International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I7P212
Volume 70 Issue 7, 108-121, July 2022

Original Article

Reducing Dimensions in Time Series Data using Remora Optimization Algorithm

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Received: 11 May 2022 Revised: 30 June 2022 Accepted: 14 July 2022 Published: 18 July 2022

Abstract - *In this paper, develop a Hybrid Recurrent Neural Network Model (HRNN) with Principal Component Analysis (PCA) for efficient weather forecasting. Initially, the databases are collected from the open-source system. After that, PCA is utilized to reduce the dimension of the input collected data. The huge amount of data reduces the forecasting accuracy with the repeated values and attributes. Hence, PCA is utilized for reducing the similar dimension of attributes. The reduction data is utilized in the proposed weather forecasting model. The HRNN combines Recurrent Neural Network (RNN) and Remora Optimization Algorithm (ROA). The proposed HRNN is working with two phases: training and testing. The collected data is divided into two parts as80% and 20%. 80% of data is utilized for the training phase of the proposed technique. The remaining 20% is utilized for the testing phase of the proposed technique. The proposed technique is implemented, and performance metrices evaluate performance. It is compared with the conventional techniques such as Whale Optimization Algorithm (WOA) and Particle Swarm Optimization (PSO) to validate the proposed technique.*

Keywords - *Recurrent Neural Network, Remora Optimization Algorithm, Principal component analysis, Hybrid recurrent neural network model.*

1. Introduction

1.1. Time Series Data

Time series is the series of components in time demand. A period series is a course of action of moderate identical stretch minutes. It examines time-series data to remove critical information and various data characteristics. Time-series data examination is crucial in incalculable organizations like money-related undertakings, drugs, online media associations, web expert centers, and others.

1.2. Time Series Analysis

The series of data centers recorded all through a foreordained time is called Time-series data. One of the critical objectives of the assessment is to figure out future worth. Extrapolation is involved while expecting the time series assessment, which is extremely confounding. Time series assessment can be significant in later

1.2.1. Pattern

The expanding or lessening model has been seen all through some vague period. For this circumstance, the ceaselessly growing essential example is noted. For instance, the count of explorers has extended through some unclear periods.

1.2.2. Irregularity

Refers to cyclic example. A comparable example that rehashes later a specific time frame.

1.2.3. Heteroscedasticity

Refers to Non-steady fluctuation or differing avoidance from the mean throughout some period.

1.3. Time Series Data Mining

The Time Series Data Mining has the accompanying angles:

1.3.1. Ordering (Query by Content)

In time series informational indexes, a dynamic area of interest has emerged. A task that has been separated into two categories for some time now, complete preparation and possible outcome putting together, is now integrated into this task. Using Entire Matching, a request time series is compared to a variety of individual time series to identify those similar to the request. The outcome has been delayed. Matching is a quick and inevitable result of comparing shorter time series with longer ones in search of the best possible match.

1.3.2. Clustering

Clustering resembles a plan that orders data into social occasions; however, these get-togethers are not pre-defined yet portrayed by the genuine data, considering the similarity between time series. It is often insinuated as independent learning. The gathering is normally refined by choosing the comparability among the data on pre-defined attributes.

1.3.3. Prediction (Forecasting)

Prediction can be viewed as a sort of packing or portrayal. What makes a difference is that estimate anticipates a future state instead of an ongoing one. Many time series gauge applications should be visible in monetary spaces, where an assumption estimation regularly incorporates backslide examination

1.3.4. Summarization
A summarization of the information is helpful and essential. A measurement synopsis of the information, for example, the mean or other factual properties, can be effectively registered. The outline can likewise be seen as a unique bunching issue that maps information into subsets with related straightforward (text or graphical) portrayals and gives a more elevated perspective on the information. The synopsis might be done at various granularities and for various aspects.

1.3.5. Inconsistency Detection
In time-series information mining and observing, the issue of distinguishing anomalous/astonishing/novel examples has drawn much consideration. Rather than aftereffect coordinating, irregularity discovery is recognizable proof of already obscure examples. From an overall perspective, bizarre conduct goes astray from "typical" conduct.

1.3.6. dimensionality
As the name suggests, "dimensionality" refers to how many distinct characteristics a dataset possesses. When it comes to health care, for example, huge numbers of variables are well-known (for example, pulse, weight, cholesterol level). Ideally, this data could be compiled into a single accounting page, with a section for each of the different aspects. Because of the interdependence of so many variables, this is a challenging task to accomplish in practice (like weight and pulse).

