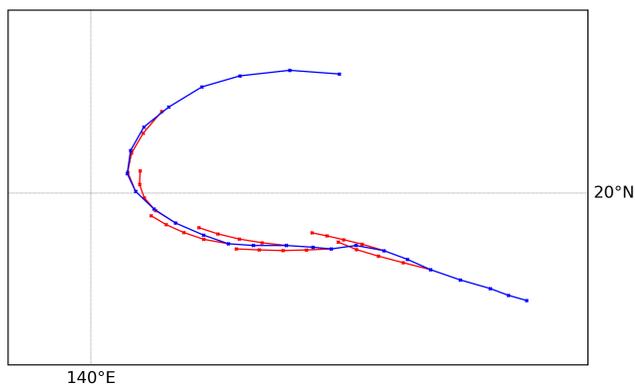


Fig. 11. TCs track forecast results for typhoon Fengshen 1925 . The blue line represents the ground truth track. The red line represents the forecast results.

TABLE VII

THE TRACK FORECAST RESULT OF DBF-NET FOR TYPHOON TRAMI 1824. **INT** STANDS FOR THE INTENSITY LEVEL OF THE TC. **AVG** STANDS FOR THE AVERAGE PREDICTION MDE.

Typhoon Trami 1824					
MMDDHH	INT	MDE (km)			
		6h	12h	18h	24h
092118	TS	54.56	111.16	137.78	194.56
092206	STS	19.60	41.45	40.61	75.08
092218	TY	63.42	103.65	136.77	147.31
092306	STY	5.89	49.85	62.80	92.46
092318	STY	1.05	26.49	46.63	68.26
092406	SuperTY	11.45	21.48	11.23	66.31
092418	SuperTY	22.59	33.89	65.07	83.58
092506	SuperTY	8.75	23.03	34.63	20.56
092518	SuperTY	24.11	27.85	52.71	62.20
092606	STY	23.19	51.10	83.84	129.74
092618	STY	26.29	44.59	65.90	94.28
092706	STY	13.92	28.89	62.13	86.24
092718	STY	33.67	58.95	55.01	50.70
092806	STY	18.94	24.64	26.86	52.50
092818	STY	3.85	23.75	91.57	108.31
AVG		23.48	41.70	58.40	82.43

This shows that the model itself has learned the potential features of TCs track movement. For Typhoon Hagibis 1919, there also a inflection point at time "100718" (as shown in Fig. 10 and Table 10). Although the forecast result is relatively bad (177.07km for 24h forecasting), the DBF-Net also could fix the prediction by bringing the observations from the next time step (24.93km for 12h forecasting at time "100806"). This shows that the historical information closest to the initial forecast time is more important. For Typhoon Fengshen 1925, its trajectory presents a 180° turning trend, which is unconventional. As shown in Fig. 11, DBF-Net could correctly predict the turning trend of the TC. However, the forecasting length of the track vector is uniformly smaller than the ground truth and causes the average MDE to be relatively large (in Table 11).

In Table VII~ IX, we also report the intensity level (INT) at each time step. By comparing the results in Tables 7~9, it can be found that the DBF-Net has a relatively lower MDE when the intensity level is larger. Especially for the

TABLE VIII

THE TRACK FORECAST RESULT OF DBF-NET FOR TYPHOON HAGIBIS 1919. **INT** STANDS FOR THE INTENSITY LEVEL OF THE TC. **AVG** STANDS FOR THE AVERAGE PREDICTION MDE.

Typhoon Hagibis 1919					
MMDDHH	INT	MDE (km)			
		6h	12h	18h	24h
100606	STS	28.26	68.36	90.68	107.11
100618	TY	11.00	30.92	31.60	30.41
100706	SuperTY	38.75	62.95	26.88	41.82
100718	SuperTY	42.27	75.44	132.27	177.07
100806	SuperTY	26.80	24.93	60.36	77.02
100818	SuperTY	51.18	54.16	82.65	93.71
100906	SuperTY	30.06	56.08	45.70	9.55
100918	SuperTY	29.00	56.08	86.27	109.05
101006	SuperTY	47.06	75.26	90.90	99.15
101018	STY	28.45	52.75	84.87	97.22
AVG		29.43	51.41	66.84	86.77

TABLE IX

THE TRACK FORECAST RESULT OF DBF-NET FOR TYPHOON FENGSHEN 1925. **INT** STANDS FOR THE INTENSITY LEVEL OF THE TC. **AVG** STANDS FOR THE AVERAGE PREDICTION MDE.

