International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

Marine Weather Data Based Rain Prediction Using Reinforced Memory Based on Partial Differential Hamiltonian Quantum Neural Network Classification

Deepa Anbarasi J[1], Dr. V. Radha[2]

[1]*Research Scholar, Department of computer science, Avinashilingam institute of home science and higher education for women, Coimbatore.*

[2]*Proffoser, Department of computer science, Avinashilingam institute of home science and higher education for women, Coimbatore.*

Date of Submission: 15-08-2023 Date of Acceptance: 25-08-2023

ABSTRACT: Maritime ventures are all times insecure, but there are several things that meteorological organizations can do to minimize the risks. Among them, weather is one of thevarious characteristics,that give rise to maritime work to be threatening, however weather forecasting can put a stop to accidents and itresulting in cargo losses, injuries, andcasualties too. Time series prediction of marine weather in meteorology can aid a decision-making processfor the impediment of disasters. Moreover, some issues are frequently overlooked by prediction methods for inadequate volume of memory contingency of vanishing gradient, elevated prediction error and it designing a method, that provides the accurate forecast of marine weather. In this work, a method called, Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) for marine weather forecasting is proposed. This method combines Reinforced Long Short-term Memory (Reinforced LSTM) with Partial Differential Quantum Hamiltonian Recurrent Neural Network (PDQH-RNN) to forecast marine weather. In this work, Reinforced LSTM based onPDQH-RRNN is geared as the prediction model to overcome thedimension inadequacy by utilizing Reinforced LSTM, that in turn alleviate the vanishing gradient by proliferating input sequence to layers of Reinforced LSTM. With this, prediction error gets minimized and therefore it ensures the accurate marine prediction by utilizing exponentially weighted average function. The partial derivativeswereessential for the learning that obtained and utilizing the adjacent model. By employing PDQH-RNN, the wind speed using spatial correlation are first obtained to determine the adverse events and utilizing wind data (i.e., zonal winds, meridional winds, humidity, air temperature and sea surface temperature) is measured down to a depth of 500 meters. Moreover, the reference point wasappropriately fringed across the direction of the prevailing winds, with the objective for obtaining the temporal associations.involved.As a result, the prediction time involved was greatly reduced, therefore it improves the true positive rate also. The performance parameters wereconsidered for the evaluation of the performance and the efficiency of the proposed marine weather forecasting methodclassification error, classification accuracy, classification time and true positive rate.

Keywords: Marine Weather Forecasting, Reinforced Long Short-Term Memory, Partial Differential, Quantum, Recurrent Neural Network

I. INTRODUCTION

A novel Spatial Feature Attention Long Short-Term Memory (SFA-LSTM) method was proposed in [1] with the objective of acquiring spatial and temporal relations of the multiple meteorological features towards the temperature forecasting. Here, spatial and temporal representations of feature were aligned directly to forecast data in an accurate manner. On one hand, spatial feature attention with mutual influence acquired the target feature. On the other hand, encoder-decoder architecture was employed to learn temporal dependencies using LSTM layers in the encoder phase and spatial feature relations in the decoder phase. As a result, the SFA-LSTM method forecasted the temperature by learning time steps and weather variables, therefore,it was reducing the mean square error with better prediction accuracy. However, the prediction time involved was not analyzed.

The time taken in prediction remains one of the major factors for weather prediction, because only with the early prediction hazardous, that events can be avoided. To address on this aspect, Nonlinear Autoregressive Exogenous-based Correlation model is introduced with efficient mapping between the past and present events and classification can be made efficiently. Therefore, it was reducing the prediction time significantly.

A spatiotemporal deep learning-based framework was proposed in [2] with the objective of forecasting. Monthly Effective Drought Index employing three distinct techniques, namely, univariate and multivariate is based on neighboring spatial points and finally multivariate is based on neighboring spatial points respectively. Moreover, with the application of Eigen vector values are extremely wet the events, that is also identified. With the inclusion of multivariate technique, it was inferred and accuracy was inferred on apprehending the dominant feature, that in turn influenced precipitation regimes in the Pacific, therefore resulting in the improvement of precision, recall and accuracy rate.

Despite improvement in three different performance metrics, like, precision, recall and accuracy, however, a small amount of error is said to occur, during the learning process. This error factor was not focused. To address on this issue, Derivative Rectified Linear Unit activation function is applied in the Reinforced Long Short-Term Memory algorithm. This reducethe number of incorrect observations or sample instances that were wrongly classified. Therefore, it reducing the classification error involved in marine weather forecasting.

Climate predictions have considerable prospectively to enhance thestrategic planning in numerous divisions of both private and public sectors. This prospective has been extensively identified by business establishments and it providing theclimate services in numerous climate data portals. Studies conducted have obtained the series fordeveloping the climate services, thus permit for definite purposes and tailored predictions were necessitated,which was frequently require personal contact between users and experts.

Evaluation of marine weather forecasts in the atmospheric model at transient time scales was analyzed in [3]. The error magnification was also evaluating toutilizing the model analysis therefore observations made in the course of the mission. The discerned flexibility of sub-seasonal rainfall was correlated with mid-latitude systems were well reproduced in the model forecasts. Till date, the prospective of climate conditions was designed on the basis of historical occurrences. In [4], prospective were obtained from an ensemble of seasonal predictions given by the German Meteorological Service. As a result, risk assessments were made efficiently. Seasonal predictions with global and regional models were designed in [5] to provide moderate skill in predicting inter-annual variations.

Wind speed influences, several agricultural pursuits and crop features, together forgrowth and development. Bestowing farmers with future wind speed information in turn would enhance the profits by permitting them to lay hold of avoiding circumstances actions at odds with unfavorable influences of high-speed winds and will.Therefore, itenhancescrop cultivation in a significant manner. So, wind speed forecasting is considered to be advantageous to agricultural management.

In [6], a high-resolution wind speed forecast mechanism for agricultural purposes in South Korea was designed. The mechanism was generated the wind speed forecast was taking into consideration both the aboveground and spatial resolution into factor. Moreover, random forests, support vector and extreme learning machine were also validated as candidate models for downscaling wind speed data. Deep neural network was applied in [7] for learning long time dependency that factors involving the wind speed involving in daily, weekly and monthly data. As a result, prediction accuracy was improved with minimum error. However, the current deep learning did not take to consider the sea surface temperature (SST) for weather prediction. In [8], several deep learning (DL) techniques were employed to utilizing the past meteorological features with the objective of predicting day ahead SST. With this high reliability was ensured.

Several past endeavors have been made to utilizing the machine learning techniques, that also lacked intermittent restrictions in features. As a result, inflated errors were discerned. In addition, classification time and accuracy were noticed to be prejudiced in many of these past studies [1] and [2]. Therefore, to address this significant research

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

gap, we propose Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) for marine weather forecasting.

1.1 CONTRIBUTIONS

The major contribution of the proposed Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) for marine weather forecasting is elaborated below.

- To accurately perform the marine weather forecasting, a novel method called, Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) and itwas developed. It uses the Nonlinear Autoregressive Exogenous-based Correlation model for data mapping and Reinforced Long Short-Term Memoryto generate reinforced results. Followed by, a classification model is carried out a means of Partial Differential Quantum Hamiltonian Recurrent Neural Network.
- In Reinforced Long Short-Term Memory process, Back Propagation Time-based Weight update is applied to tune the weight and by employing the Derivative Rectified Linear Unit activation function.Marine weather data are retained according to the decision made. Due to this, the performance of classification error is reduced and also improves the accuracy involved in marine weather forecasting.
- To propose Partial Differential Quantum Hamiltonian Recurrent Neural Network-based classification algorithm,that takes into consideration and only the correlation between nearby particles (i.e., adjacent air temperature and sea surface temperature) for classification. The partial derivatives exploit the advantages of spatial correlation for hourly or daily average wind and hence itwarrants the accurate marine weather forecasting.
- Finally, a comparison of the proposed method with related methods reveals that it is efficient specifically in terms of classification time, classification accuracy, classification error and true positive rate.