1.3.7. High dimensionality
High Dimensional implies that the quantities of aspects are incredibly high — so high that computations become amazingly troublesome. With high layered information, the number of elements can surpass the number of perceptions. For instance, microarrays, which measure quality articulation, can contain many examples. Each example can contain a huge number of qualities.

1.4. Weather Forecasting Model
Many aspects of our business are adversely affected by the current weather conditions. It has taken a long time for meteorologists to refine their framework for determining weather forecasts (WF), but they have finally done so [1]. WF's accuracy is limited by a lack of understanding of wind processes, the limitations of weather perception, and the enormous computational power required to address environmental conditions depicted in an NWP model. Method [1]. WF has recently shifted its focus to in-depth learning discoveries, the majority of which focus on the relationship between current situations and verifiable information. The NWP, on the other hand, is critical to the operation of WF, particularly for long forecast times. It's a good idea to use NWP with in-depth detection of how WF works on precision.

The algorithm became more algorithmic, and evaluation models became more accessible to scientists, forecasters, and other associates with the advancement of meteorological innovation and software engineering [4]. Later in the NWP's development, the elite performance detection force worked with developing and interpreting provincial or restricted regional models, such as the Weather Research and Forecasting (WRF) model. Due to the WRF model's high target rate, accuracy, open-source nature, local area support, and wide assortment for easy use in different regions, it has become the world's most widely used wind NWP model [5]. This paper is a Rapid-refresh Multi-scale Analysis and Prediction System that focuses on the experiences of data from automatic weather stations (AWSs) (RMAPS). Many different climates and forecasts have been used to sum up, this research.

Information-powered PC display frames can be employed to reduce the computational power of NWPs. Because of their adaptability and capacity to learn from prior experience, artificial neural networks (ANNs) are particularly well-suited for this task. An important feature of ANN techniques [28] deep nonlinear peculiarities is this element's exceptional involvement in application areas. Recurrent Neural Networks and Temporal Convolution Networks (TCN) can analyze multiple time series (RNN). RNN's Long Short-Term Memory (LSTM) has recently been associated with an impressive concept because of its unmatched presentation. LSTM Models of this type stand out because of their extensive display [8]. Some layers of a common structure called centers are used by deep organizations, which often employ stacked brain systems. The calculation is performed at the hub level to combine information from multiple coefficients. An organization's start-up tasks are set based on input-weighted items. The regenerative technique is frequently used to create and evaluate brain network models for accurate weather forecasting because time-series information that includes real numbers is used to capture climate data.

2. Literature Review
Researchers for weather forecasting develop various techniques. Few techniques are analyzed in this section.

Matthew Chantry et al. [11] have introduced the worth of AI as a gas pedal for the definition schemes of functional weather conditions estimating frameworks, explicitly the definition of nonholographic gravity wave drag. Emulators of this plan can be prepared to create steady and exact outcomes up to seasonal forecasting timescales. For the most part, networks that are more complicated produce emulators that are more accurate. Via preparing on an expanded intricacy rendition of the current definition conspire, assemble emulators that produce more precise estimates.

Dan Niuet al. [12] have introduced a momentary weather condition determining model because of wavelet parcel denoising and Catboost, which exploits the combination data consolidating the verifiable perception information with the earlier information from NWP. The element choice and spatiotemporal quill expansion were investigated to develop execution further. The proposed strategy was assessed on the datasets given by Beijing weather conditions stations. Trial results show that contrasted and some profound learning or AI techniques like LSTM, Seq2Seq, and irregular woods, the proposed Catboost model integrated with wavelet parcel denoising can accomplish more limited combination time and higher forecast exactness.

By investigating worldly display approaches of long transient memory (LSTM) and fleeting convolutional networks (TCN), Pradeep Hewageet al. [29] have introduced a piece of clever light information-driven weather conditions determining model and contrast its display with the current old-style machine learning approaches, factual estimation methods, and a powerful troupe strategy, in addition to the well-established weather examination and gauging. More explicitly, Standard Regression (SR), Support Vector Regression (SVR), and Random Forest (RF) are carried out as the traditional AI approaches. Autoregressive Integrated Moving Average (ARIMA), Vector Auto Regression (VAR), and Vector Error Correction Model (VECM) are carried out as factual estimating approaches all the more clearly. To top it all off, this study used an innovative data collection strategy called Arbitrage of Forecasting Experts (AFE).