Typhoon Fengshen 1925					
MMDDHH	INT	MDE (km)			
		6h	12h	18h	24h
111206	TS	34.07	50.98	26.22	63.83
111218	TS	39.65	99.83	116.08	183.11
111306	STS	44.77	38.92	48.00	60.31
111318	STS	59.19	75.96	90.71	152.12
111406	STS	27.19	81.96	126.19	183.04
111418	TY	14.69	68.90	102.61	140.09
111506	STY	9.65	17.76	38.13	50.84
AVG		28.05	62.49	92.39	137.03

TCs with the intensity level of "SuperTC", the predicted MDE is comparable to the NWP model. This phenomenon also explains the relatively poor forecast results of Typhoon Fengshen 1925.

IV. DISCUSSION AND FUTURE WORK

The proposed DBF-Net provides a relatively efficient way to fuse multi-modal spatio-temporal data for tropical cyclone track forecasting. The extensive experiments further verify the importance of fusing the two types of data for better forecast accuracy. However, as shown in Table V, the forecast results of deep learning-based DBF-Net still have a certain gap compared with the traditional complex NWP methods, although DBF-Net has a greater advantage in terms of computational consumption. Fortunately, recent works on precipitation forecasting demonstrate the potential of deep learning-based methods for weather/climate forecasting [32], [33]. Therefore, there are still many aspects to be studied for deep learning-based TC track forecast methods in the future to improve the forecast accuracy. The following four issues could be considered in the future:

- Recent deep learning-based precipitation forecasting methods mainly treat the forecast problem as a video frame prediction task [32], [33]. The large-scale image-like data with a high temporal resolution, such as radar map and satellite image, is the primary input of the proposed methods. Although the similar idea also investigates in TCs track forecast area recently [16], the model architecture and scale of the training set are still limited compared with the MetNet [32] and DGMR [33] which can be further studied.
- The experiment results in Table VI shows the relatively bad performance for forecasting only based on TC features, especially for long-term forecast results (24h). The reason for this may be due to the inadequacy of the LSTM structure. The popular Transformer-based model with attention mechanism [4], [5] could be a great choice for capturing the temporal features of sequence data more efficiently.
- The assumption of regular mesh of the reanalysis 3D pressure data is adopted in this paper for simplicity. And the vanilla convolution operation in 3D version is used to extract the spatio-temporal features. However, there exist irregular distribution of meteorology field across the different spatial location. In order to solve this problem, the graph convolution [34] and spherical CNNs [35] could be used for further study.
- Different from the data-driven deep learning-based forecast methods, the NWP methods mainly follow the physics laws by solving the partial differential equations (PDEs) with few boundary and initial condition samples and achieving outstanding forecast results. These physics laws can be treated as prior information for TCs track forecast which is still ignored by deep learning-based methods. Recently, many works try to merge the physics information into the deep learning framework for weather forecasting to maintain the advantages of numerical and deep learning based methods at the same time [36]–[38], so as to improve the performance of deep learning-based TCs track forecasting.

V. CONCLUSION

In this paper, we study the Tropical Cyclone (TC) track forecasting for multiple future time steps by proposing a novel deep learning based model, named DBF-Net, to make full use of both inherent features of TCs and reanalysis 3D pressure fields data and fuse the multi-modal features efficiently. DBF-Net contains two branches with encoder-decoder architectures and can be split into three part. The first part is the LSTM-based TC features encoder module that captures the high-level temporal features from historical inherent features of TCs. The second part is the pressure field branch that extracts the spatio-temporal features by learning the temporal dynamic changing of GPH data with a 3D-CNN-based encoder-decoder network. The last part is a LSTM-based decoder module that fuses the multi-modal high-level features from different branches and produces the multi-horizon prediction.

Experiments on 39 years of historical TCs track dataset in the Northwest Pacific Ocean show that the 24h track fore-

cast accuracy reaches 119.05km which outperforms previous statistical/deep learning forecast methods. Our DBF-Net also achieves comparable performance compared with the global pattern T213/T639 with orders of magnitude faster. The case study of three different typhoon events further shows the ability of predicting the turning trend of our proposed method.

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