1.2 ORGANIZATION OF THE PAPER

The synopsis of this article is organized as follows: In Section 2, related works in the area of marine weather forecasting, machine learning and deep learning is elaborated. In Section 3, the proposed Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) for marine weather forecasting is described in detail with figurative representation and algorithms. Experimental results and performance evaluations of the quantitative analysis with medical images are provided in Section 4. Finally, a brief conclusion is drawn in Section 5.

II. RELATED WORKS

Marine functions are non-routine operations of constrained time span for controlling the objects and vessels in marine environment. Those types of functions can only be done inside the sea state curtailments. Weather demography is utilized operations for planning and on the other hand, forecasting of weather is essential for determining on when to initiate the functioning. Owing to this, the wind accuracy and forecasting of wave condition is considered as a pivotal element in operation planning during execution.

A novel multi-model ensemble learning technique was designed in [9] with the objective of predicting next-day air temperature. However, with the uncertainty factor, observation of error in turn compromised the accuracy also. To address on this research gap, adaptive-network-based fuzzy inference system was presented in [10] that in turn not only determined the error factor but also efficiently predicted the favorable environment circumstances for marine weather forecasting. In [11], an arbitrary, probabilistic, and non-parametric mechanism was designed on the basis of Gaussian processes (GPs). With these interconnected forecasts were made with the available information, therefore itimproving the prediction accuracy.

Weather forecasting conceivably be a state-of-the-art method for apprehending the alternates in the time ahead. But the prevailing methods everlastingly acquire the little prediction accuracy for forecasting short term data. This is owing to the reason that the numerical prognostication mechanisms are not executing well in numerous situations. A survey of load forecasting techniques was elaborated in [12]. In [13], neural network taking to consider the multi-timescale features of convolutional neural network and a long short-term memory neural network, that were presented with the objective of forecasting short-term measures in the eastern ports of Hokkaido, Japan. With this integrated mechanism efficient forecasting was said to be ensured.

Accurate weather forecasting has manifested to be a demanding piece of work for both the researchers and meteorologists. This is owing to the reason that information pertaining to weather is crucial in every part of life, to name a few being, agricultural activities, tourism department, mining, generation of power and so on. Also, forecasting of weather has set foot into the epoch of Big Data, itowing to the evolution of satellite meteorological observation and also fast boom in voluminous weather data. Hence, the conventional computational intelligence mechanisms are not sufficient for weather prediction in an accurate fashion.

A survey of weather forecasting in deterministic manner was investigated in [14]. Yet another comprehensive review on deep learning techniques for wind forecasting was presented in [15]. The main issue involved in SST prediction remains in acquiring both spatial and temporal features, that has not been explored by the prevailing methods. In [16], a dense Dilated Convolutional LSTM (D2CL) method was designed with the objective of predicting SST. Here, initially dilated convolutional network was integrated with LSTM for learning spatial and temporal characteristics concurrently. Next, dilated kernel sizes were utilized for extracting features and finally, feature loss was reduced to employing the dense connection.

Apprehending the pivotal information for concerning both spatial and temporal domain is mandatory for making forecasting in an accurate fashion. The potentialities of deep learning algorithms are said to be applied in such situations and it owing to their improved potentiality in discerning complicated associations. In [17], a framework was presented for identifying the features using long short-term memory deep learning model with the objective of forecasting spatial temporal hydrological features in the South Pacific region, therefore it ensuring the accuracy to great extent

In [18], accuracy of LSTM neural network algorithm adaptations on thunderstorm severity employing the remote sensing weather data and it was presented. With this, not only accuracy was ensured but also it reduced the error involved in remote sensing for marine weather forecasting. However, the complexity involved in learning was not focused. To concentrate on this issue, Discrete Wavelet Packet Transform (DWPT) was integrated with Bidirectional Long Short-Term Memory (BLSTM) in [19]. By employing this integration model, not only resulted in the improvement of forecasting performance but also reduced the learning complexity. A review of learning models was investigated in [20] for monitoring and predicting weather in an intelligent fashion.

Motivated by the above facts, in this work, Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) for marine weather forecasting is proposed. The elaborate description of the RPDQ-HNN method is given in the following sections.

III. METHODOLOGY

Marine weather forecasting is one of the crucial issues in the domain of meteorology. Marine weather forecasting refers to the procedure by which meteorological organizations strive to forecast subsequent weather conditions.Several methods have been previously proposed to predictthe marine weather and it was based on spatial-temporal relations, for consideringthe neighboring spatial points and machine learning. In this section, a method called, Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) is presented for marine weather forecasting. The RPDQ-HNN method integrates Reinforced Long Short-Term Memory (Reinforced LSTM) with Partial Differential Quantum Hamiltonian Recurrent Neural Network (PDQH-RNN) to accurately and robustly forecast marine weather. Figure 1 shows the structure of the Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) method for marine weather forecasting.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

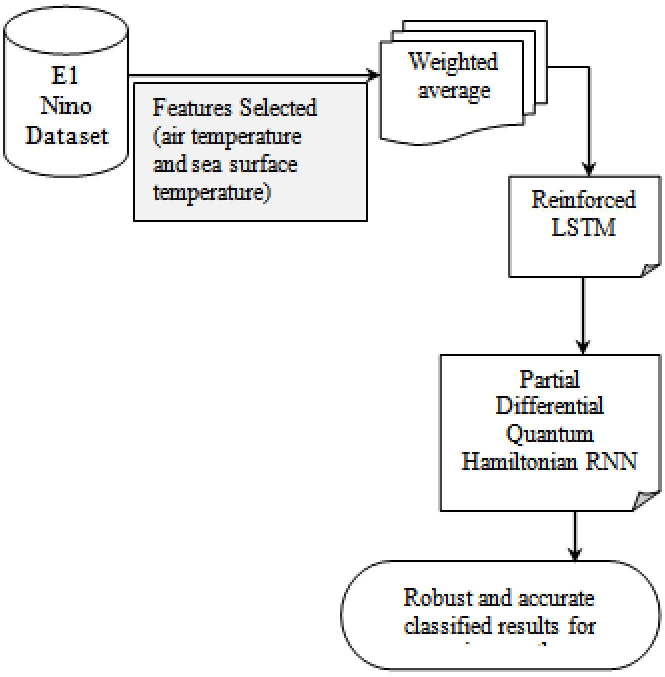

Figure 1 structure of the Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) method for marine weather forecasting.

As shown in the above figure with the E1 Nino dataset provided as input and the five features was selected for further processing (i.e., classification purpose), Reinforced Long Short Term Memory (Reinforced LSTM) is initially applied to reduce the vanishing gradient issues (i.e., where the gradient will be vanishingly small, putting a stop to the weight from updating its value). Here, weighted average function is utilized to address the vanishing gradient issue. Next, partial derivatives required for learning are obtained to employingthe adjacent model. Also, a reference point utilized in our work is fringed in an appropriate manner for obtaining temporal associations. In the following sections the elaborate mechanism involved in the design of RPDQ-HNN method for marine weather forecasting is presented and followed by the dataset description and correlation model.