To forecast surface temperature and humidity, wind speed, and wind direction, Yuanpeng Li et al. [14] have developed an end-to-end hybrid regression model called Ensemble of Spatial-Temporal Attention Network and Multi-Layer Preceptor (E-STAN-MLP). According to the proposed model, which incorporates data from historical observations and the NWP system, it is more accurate than the NWP system or previously reported algorithms. Part one and part two make up the E-STAN-MLP model. One method was to model meteorological time series using a recurrent neural network based on spatial-temporal attention. However, the other multilayered perception architecture forecasts the regression value without considering time dependence. A step-by-step fusion strategy was used to integrate the results at each time stamp.

STConvS2S (Spatiotemporal Convolution Sequence to Sequence Network) is a profound learning design that can learn both spatial and fleeting information conditions using just convolution layers. [15] Rafaela Castro et al. To anticipate successions using authentic information, we propose a design that overcomes two limitations of convolution organizations: (1) they violate the transient request during the educational experience, and (2) they require that the lengths of the information and output sequences be equivalent. According to computational trials, data from South America shows that our engineering catches the spatiotemporal setting and outperforms or matches best-in-class structures for predicting assignments. Regarding predicting future successions, one of our proposed designs was 23 percent better than the RNN-based model used as a pattern.

3. Proposed System Model

When Vilhelm Bjerknes developed the WRF model in the late 1990s, he collaborated with numerous environmental and meteorological organizations. Several different thermodynamic conditions must be considered when making weather-based forecasts using this model. The WRF's main task is to zero in on the environmental time scale by combining material science data from the land, climate, and oceans. Since 2000, the WRF model has been the world's largest eco-model. The HDNN model is used to forecast the weather in this paper. The detailed block diagram is presented in figure 1.

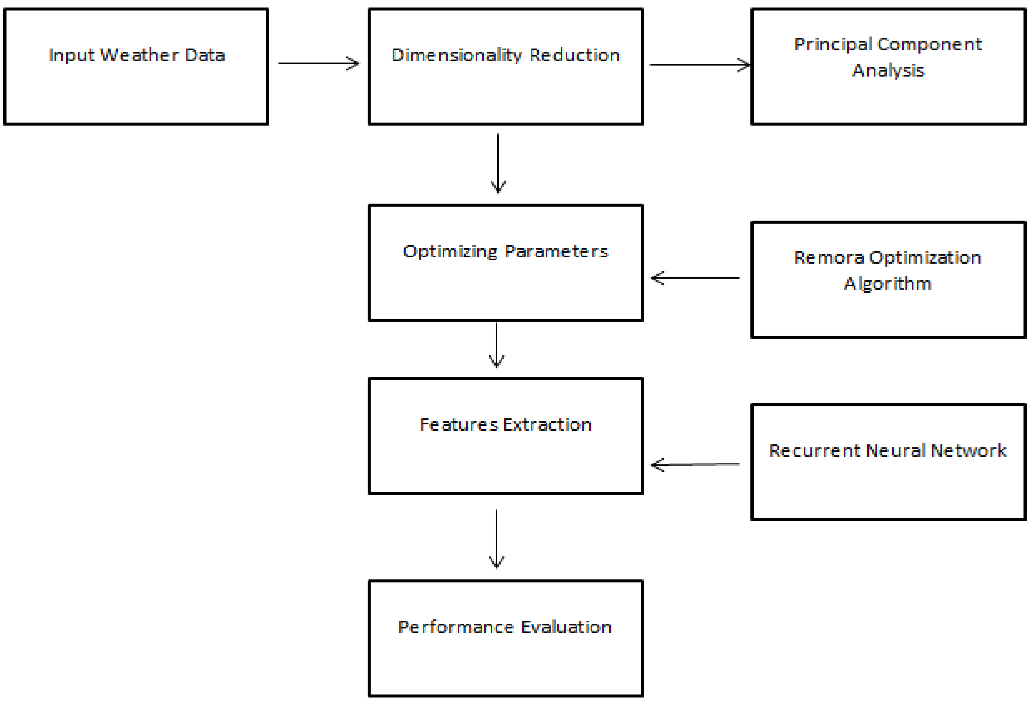

Fig. 1 Proposed System Model

3.1. Principal Component Analysis

PCA is a variable decrease framework that can be useful if there should be an occurrence of datasets with a horde of applicable information. Head parts are an immediate mix of variables noticed and requested by the nature of significant information related to their vacillations: the essential part isolates the most serious measures of data, and the various ones improve extra information under the detached reach. With various parts. The primary job of this strategy is to decrease the degree of elements. This is achieved by the immediate difference in the noticed elements (m) arranged by the eigenvectors of the relationship work in the Cartesian construction. The interest arranges eigenvectors for how much information is decreased; thus, the variable with the main uncertainty is anticipated at the essential place and the second at the following community. Key parts are taken to decrease the information base element [16].

To empower PCAs in data sets, it is essential to normalize data by their mean and consistent deviations to get more uniform allotments. Furthermore, the PCA makes even, irrelevant, clear mixtures, understanding the typical sorts that can be sensibly anticipated. It should be possible on both PCA covariance and the relationship network. Estimating the data network with a definitive objective of all variables zero mean and unit transformation (i.e., normalizing them) makes the two techniques indistinct.

Let X be a standardized information framework, where the number of absolute conjecture occasions utilized for the review and the number of various weather conditions where the figures are accessible. The subsequent advance is to figure out the eigenvalues and eigenvectors of the relationship network. Allow Γ to indicate the eigenvectorsmatrix. It is currently conceivable to change the first factors into new factors without overt data repetitiveness (uncorrelated) as follows:

$$X_{PCA} = \Gamma * \mathrm{X}$$

After this activity, the first information is changed into new uncorrelated information without diminishing the dimensionality. Altogether, to reduce the information to a P-layered space, the first framework X is increased by just the first eigenvectors (called loadings). Each section of the subsequent grid is the main part, the score.

3.2. Recurrent Neural Network

In the RNN, the ROA is used to choose ideal weighting boundaries for empowering effective weather conditions anticipating. The detailed portrayal of the RNN and ROA is introduced in this part. Six completely associated layers create the proposed RNN. Typically, the RNN model is prepared with the assistance of a back spread. This proposed RNN is achieved with the assistance of ROA. The proposed RNN includes five neurons in the data layers, 1024 neurons in every four mystery layers, besides one neuron in the outcome layer. From datasets, the attributes are delivered off the RNN input portion. RNN is an assortment of general feed-forward cerebrum networks with mystery layers. In the RNN, each secret layer accomplishes input from the past layer and commencements of itself for going before input. The repetitive brain network is planned with the MLP and comprises stowed away unit actuations taken care of back in the framework considered with the data sources. In this RNN, the time T can be discretized with the underlying refreshing cycle at each period. The time frame might have fluctuated to the capacity of genuine neurons or planned multiplication techniques. In the proposed RNN work, two initiation capacities are used dramatic direct unit (ELU) and redressed straight actuation unit (ReLU) [17]. The ELU work is numerically formed as follows,

$$F(x) = a(e^{x}-1), X<0, \text{ otherwise } F(x) = X \quad (1)$$

Where, x can be portrayed as a boundary and can be depicted as contribution to a neuron.

The RLU capacity can be numerically planned as follows,

$$F(x) = \max(0,x) \quad (2)$$

Where x can be portrayed as a contribution to the neuron.

To alleviate the overfitting, a dingo enhancer is used in the RNN network to prepare. Also, the dropout layer is used among completely associated layers to alleviate overfitting. Regularly, the dropout proportion is 0.5. The RNN preparation contains two sections: preparing unbiased and a dingo streamlining agent to lessen this goal work. This examination used a dingo analyzer to diminish the Mean Square Error (MSE). In this proposed approach, the learning rate is thought of as 0.001. The proposed RNN structure is represented in figure 2.