1.1 Dataset Description and Representation

The RPDQ-HNN method is trained and tested using E1 Nino dataset.Let ' $F(t) = \{F_1(t), F_2(t), \ldots, F_n(t)\}$ ' denotes a set of ' n ' attributes or features selected or observed in one day. Each row comprises of one day observation and each observation comprises of '$n = 5$' features or attributes (weather attributes are grouped into five columns and it also includes attributes such as zonal wind, meridional wind, humidity, air temperature and sea surface temperature) Table 1 given below lists the representation of a case.

Table 1 Representation of a case

Observation	Zonal wind	Meridional wind	Humidity	Air temp	Sea surface temp
Day 1	-6.6	-4.3	81.3	27.71	28.28
Day 2	-8.4	-4.2	83.5	27.91	28.26
Day 3	-8.4	-5	79.2	27.87	28.22

Day 4	-6.5	-5.9	75.4	27.5 6	28.22
Day 5	-6.8	-5.3	81.3	27.5 2	28.17
Day 6	-5.1	-0.4	94.1	26.0 4	28.14
Day 7	-4.3	-3.3	93.2	25.8	27.87

With the purpose of predicting the consecutive days, weather attribute values the first row (i.e., day 1 observation) is presented as an input, and attribute value of day 2 is predicted by using the proposed method as output. In a similar manner, predicting the consecutive week's weather attributes values, the first six rows (i.e., day 1 to day 6 observations) are presented as input and attribute value of next week is predicted by utilizing the proposed method as output and so on. The input vector matrix for the case representation (as provided in table 1) is mathematically expressed as given below.

$$IM = \begin{bmatrix} O_1F_1 & O_1F_2 & O_1F_3 & \dots & O_1F_n \\ O_2F_1 & O_2F_2 & O_2F_3 & \dots & O_2F_n \\ O_3F_1 & O_3F_2 & O_3F_3 & \dots & O_3F_n \\ \dots & \dots & \dots & \dots & \dots \\ O_mF_1 & O_mF_2 & O_mF_3 & \dots & O_mF_n \end{bmatrix} \quad (1)$$

With the above input vector matrix as given in equation (1), further processing is carried out for robust and accurate marine weather forecasting.

1.2 Nonlinear Autoregressive Exogenous-Based Correlation Model

As far as time series data are concerned, or prediction of marine weather is concerned, a nonlinear autoregressive exogenous-based correlation model has exogenous inputs. This means, that the Nonlinear Autoregressive Exogenous-based Correlation model associates the present value of a time series data to both the past values and prevailing values respectively. Moreover, the model also includes an error interval and perception of other factors will not validate the present value of time series to be predicted precisely. Figure 2 shows the structure of Nonlinear Autoregressive Exogenous-based Correlation model.

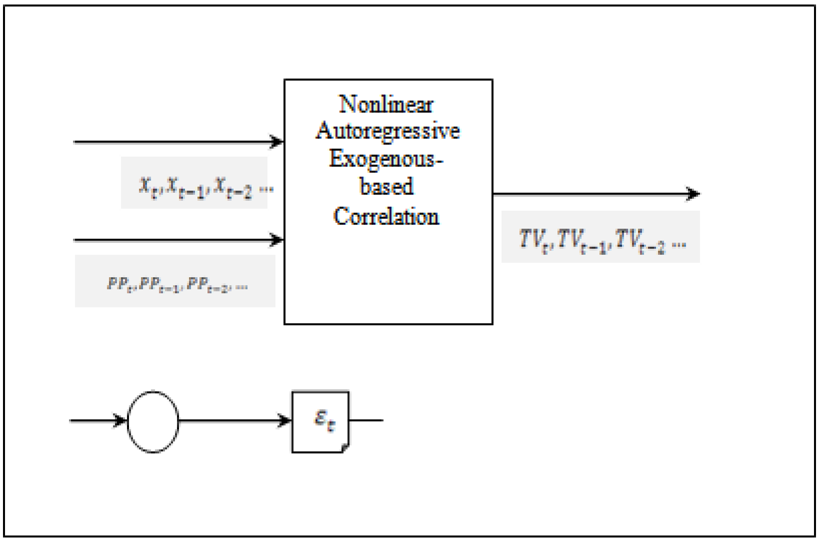

Figure 2 Structure of Nonlinear Autoregressive Exogenous-based Correlation model

As shown in the above figure, the structure of Nonlinear Autoregressive Exogenous-based Correlation model involves of three distinct factors, exogenous inputs, past predicted values and the error term. With these three distinct factors, a Nonlinear Autoregressive Exogenous-based Correlation model is formulated as given below.

$y_t =$

$$NF\begin{Bmatrix} (x_t, x_{t-1}, x_{t-2} \ldots), \\ (PP_t, PP_{t-1}, PP_{t-2}, \ldots), (TV_t, TV_{t-1}, TV_{t-2} \ldots) \end{Bmatrix} + \varepsilon_t \quad (2)$$

From the above equation (2), 'x_t, x_{t-1}, x_{t-2}', 'PP_t, PP_{t-1}, PP_{t-2}' and 'TV_t, TV_{t-1}, TV_{t-2}' represents the exogenous inputs, past predicted values and target values respectively. Here, information about 'x_t, x_{t-1}, x_{t-2}' (i.e., 'IM') helps predict 'y_t' along with a negligible error term 'ε_t' respectively.

1.3 Reinforced Long Short-Term Memory (Reinforced Lstm)

The prediction of aggregating quantities from the sequences of input vector matrix 'IM' is paramount in deep learning and it owing to the arbitrary nature of time. Reinforced learning has potentiality of learning inearlier vector dependencies. Earlier vector dependencies are very much crucial as far as marine weather forecasting is concerned. Figure 3 given below shows the structure of Reinforced Long Short-Term Memory

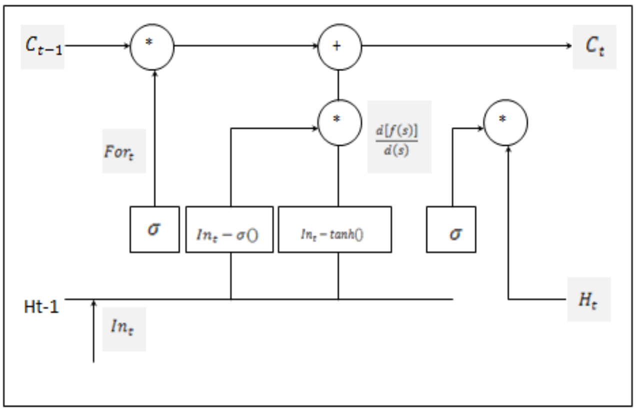

Figure 3 structure of Reinforced Long Short Term Memory

As shown in the above figure, with 'In_t' inputs and 'S_t' samples obtained as input, the cell state 'C_t' is evaluated with the objective of forecasting marine weather by retaining prime factors '$\frac{d[f(s)]}{d(s)}$' and discarding irrelevant factor 'For_t'. The reinforced learning in our work performs marine weather forecasting or prediction at a time 't' is as given below.

$$H_t = A(W_h[H_{t-1}, S_t] + B_h) \quad (3)$$

$$y_t = f(W_y * H_t + B_y) \quad (4)$$

From the above equations (3) and (4), 'H_t' represents the hidden state, 'A' representing the corresponding activation function at the hidden layer, 'y_t' denotes the weather output being predicted with the weights designated in hidden layer 'W_h' and output layer 'W_y', 'B_h' and 'B_y' denoting the bias for hidden and output layer, and finally 'f' forming the output function for marine weather prediction respectively for the samples 'S' obtained at time 't'. Marine weather prediction performance specifically depends on the weight updates and activation function. In our work,Back Propagation Time-based Weight update is utilized, that fine tunes the weight with the objective of minimizing the classification error by back-propagating to fixed count 'k', and the aggregate of error to the respective weighted average of the back-propagated states are calculated for the change in weight. In our work Back Propagation Time-based Weight update is utilized, that fine tunes the weight with the objective of minimizing the classification error.