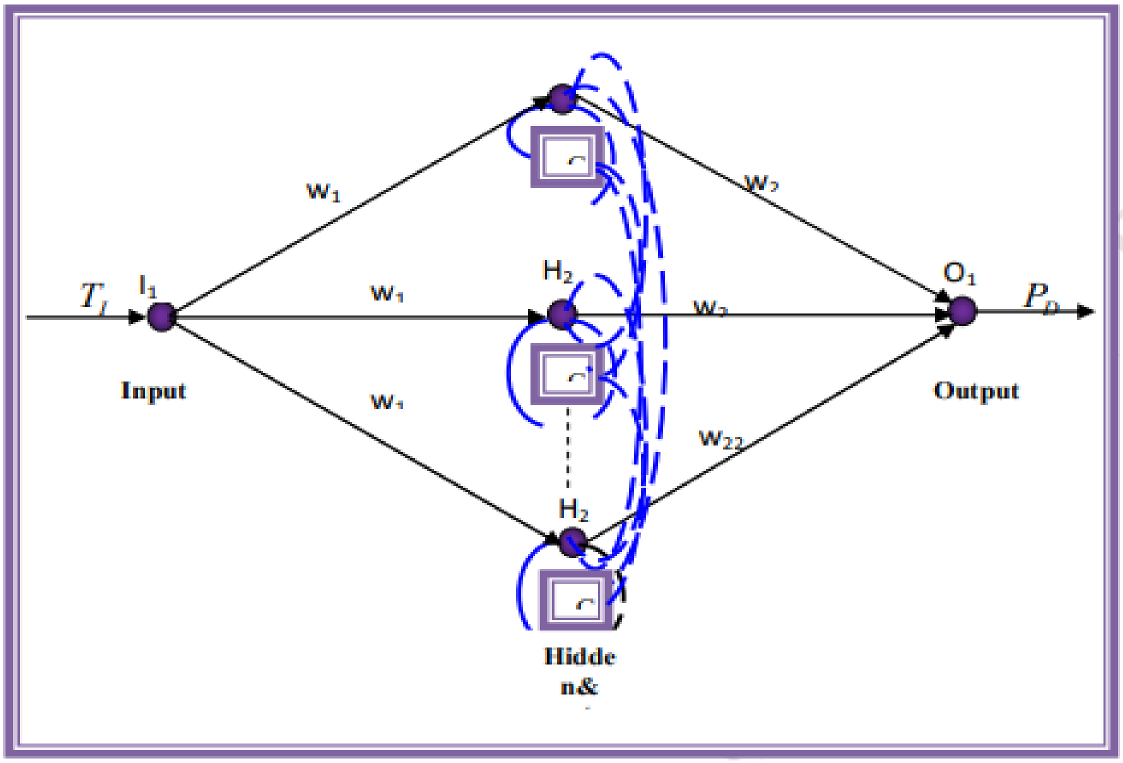

Fig. 2 RNN architecture of the proposed methodology

The neuron in the output layer is related to and differentiated from the expected human activity recognition and the pre-defined human activity recognition (target data). The model performance evaluation depends on the rail-clearance test (80/10/10) plot. The actual product of the method was completed in the product database, while the approved database was used to adjust the hyper-boundaries; The general presentation of the model was evaluated in the experimental dataset. The dingo optimizer introduced teachable loads. Weight updates were performed in small clusters, and the size of the experiments for a group was set to 20. Production ends when the company does not work on its exhibition, subject to approval for a pre-defined number of ages. The figure was set at 80, and the execution was rated as unlucky and accurate [30]. The misfortune is the MSE, the difference in the approximate output distribution from the actual distribution of the names.

3.3. Remora Optimization Algorithm

The ROA is utilized to choose optimal RNN parameters for weather forecasting. During initialization progress, the RNN parameter is selected optimally.

3.3.1. Initialization

In the projected remora optimization algorithm, it can be assumed that the candidate assumes there is remora in this position R in the search location, and it is a parameter of the issue [19]. The remora swims super dimensional or three-dimensional, two-dimensional, and one-dimensional space, and their position vector changes. The present positions of the remora are formulated as follows,

$$r_1 = (r_{I1}, r_{I2}, \ldots r_{ID}) \tag{3}$$

Here, D it can be described as the dimension in the remora search space and I can be described as the number of remoras. During the search space of the remora, the food of the remora is presented as follows: the best solution of the optimization algorithm [30].

$$r_{bst} = (r^*_{1}, r^*_{2,\ldots,} r^*_{D}) \tag{4}$$

In this algorithm, every candidate solution contains a related fitness function. Here, the fitness function is formulated as follows,

$$F(r_1) = F(r_{I1}, r_{I2}, \ldots, r_{ID}) \tag{5}$$

$$F(r_{best}) = F(r^*_{1}, r^*_{2,\ldots,} r^*_{D}) \tag{6}$$

Here, F it can be described as the fitness function of the problem.

Based on equation (4), the optimal solutions are saved in the optimal remora location. Here, remora is considered the main essential parameter to compute the solution addition and can be scattered in the searching space. Different marine organisms can be a tool to manage remora in location upgrading. In addition, it contains the specific path to the location updating process. With the search space, remora can compute the optimal location, which is considered two modes: exploration and exploitation. The pseudo-code of the ROA is presented in algorithm 1.