$$\psi = \sum_{i=1}^{k} \frac{\partial \varepsilon_i}{\partial W_i} \quad (5)$$

From the above equation results (5), 'ψ' forms the aggregate of error fixed count 'k'. Then, the corresponding weighted average of the 'k' back-propagated states is mathematically stated as given below.

$$\frac{\partial \varepsilon}{\partial W} = \frac{\partial \varepsilon}{\partial W_1} + \frac{\partial \varepsilon}{\partial W_2} + \frac{\partial \varepsilon}{\partial W_3} + \cdots + \frac{\partial \varepsilon}{\partial W_k} \quad (6)$$

Marine weather prediction performance is employing Reinforced learning and it also depends on the activation function. In our work, Derivative Rectified Linear Unit activation function is employed, that obtains the current state weather input (i.e., five features selected) and previous state weather input with, which predicts the final output taking into consideration the hidden state weather result.

$$\frac{d[f(s)]}{d(s)} = \begin{cases} 1, for\ s > 0 \\ 0, for\ s < 0 \\ not\ exist, for\ s = 0 \end{cases} \quad (7)$$

With the above utilization of Derivative Rectified Linear Unit activation function in turn alleviates the vanishing gradient issue by proliferating input sequence to layers of Reinforced LSTM. With this, the classification error gets minimized and therefore it ensures the accurate marine prediction by utilizing weighted average function.However, large weight updates refer to the aggregated input to activation function and it was always found to be negative, irrespective of the input. To address on this factor, Reinforced Long Short-Term Memory is designed. Wherein cell state 'C_t' is employed for stockpiling past marine weather forecast data, operation is carried out to update the cell state, wherein the old information is dripped and new information is added.

Here, triplet sigmoid functions for three gates, namely, forget gate 'For_t', input gate 'In_t' and output gate 'Out_t', in addition to tanh function for candidate vector are employed. With these functions, forget gate makes decision, whether to retain the present input or not. Using Reinforced Long Short Term Memory, the impact of current weather forecast data is analyzed over the past weather forecast data via candidate vector. The results are stored in the forget gate as given below.

$$For_t = \begin{cases} 1, store\ marine\ weather\ data \\ 0, discard\ marine\ weather\ data \end{cases} \quad (8)$$

From the above equation (8), the forget gate 'For_t' stores the marine weather data according to the decision made via the Derivative Rectified Linear Unit activation function upon occurrence of results of '1' and vice versa. With this, the value arrived at the input gate is found to be '$[0, \infty]$' that in turn discards the vanishing gradient issue, hence permitting to learn from every input marine weather data.

$$In_t = S_t * \sigma(W_{In}[S_t, H_{t-1}] + B_{In}) \quad (9)$$

Then, candidate vector 'C_t' is activated for employing the current input marine weather data and previous hidden preprocessed marine weather data, that generates a value between '-1' and '$+1$' as given below.

$$C_t = S_t * tanh(W_C[H_{t-1}, S_t] + B_C) \quad (10)$$

Finally, the sigmoid function evaluates the probability distribution over 'n' distinct samples. With the aid of the measured probability distribution values, the target output for the given inputs is obtained as given below.

$$y_t = \sigma\left(W_y[H_{t-1}, S_t] + B_y\right) \quad (11)$$

The output layers evaluate all the outputs from the above equation (11) and the convergence is said to persist until the error of hidden value is zero. The pseudo code representation of Reinforced Long Short-Term Memory is given below.

Input: Dataset 'DS', Features '$F = \{F_1, F_2, \ldots, F_n\}$', Observation '$O = \{O_1, O_2, \ldots, O_m\}$'
Output: Error-minimized and accuracy marine weather
Step 1: **Initialize** 'n', 'm', 'k' Step 2: **Begin** Step 3: **For** each Dataset 'DS' with Features 'F' and Observation 'O' Step 4: Formulate input matrix as given in equation (1) Step 5: Formulate Nonlinear Autoregressive Exogenous-based Correlation model as given in equation (2) Step 6: Formulate hidden and output states as given in equations (3) and (4) Step 7: Evaluate Back Propagation Time-based Weight update as given in equation (5) Step 8: Evaluate Derivative Rectified Linear Unit activation function as given in equations (6) and (7) Step 9: Analyze the impact of current weather forecast data over past weather forecast data via forget gate as given in equation (8) Step 10: Formulate with respect to input marine weather data as given in equation (9) Step 11: Obtain candidate vector results as given in equation (10) Step 12: Obtain the target output for the given inputs as given in equation (11) Step 13: **Return** reinforced results Step 14: **End for** Step 15: **End**

Algorithm 1 Reinforced Long Short Term Memory

As given in the above Reinforced Long Short Term Memory algorithm, with the objective of overcoming dimension inadequacy, that in turn reduces the issues for concerning the vanishing gradient, input vector matrix is first obtained. Followed by, which Nonlinear Autoregressive Exogenous-based Correlation model is formulated for obtained the input vector matrix. Next, hidden and output states are formulated, wherein the weight updates are performed by employing Back Propagation Time-based function. The activation function is generated in our work Derivative Rectified Linear Unit function. Then, to analyze the impact of current weather forecast data over past weather forecast data, reinforced learnt results are applied to Long Short Term Memory. To minimize the classification error involved during prediction, marine weather data are retained according to the decision made via the Derivative Rectified Linear Unit activation function. Finally, the target output for the given inputs is obtained with improved accuracy.

1.4 Partial Differential Quantum Hamiltonian Recurrent Neural Network

With the trained network, that in turn to generate the predicted attribute of rainfall using Reinforced Long Short Term Memory algorithm, next, partial derivatives is essential for the learning are obtained and it was utilizing the adjacent model. The adjacent model is formulated by means of Partial Differential Quantum Hamiltonian Recurrent Neural Network (PDQH-RNN). By employing the PDQH-RNN, the wind speed was employing the spatial correlation are initially obtained to determine adverse events (i.e., from zonal winds, meridional winds, humidity, air temperature and sea surface temperature) has measured down to a depth of 500 meters. First, the Quantum Hamiltonian is applied to the hidden state weather output.

The Quantum Hamiltonian model is derived from the magnetic model is taking into consideration, only the association or correlation between nearby particles (i.e., adjacent air temperature and sea surface temperature). In other words, it is a model, where only the association or correlations and performance factors between adjacent particles (i.e., air temperature and sea surface temperature) are taken into consideration, whereas all other interconnections are discarded for further processing. Figure 4 given below shows the structure of Partial Differential Quantum Hamiltonian Recurrent Neural Network.

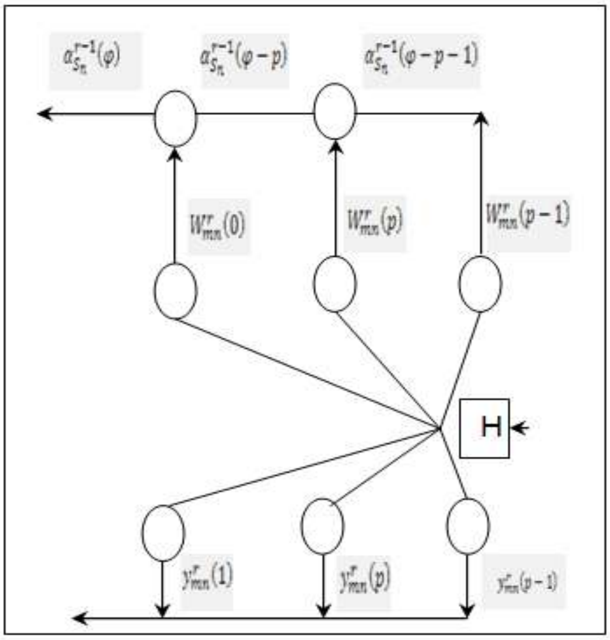

Figure 4: Structure of Partial Differential Quantum Hamiltonian Recurrent Neural Network

The function of Partial Differential Quantum Hamiltonian Recurrent Neural Network is described in figure 5.4. In network, each layer is represented as '1', 'p' and '$p-1$' along with obtained weights partial derivatives. Based on weight, Quantum Hamiltonian function is determined as given below.

$$HI = Corr \sum f(s)[a] f(s)[b] \qquad (12)$$

From the above equation (12), 'HI', indicates the correlation between adjacent hidden state weather result '$f(s)[a]$' and '$f(s)[b]$' respectively. With the resultant Quantum Hamiltonian function output, the reference point is appropriately fringed across the direction of the prevailing winds, with the objective for obtaining the temporal associations involved. As a result, the prediction time involved is greatly reduced, therefore it improves the true positive rate also.

The recurrent neural networks consist the layers for structured in a feedforward pattern with arbitrary units or neurons (i.e., here neurons represents the zonal winds, meridional winds, humidity, air temperature and sea surface temperature) respectively.

Let us consider the '$r-th$' layer consisting of 'S_n' neurons with 'S_0' and 'S_m' representing the number of neurons in the input and output layer respectively. Here '$S_n^r(t)$' denotes the output of the '$n-th$' neurons of the '$r-th$' layer at time instance 't', '$S_n^0(t)$' represents the input signals whereas '$S_n^m(t)$' represents the output signals, '$A_n^r(t)$' denoting the activation function of the '$n-th$' neurons of the '$r-th$' layer at time 't' and finally '$y_{mn}^r(t)$' forming the output at time 't' associating '$n-th$' neuron in the '$r-th$' layer with the '$m-th$' neuron of the '$r-1\,th$' layer respectively. Then, the partial derivatives essential for the learning are mathematically stated as given below.

$$\alpha_{S_n}^r[\varphi] = HI\left[\frac{\partial y_t}{\partial S_n^r[t-\varphi]}\right] \qquad (13)$$

$$\alpha_{A_n}^r[\varphi] = HI\left[\frac{\partial y_t}{\partial A_n^r[t-\varphi]}\right] \qquad (14)$$

From the results of the above equations (13) and (14), the spatial correlation of the hourly or daily average wind speed are said to be obtained down to a depth of 500 meters. The pseudo code representation of Partial Differential Quantum Hamiltonian Recurrent Neural Network is given below.

Input: Dataset 'DS', Features '$F = \{F_1, F_2, \dots, F_n\}$', Observation '$O = \{O_1, O_2, \dots, O_m\}$'
Output: Robust classified results
Step 1: **Initialize**'r − th' layer, 'n', 'm' Step 2: **Begin** Step 3: **For** each Dataset 'DS' with Features 'F' and Observation 'O' Step 4: Formulate Quantum Hamiltonian function between adjacent hidden state weather result as given in equation (12) Step 5: Evaluate partial derivatives of the output with respect to sample signals as given in equation (13) Step 6: Evaluate partial derivatives of the output with respect to activation function as given in equation (14) //process for classification Step 7: **If**value (air temperature and sea surface temperature) lies between 20 and 30 degree Celsius Step 8 : No prediction of rain Step 9: **Return results** Step 10: **End if** Step 11: **If** value (air temperature and sea surface temperature) less than 20 degree Celsius and greater than 30 degree Celsius Step 12: Prediction of rain Step 13: **Return results** Step 14: **End if** Step 15: **End for** Step 16: **End**

Algorithm 2 Partial Differential Quantum Hamiltonian

Recurrent Neural Network

As given in the above Partial Differential Quantum Hamiltonian Recurrent Neural Network algorithm, with the E1 Nino Dataset acquired as input and five features selected for marine weather forecasting and several samples utilized. First, Quantum Hamiltonian function is applied to hidden state weather result in adjacent fashion to obtain adverse events, and utilizing wind data. Next, with the obtained results, partial derivatives are applied to across the direction of prevailing winds for obtaining temporal associations. Finally, robust

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

classified results are obtained, that forms the basis for accurate and timely marine weather forecasting.

IV. EXPERIMENTAL SETUP

In this section, the experimental evaluation of the proposed Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) for marine weather forecasting method is provided. First, the employed setup is introduced and then experimental results are presented and discussed in detail.

1.5 DISCUSSION

Regarding the E1 nino dataset, obtained from https://www.kaggle.com/uciml/el-nino-dataset, we use the features or variables:, date, latitude, longitude, zonal winds (west<0, east>0), meridional winds (south<0, north>0), relative humidity, air temperature, sea surface temperature and subsurface temperatures down to a depth of 500 meters. Amongst these features, five features were selected for classification purpose, they are zonal winds, meridional winds, relative humidity, air temperature, sea surface temperature and subsurface temperatures respectively. Moreover, the latitude and longitude in the data showed that bouys moved to across the distinct areas. The latitude values stayed within a degree from approximate location, whereas the longitude values were five degrees off of the approximate location. The E1 nino dataset was divided into two sets, namely the training set and the testing/validation set. Most data samples (80%) were used for training and minimum data samples (20%) were taken for testing/validation. The confusion matrix of the proposed RPDQ-HNN method is demonstrated in table 2.

Table 2Confusion Matrix

Number of sample instances =1000	Predicted: No Rain	Predicted: Rain	Total samples
Actual: No Rain	TN=74	FP=421	495
Actual: Rain	FN=22	TP= 483	505
	96	904	

A confusion matrix has a fashionable measure and it was utilized for solving the classification problems. A confusion matrix is measured from predicted and actual values. Every row value of confusion metrics denoted the corresponding actual class and every column value represented the corresponding predicted class. The value that appears in each cell demonstrates the prediction class. The number of sample instances (i.e, 1000) is taken in the dataset. TN indicates true negative, FP signifies false positive, FN represents false negative, and TP symbolizes true positive. The designed technique classifies every day into rain or no rain and will give us probabilities of rain or no rain e.g. for a specific day, it might predict rain with **90%** certainty and no rain with **10%**.

1.6 EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the performance of marine weather forecasting was using the proposed Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) method is performed using JAVA programming language. To measure and validate the RPDQ-HNN method, E1 NINO dataset extracted from kaggle are used. In this work, experiments are performed on factors such as, classification accuracy, classification time, classification error and true positive rate with respect to distinct numbers of instances.To make fair comparison between the proposed RPDQ-HNN and existing methods, Spatial Feature Attention Long Short-Term Memory (SFA-LSTM) [1] and spatiotemporal deep learning-based framework [2], same dataset and similar instances are applied. An overall of 10 simulation runs were performed.