Algorithm 1: Pseudo-code of ROA algorithm

Input: Initial random weighting parameters

Outputs: Optimal weight parameter

Initialize the remora position

While$(T >= t)$

Check the search agent search space

Compute fitness function

for every remora indexed by i

$$H(I) = Round\ (RAND);$$

IF $H(I) == 0$ then

update the position related to the attached whales

Elseif $H(I) == 1$ then

update the position using the normal process

End if

Process of experience attack

update the position of the search agent

end for

end while

3.3.2. Fitness Evaluation

The fitness function is mathematically formulated as follows,

$$FF = MIN\ \{MSE\} \tag{7}$$

$$MSE = \frac{1}{N*M}\sum_{X=1}^{N}\sum_{Y=1}^{M}[I_{attribute}(A,B) - I_{d-attribute}(A,B)]^2 \tag{8}$$

Where $I_{d-attribute}(A,B)$ is described as output attributes and $I_{attribute}(A,B)$ is described as input attribute? Based on the fitness function, the RNN parameters are selected to enhance the optimal weather forecasting process.

3.3.3. Exploration Stage

When remora is attached to the swordfish, the position of remora is updated. Related to the elite information of this technique, the location update equation is enhanced and formulated as follows,

$$r_I^{T+1} = r_{best}^{T} - \left(rand(0,1) * \left(\frac{r_{best}^{T} + r_{Rand}^{T}}{2}\right) - r_{Rand}^{T}\right) \tag{9}$$

Where r_{Rand} can be described as random location T can be described as the maximum number of iterations. The optimal solution is considered the optimal position of the remora update. Additionally, the random choice of remora can be combined to empower the search space of exploration. The remora choice for various hosts related on it has attack prey or not. The fitness function parameter achieved in the current generation is more efficient than before. The present fitness parameter is computed based on experience attack [20].

3.3.4. Experience Attack

To compute the required variation of the host, the small step related to the host and the same to the accumulation experience. This experience attack is computed based on the below equation,

$$r_{attend} = r_I^T + (r_i^T - r_{pre}) * randn \quad (10)$$

Wherer_{attend} can be described as a tentative step and r_{pre} as the position before creation that is defined as reasonable. The fitness function parameters of the presented solution and attempted solution is compared and best solution is selected based on below formulation,

$$f(r_i^T) > f(r_{attend}) \quad (11)$$

Remora can choose various feeding techniques for local optimization that can be presented in the upcoming portion. The fitness function parameter of the attempted solution can be higher than the present solution, which is a back-to-host chosen.

$$f(r_i^T) < f(r_{attend}) \quad (12)$$

3.3.5. Exploitation Stage

In the exploitation stage, the remora position updating is presented in the below equations,

$$r_{I+1} = d * e^{a*} cos(2\pi\alpha) + r_i \quad (13)$$

$$\alpha = Rand(0,1) * (A - 1) + 1 \quad (14)$$

$$A = -\left(1 + \frac{t}{T}\right) \quad (15)$$

$$d = |r_{best} - r_I| \quad (16)$$

Where, A can be described as the random variable presented in the range of [-1,1] and reduced to [-2, -1],   can be described as the distance between prey and hunter.

3.3.6. Host feeding behavior

Host feeding can be described as the subdivision in the exploitation procedure. In this phase, the solution space is decreased to the location space of the host. Moving on or present in the host can be the limitation of as small phases that can be reduced by,

$$r_i^T = r_i^T + A \quad (17)$$

$$A = b * (r_i^T - c * r_{best}) - V \quad (18)$$

$$V = 2 * \left(1 - \frac{t}{\text{Maximum iteration}}\right) \quad (19)$$

Where A can be described as the small variation related to the space volume of the remora and host, to achieve the remora and host location in the search space, the remora factor C was utilized to remora narrow position.

3.3.7. Computational Complexity

To validate the ROA, the complexity of the technique can be presented related with the maximum iteration, dimension and number of remoras. It can be worth nothing that there is no sort technique. The complexity of the technique is denoted as $o(n)$. The complete complexity is formulated as follows,

o(roa) = o(fitness function) * (o(t*(o(initialization) + o(exploration + o(exploitation))) (20)

= 0(f() * o(t * (o(n)+o(n*t*d) + o(o(n*t*d)) (21)

= o(f(r)) * o(n*(td+1)) (22)

Related to the fitness function, the complexity is denoted as $0(f(r)$. Computational complexity is denoted as $o(n * t * d)$ for exploration stage, and the exploitation stage is expressed as $o(n * t * d)$.