1.7 Classification time analysis

Classification of oceanographic and surface meteorological readings was taken from a series of buoys into prediction of seasonal-to-inter annual climate variations or wrong prediction in the early stage aids in providing climate variations and in further it was making the maritime industry safer and permitting the crew to make efficient decisions about avoiding dangerous weather. Therefore, time involved in classification between correct prediction and wrong prediction play a significant

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

role in forecasting oceanic conditions weeks to months in advance, it will help communities, industries, and other groups etc. The classification time is mathematically expressed as given below.

$$CT = \sum_{i=1}^{n} S_i * \text{Time [Classification]} \quad (15)$$

From the above equation (15), the classification time 'CT', is measured on the basis of the sample instances or observation provided as input 'S_i' and the time consumed in classification via Quantum Hamiltonian function. It was measured in terms of milliseconds (ms). Table 3 given below shows the performance results of the classification time with respect to varying sample instances acquired from the E1 Nino dataset. The results obtained, it confirm that the classification time of the RPDQ-HNN method is improved upon comparison with the other existing methods [1], [2].

Table 3 Classification time measure of the proposed RPDQ-HNN method, SFA-LSTM [1] and spatiotemporal deep learning-based framework [2]

Number of sample instances (number)	Classification time (ms)		
	RPDQ-HNN	SFA-LSTM	spatiotemporal deep learning-based framework
1000	550	730	950
2000	650	880	1035
3000	780	985	1155
4000	950	1055	1345
5000	1035	1235	1825
6000	1085	1355	2135
7000	1135	1525	2245
8000	1245	1845	2583
9000	1385	2015	2835
10000	1525	2035	3025

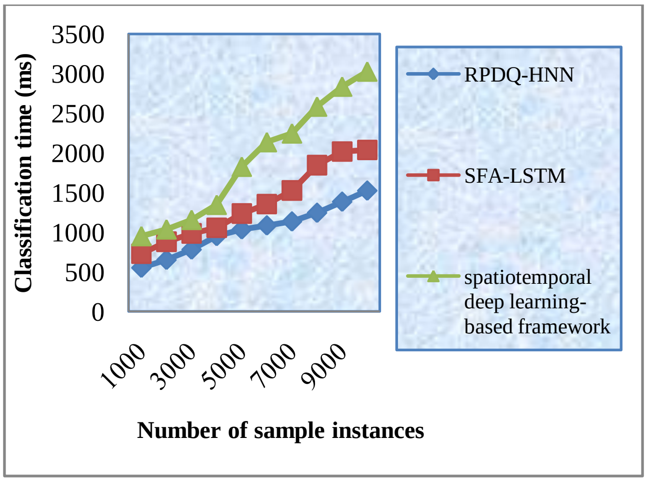

Figure 5 Graphical representation of classification time

Figure 5 given above shows the classification time for 10000 distinct numbers of sample instances obtained from oceanographic and surface meteorological readings was taken from a series of buoys as input. From the above figure it is inferred that the classification time is found to be directly proportional to number of sample instances provided as input. To be more specific, increasing the number of sample instances results in an increase in the testing made throughout the equatorial pacific and also an increase in data collected as samples with the Tropical Atmosphere Ocean (TAO) array or input vector matrix and obviously the classification time was also found to

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

be increased. With '1000' numbers of sample instances is considered for experimentation and the time involved to classifying the single meteorological readings being ' 0.55ms 'time involved to classifying single meteorological readings being '0.73ms' using [1] and time involved to classifying single meteorological readings being '0.95ms' using [2], the overall classification time was observed to be 550ms, 730ms and 950 ms by using the three methods. From the results, it is hypothesized that the classification time using RPDQ-HNN is comparatively lesser than [1] and [2]. The improvement in classification time owes to the application of Nonlinear Autoregressive Exogenous-based Correlation model. By applying this model, it associates the present value of a time series data to both the past values of and prevailing values respectively. With this high correlative associative factor, exogenous inputs, past predicted values and the error term are utilized, that in turn classifies the oceanographic and surface meteorological readings. As a result, the classification time involved in marine weather. forecasting is said to be reduced using RPDQ-HNN method by 23% compared to [1] and 44% compared to [2] respectively.

1.8 CLASSIFICATION ACCURACY ANALYSIS

The accuracy with, which the classification is made to form the basis for the success of marine weather prediction by using oceanographic and surface meteorological readings was taken from a series of buoys. In other words, classification accuracy is a performance parameter that encapsulates the performance of a classification model. The classification accuracy is mathematically stated as given below.

$$CA = \sum_{i=1}^{n} \frac{S_{AC}}{S_i} * 100 \qquad (16)$$

From the above equation (16), classification accuracy 'CA' is measured on the basis of observations or sample instances provided as input for simulation 'S_i' and the sample instances that were accurately classified 'S_{AC}', therefore forming means for correct prediction (i.e., therefore resulting in the improvement of prediction accuracy). It was measured in terms of percentage (%).Table 4 given below provides the performance results of classification accuracy versus number of samples instances collected from the E1 Nino dataset. For simulation purpose, number of sample instances taken is in the range of 1000 to 10000. Upon comparison, the RPDQ-HNN method provides improved performance of classification accuracy than the existing methods, [1] and [2].

Table 4 Classification accuracy measure of the proposed RPDQ-HNN method, SFA-LSTM [1] and spatiotemporal deep learning-based framework [2]

Number of sample instances (number)	**Classification accuracy (%)**		
	RPDQ-HNN	SFA-LSTM	spatiotemporal deep learning-based framework
1000	99.2	98.3	97.5
2000	95.85	92.15	91.55
3000	95.35	90.85	90
4000	94.55	87.35	85.35
5000	94	86.85	83
6000	93.75	85	81
7000	93.25	83.15	78.55
8000	92.55	81	75
9000	92	80.55	73.25
10000	91.75	78.15	71

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

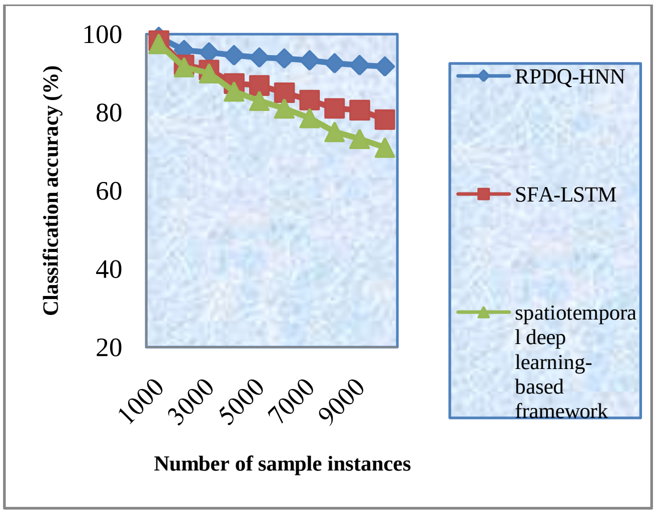

Figure 6 Graphical representation of classification accuracy

Figure 6 given above shows the classification accuracy with respect to 10000 distinct numbers of sample instances or observations. From the above figure, an inverse proportionate between number of sample instances and classification accuracy is identified. To be more specific, increasing the number of sample instances causes an increase in the understanding and prediction of seasonal-to-inter annual climate variation. This in turn causes in a proportionate for decrease the classification accuracy also. Let us consider a scenario with 1000 number of sample instances, sample instances accurately classified using RPDQ-HNNmethod was found to be 992, 983 using [1] and 975 using [2] respectively. With this the overall classification accuracy using the three methods were found to be 99.2%, 98.3% and 97.5% respectively. With this the classification accuracy was found to be better using RPDQ-HNN method,when compared to [1] and [2]. The reasons behind the improvement were owing to the application of Reinforced Long Short-Term Memory algorithm. By applying this algorithm, only relevant and significant features involved in classification process were utilized with, which weight updates were performed based on the Back Propagation Time-based function. As a result, reinforced results for prediction were made according to time factor. This in turn improved the classification accuracy using RPDQ-HNN method by 9% compared to [1] and 15% compared to [2] respectively.

1.9 CLASSIFICATION ERROR ANALYSIS

During marine weather forecasting, forecasting can be done based on the classification model applied. During the classification process, a significant amount of error or sample instances are said to be wrongly predicted and therefore the results in error. In other words, classification error is a performance metric that measures the percentage of observations or sample instances that were incorrectly predicted by Partial Differential Quantum Hamiltonian Recurrent Neural Network based classification model. Classification error is measured as given below.

$$\mathrm{CE} = \frac{\mathrm{Num}_{\mathrm{IR}}}{\mathrm{Tot}_{\mathrm{R}}} * 100 \qquad (17)$$

From the above equation (17), classification error 'CE' is measured by utilizing the number of incorrect observations or sample instances that were wrongly classified '$\mathrm{Num}_{\mathrm{WC}}$' to the total available observations or sample instances '$\mathrm{Tot}_{\mathrm{S}}$' for marine weather forecasting. It was measured in terms of percentage (%).Table 5 reports the simulation of different results of classification error on three different methods with respect to different numbers of sample instances.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

Table 5 Classification error measure of the proposed RPDQ-HNN method, SFA-LSTM [1] and spatiotemporal deep learning-based framework [2]

Number of sample instances (number)	Classification error (%)		
	RPDQ-HNN	SFA-LSTM	spatiotemporal deep learning-based framework
1000	3.5	5	6.5
2000	3.8	5.55	7
3000	4.15	6	8.35
4000	4.35	6.35	8.95
5000	4.85	6.95	9
6000	5.15	7.25	9.25
7000	5.35	7.55	9.85
8000	5.85	8	10
9000	6.26	8.35	11.25
10000	6.85	9	12

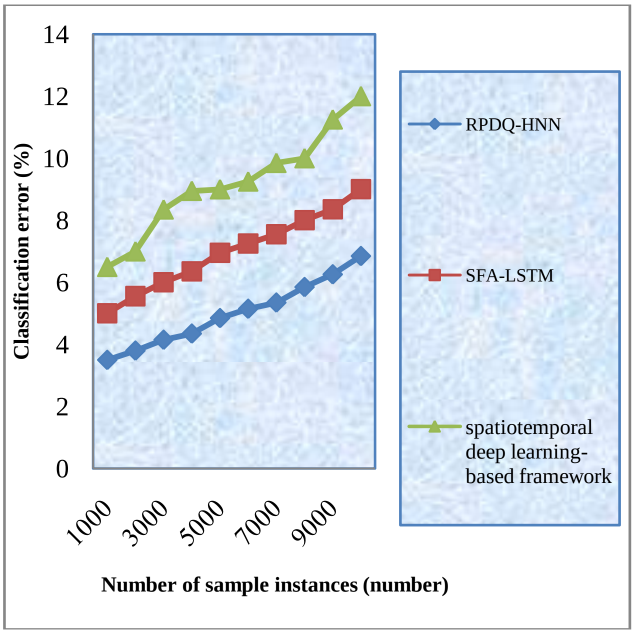

Figure 7 Graphical representation of classification error

Figure 7 given above illustrates the classification error for three different methods. The classification error is considered to be one of the significant performance metrics, during marine weather prediction. This is due to the reason that not all the sample instances are said to be accurately classified into their appropriate classes (i.e., rainy as rainy and non-rainy day as non-rainy day) and certain results are also wrongly classified due to abnormality values, which was observed in both the latitude and longitude in the data. From the above figure a small portion of increasing trend is said to be observed with the increase, in the sample instances in all the three methods from the E1 Nino dataset. However, simulations conducted with 1000 numbers of sample instances, the classification 3.5%, 5.5% and 6.5% using the proposed and the existing two methods respectively. With this measure, the classification error was reduced using RPDQ-HNN method upon comparison with the two other existing methods. The reason behind the improvement was due to the application of Derivative Rectified Linear Unit activation function in the Reinforced Long Short Term Memory algorithm. By applying this algorithm, vanishing gradient issue was said to be

International Journal of Advances in Engineering and Management (IJAEM)
Volume 5, Issue 8 Aug 2023, pp: 589-606 www.ijaem.net ISSN: 2395-5252

eliminated by proliferating input sequence to layers of Reinforced LSTM. Also by utilizing average weighted function, appropriate marine weather forecasting was made by conditional checking. Accordingly two classes, correct prediction or wrong prediction were formed. With this, the classification error was significantly reduced using RPDQ-HNN method by 29% compared to [1] and 46% compared to [2].

1.10 TRUE POSITIVE RATE ANALYSIS

True positive rate refers to the probability of a positive test, determined on truly being positive.

$$TPR = \frac{TP}{TP + FN} \quad (18)$$

From the above equation (18), the true positive rate ‘TPR’ is measured and it is based on the number of true positives ‘TP’ (i.e., instances correctly predicts the positive cases) and on the number of false negatives ‘ FN ’ (i.e., instances incorrectly predicting the positive cases as negative and vice versa). Finally, table 6 given below lists the true positive rate using the three methods, RPDQ-HNN, SFA-LSTM [1] and spatiotemporal deep learning-based framework [2] respectively.

Table 6 True positive rate measure of the proposed RPDQ-HNN method, SFA-LSTM [1] and spatiotemporal deep learning-based framework [2]

Number of sample instances (number)	True positive rate		
	RPDQ-HNN	SFA-LSTM	spatiotemporal deep learning-based framework
1000	0.97	0.96	0.94
2000	0.95	0.93	0.92
3000	0.94	0.92	0.9
4000	0.93	0.89	0.86
5000	0.92	0.87	0.79
6000	0.9	0.86	0.75
7000	0.88	0.83	0.73
8000	0.86	0.8	0.72
9000	0.84	0.79	0.71
10000	0.82	0.78	0.7

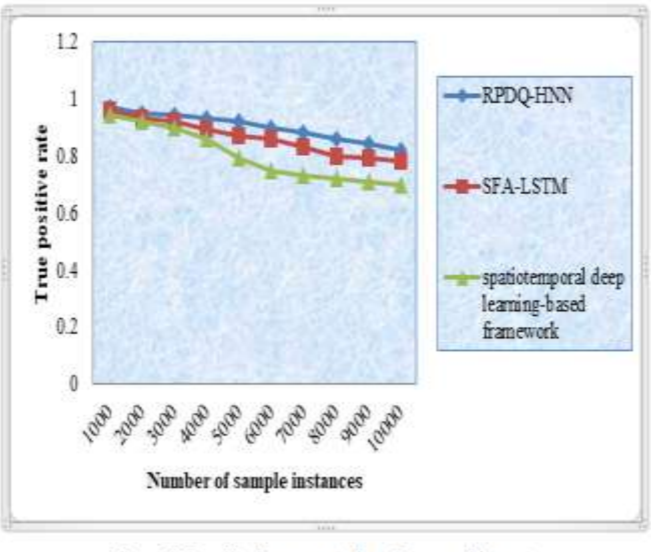

Figure 8 Graphical representation of true positive rate

Finally, figure 8 given above illustrates the true positive rate analysis for 10000 distinct numbers of sample instances was acquired from E1 Nino dataset. With x axis, representing the number of sample instances and y axis, representing the true positive rate and a decreasing trend is observed by using all the three methods. However, in a total of 1000 sample instances, 960 sample instances were made correct prediction, the RPDQ-HNN method correctly predicts 940 samples, in this case the true positive rate is 940 and false negative rate is 20, therefore the true positive rate by using RPDQ-HNN method was observed to be 0.97. In a similar manner, by using SFA-LSTMmethod correctly predicts 930 samples, in this case the true positive rate is 930 and false negative rate is 30, therefore, the true positive rate byusing SFA-LSTM method was observed to be 0.96. Finally, by using spatiotemporal deep learning-based framework method correctly predicts 910 samples, in this case the true positive rate is 910 and false negative rate is 50, therefore the true positive error by using spatiotemporal deep learning-based framework was found to be0.94. The reason behind the improvement by using SFA-LSTM method for the performance metric true positive rate, due to the application of Partial Differential Quantum Hamiltonian Recurrent Neural Network algorithm. By applying this algorithm, Quantum Hamiltonian function was applied to hidden state weather result and derived the adjacent factors to obtain the adverse events. This in turn reduced the false negative rate and therefore the true positive rate using SFA-LSTM method was found to be improved by 5% compared to [1] and 13% compared to [2] respectively.