4. Results and Discussion

The performance of the proposed method is evaluated and justified in this section. In this section, performance and comparison analysis validate the projected technique performances. The proposed method is implemented in an Intel Core i5-2450M CPU 2.50GHz laptop and 6GB RAM to validate the presence of the projected weather forecasting. This method was implemented in R Programming software R2016b. To approve the presentation of the proposed strategy, the information bases of weather conditions estimating are gathered from [21], which comprises properties. The proposed strategy is executed and approved by utilizing the presentation measurements such as accuracy, precision, sensitivity, specificity, and F- Measure.

4.1. Experimental Results

The proposed model involves the following steps,

- Load Dataset
- Reduce Dimensions
- Optimize Parameters
- Feature Extraction
- Performance Evaluation

4.2. Load Dataset

The weather dataset has been loaded from the source. It contains 66336 data. It retrieves the information about the data as the name of the dataset, number of rows and columns, and total number of records in the dataset.

The processed output is:

Dataset name: Weather history

Rows : 96454

Columns : 24

Table 1. Sample Weather Dataset

Date & Time	Temperature C	Humidity	Wind speed	Wind Bearings	Visibility	Pressure	Daily Summary
13/03/2012 2:00	9.4722	0.89	14.1197	204	14.9569	1015.63	Partly cloudy throughout the day.
13/03/2012 23:00	9.35556	0.86	11.0446	258	11.4471	1017.22	Partly cloudy starting in the afternoon
14/04/2012 21:15	9.37778	0.83	11.3183	163	9.982	1008.71	Foggy until the night
15/05/2012 8:45	8.28889	0.72	17.5651	147	6.1985	1016.15	Overcast throughout the day.
15/06/2012 19:15	8.75556	0.67	20.6885	131	9.982	1004.96	Foggy in the morning
16/07/2012 7:00	9.22222	0.46	10.4006	32	10.6743	1007	Mostly cloudy until night
17/03/2012 15:45	7.73333	0.52	8.5169	153	2.6565	1014.7	Overcast until evening
18/03/2012 3:15	16.0167	0.93	4.9266	4	3.2039	1020.34	Foggy in the evening
18/08/2012 14:00	17.1444	0.71	3.9284	9	6.3434	1011.67	Mostly cloudy starting in the morning and continuing until the evening
19/07/2012 1:15	15.3889	0.82	10.4006	0	11.27	1013.12	Mostly cloudy throughout the day.
19/03/2012 12:15	18.8778	0.71	23.8924	339	5.9248	1006.26	Partly cloudy until evening
19/03/2012 23:15	11.5	0.5	20.0123	311	15.8746	1005.19	Foggy until the morning
20/10/2012 10:30	10.2	0.44	11.2056	59	11.4471	1015.7	Partly cloudy until night
20/03/2012 21:30	20.2167	0.37	0.6762	272	4.1216	1017.26	Foggy in the morning
21/05/2012 9:00	16.2944	0.56	14.9086	151	2.0126	1010.9	Foggy overnight and breezy in the morning.
21/11/2012 19:30	6.13889	1.0	17.0499	63	6.3112	1011.39	Mostly cloudy throughout the day.
22/03/2012 7:00	12.2	0.6	2.3828	20	5.2164	0	Foggy overnight

4.3. Reduce Dimensions

A large number of dimensions affect the accuracy. Using the Principal Component Analysis (PCA), the dimensions have been reduced in the dataset. After reducing the dimensions, the distinct values are identified. Here the dimensions are reduced, and the 242 values are distinct. It helps to optimize the parameters.

The processed output is:

Distinct Values: 2742

Table 2. Dimensionality Reduction

Date & Time	Temperature C	Humidity	Visibility	Pressure	Daily Summary
13/03/2012 2:00	9.4722	0.89	14.9569	1015.63	Partly cloudy throughout the day.
13/03/2012 23:00	9.35556	0.86	11.4471	1017.22	Partly cloudy starting in the afternoon
14/04/2012 21:15	9.37778	0.83	9.982	1008.71	Foggy until the night
15/05/2012 8:45	8.28889	0.72	6.1985	1016.15	Overcast throughout the day.
18/08/2012 14:00	17.1444	0.71	6.3434	1011.67	Mostly cloudy starting in the morning and continuing until the evening
19/07/2012 1:15	15.3889	0.82	11.27	1013.12	Mostly cloudy throughout the day.
19/03/2012 12:15	18.8778	0.71	5.9248	1006.26	Partly cloudy until evening
19/03/2012 23:15	11.5	0.5	15.8746	1005.19	Foggy until the morning
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21/11/2012 19:30	6.13889	1.0	6.3112	1011.39	Mostly cloudy throughout the day.
22/03/2012 7:00	12.2	0.6	5.2164	0	Foggy overnight

4.4. Optimize Parameters

After decreasing the aspects, The boundaries have been advanced. The improvement is finished by utilizing Remora Optimization Algorithm. Here the improved boundaries are Date, wind speed, ocean level, Temperature, Precipitation, Pressure, etc. The improved boundaries are utilized to extricate the component.