V. CONCLUSION

In this paper, a Reinforced Partial Differential Quantum Hamiltonian Neural Network (RPDQ-HNN) for marine weather forecasting from a series of buoys evaluating both oceanographic and surface meteorological variables critical and prediction of seasonal-to-inter annual climate variations. According to the theoretical model of the proposed method, three sections have been considered. These sections include nonlinear autoregressive exogenous-based correlation model, obtaining the reinforced results for classification for employing theDerivative Rectified Linear Unit activation function and classification via Partial Differential Quantum Hamiltonian Recurrent Neural Network algorithm. The proposed method was evaluated with different classification methods. The applied classifications was handcrafted adverse eventsand partial derivatives applied across prevailing wind direction for acquiring the temporal associations. The experimental results revealed that the classification algorithms using deep learning, called, RPDQ-HNN method performed well in terms of the classification time, classification accuracy, classification error and true positive rate. The RPDQ-HNN method reached the highest performance for marine weather forecasting in our scenario with 99.2% accuracy, 550ms classification time and classification error of 3.5%. High accuracy of RPDQ-HNN method in comparison with other applied classification methods is a paramount distinction,that makes and it was applicable for the classification of marine weather forecasting.

REFERENCES

[1]. Masooma Ali Raza Suleman, S. Shridevi, “Short-Term Weather Forecasting Using Spatial Feature Attention Based LSTM Model”, IEEE Access, Jul 2022 [Spatial Feature Attention Long Short-Term Memory (SFA-LSTM)]

[2]. Anshuka Anshuka, Rohitash Chandra, Alexander J. V. Buzacott, David Sanderson, Floris F. van Ogtrop, “Spatio temporal hydrological extreme forecasting framework using LSTM deep learning model”, Stochastic Environmental Research and Risk Assessment, Springer, Mar 2022 [spatiotemporal deep learning-based framework]

[3]. Anitha Gera, D.K. Mahapatra, Kuldeep Sharma, Satya Prakash, A.K. Mitra,G.R. Iyengar, E.N. Rajagopal, N. Anilkumar, “Assessment of marine weather forecasts over the Indian sector ofSouthern Ocean”, Polar Science, Elsevier, Apr 2017

[4]. Iuliia Polkova, Laura Schaffer, Øivin Aarnes, Johanna Baehr, “Seasonal climate predictions for marine risk assessment in the Barents Sea”, Climate Services, Elsevier, Apr 2022

[5]. Wushan Ying, Huiping Yan, Jing-Jia Luo, “Seasonal Predictions of Summer Precipitation in the Middle-lowerReaches of the Yangtze River with Global and RegionalModels Based on NUIST-CFS1.0”, Advances in Atmospheric Sciences, Vol. 39, Sep 2022

[6]. Ju‑Young Shin, Byunghoon Min, Kyu Rang Kim, “High‑resolution wind speed forecast system coupling

numericalweather prediction and machine learning for agricultural studies— a case study from South Korea", International Journal of Biomet, Springer, Apr 2022

[7]. Partha Pratim Sarkar, Prashanth Janardhan, Parthajit Roy, "Prediction of sea surface temperatures using deep learning neuralnetworks", Springer, Jul 2020

[8]. Kalpesh R. Patil, Masaaki Iiyama, "Deep Learning Models to Predict Sea SurfaceTemperature in Tohoku Region", IEEE Access, Apr 2022

[9]. Dongjin Cho, Cheolhee Yoo, Bokyung Son, Jungho Im, Donghyuck Yoon, Dong-Hyun Cha, "A novel ensemble learning for post-processing of NWP Model's next-day maximum air temperature forecast in summer using deep learning and statistical approaches", Weather and Climate Extremes, Elsevier, Jan 2022

[10]. Mengning Wu, Christos Stefanakos, Zhen Gao, Sverre Haver, "Prediction of short-term wind and wave conditions for marine operations using a multi-step-ahead decomposition-ANFIS model and quantification of its uncertainty", Ocean Engineering, Elsevier, Aug 2019

[11]. Tadej Krivec, Jus Kocijan, Matija Perne, Bostjan Grasic, Marija Zlata Boznar,Primoz Mlakar, "Data-driven method for the improving forecasts of local weather dynamics", Engineering Applications of Artificial Intelligence, Elsevier, Aug 2021

[12]. Naqash Ahmad, Yazeed Ghadi, Muhammad Adnan, Mansoor Ali, "Load Forecasting Techniques for Power System: Research Challenges and Survey", IEEE Access, Jul 2022

[13]. Yue Zhang, Masato Yamamoto, Genki Suzuki, Hiroyuki Shioya, "Collaborative Forecasting and Analysis of FishCatch in Hokkaido From Multiple Scales byUsing Neural Network and ARIMA Model", IEEE Access, Jan 2022

[14]. K.U. Jaseena, Binsu C. Kovoor, "Deterministic weather forecasting models based on intelligentpredictors: A survey", Journal of King Saud University – Computer and Information Sciences, Elsevier, Sep 2020

[15]. Zhou Wu, Gan Luo, Zhile Yang, Yuanjun Guo, Kang Li, Yusheng Xue, "A comprehensive review on deep learning approaches in windforecasting applications", The Institution of Engineering and Technology, Wiley, Nov 2021

[16]. Siyun Hou, Wengen Li,Tianying Liu, Shuigeng Zhou,Jihong Guan, Rufu Qin, and Zhenfeng Wang, "D2CL: A Dense Dilated Convolutional LSTM Modelfor Sea Surface Temperature Prediction", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 14, Oct 2021

[17]. Anshuka Anshuka, Rohitash Chandra, Alexander J. V. Buzacott, David Sanderson, Floris F. van Ogtrop, "Spatio temporal hydrological extreme forecasting framework using LSTM deep learning model", Stochastic Environmental Research and Risk Assessment, Springer, Mar 2022

[18]. Yaseen Essa, Hugh G. P. Hunt, Morné Gijben, and Ritesh Ajoodha, "Deep Learning Prediction of Thunderstorm SeverityUsing Remote Sensing Weather Data", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 15, Oct 2022

[19]. Amirhossein Dolatabadi, Hussein Abdeltawab, Yasser Abdel-Rady, I. Mohamed", Hybrid Deep Learning-Based Model for WindSpeed Forecasting Based on DWPT andBidirectional LSTM Network", IEEE Access, Dec 2020

[20]. Semere Gebretinsae, Mohd Wazih Ahmad, T.Gopi Krishna, Nune Sreenivas, Biruk Yirga, "Machine Learning-Based Intelligent Weather Monitoring and Predicting System", International Journal of Engineering Trends and Technology, Volume 70 Issue 4, 152-163, April 2022