Table 3. Parameter Optimization

Date & Time	Temperature C	Pressure	Daily Summary
13/03/2012 2:00	9.4722	1015.63	Partly cloudy throughout the day.
19/07/2012 1:15	15.3889	1013.12	Mostly cloudy throughout the day.
19/03/2012 12:15	18.8778	1006.26	Partly cloudy until evening
19/03/2012 23:15	11.5	1005.19	Foggy until the morning
21/05/2012 9:00	16.2944	1010.9	Foggy overnight and breezy in the morning.
21/11/2012 19:30	6.13889	1011.39	Mostly cloudy throughout the day.
22/03/2012 7:00	12.2	0	Foggy overnight

4.5. Feature Extraction

After Optimizing, the element has been separated. Here the component temperature is to be removed given that the future temperature esteem is anticipated. The component can be separate and foresee the future worth. Select the specific day of the week and pertinent time the future worth of temperature is anticipated.

The processed result is: Select the day of week 4 and select the time 1.00, then get the temperature esteem is 12. This is worth getting from the separated element after the lessening aspect.

4.6. Performance Evaluation

The performance has been evaluated and compared with the conventional techniques. The accuracy is measured and illustrated in figure 3 to validate the projected technique with 99% accuracy. Similarly, the WOA and PSO are achieved at 89 and 85. Based on the analysis, the projected technique achieved efficient outcomes.

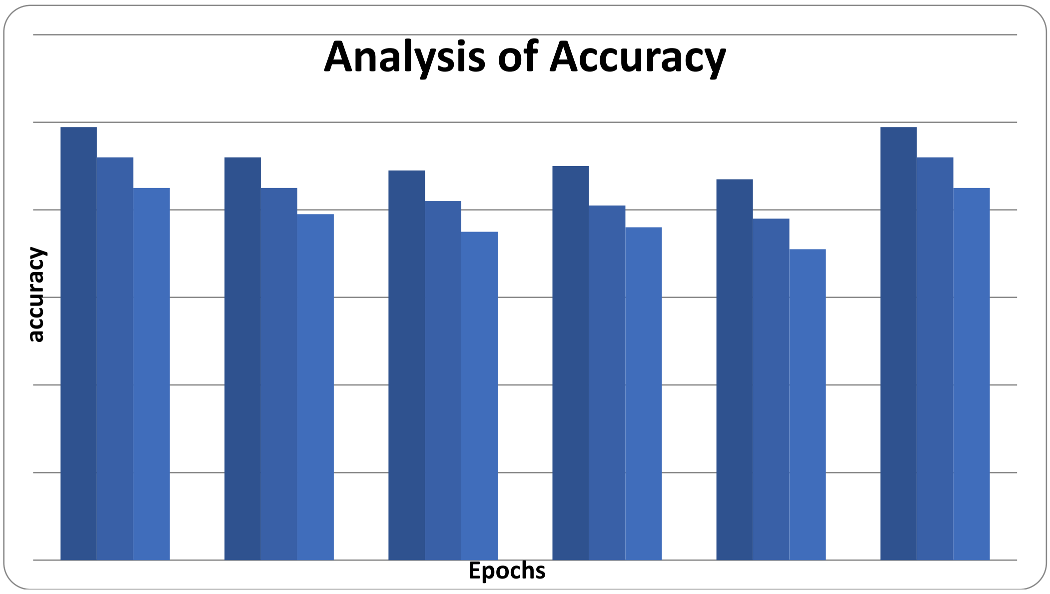

Fig. 3. Analysis of accuracy

The proposed method is compared with the conventional techniques such as WOA and PSO. The proposed method is achieved

Table 4. Analysis of accuracy

Proposed ROA	WOA	PSO
99	89	85
95	92	84
96	85	82
94	90	87
92	87	83
99	89	85

To validate the projected technique, the precision is measured and illustrated in figure 4.

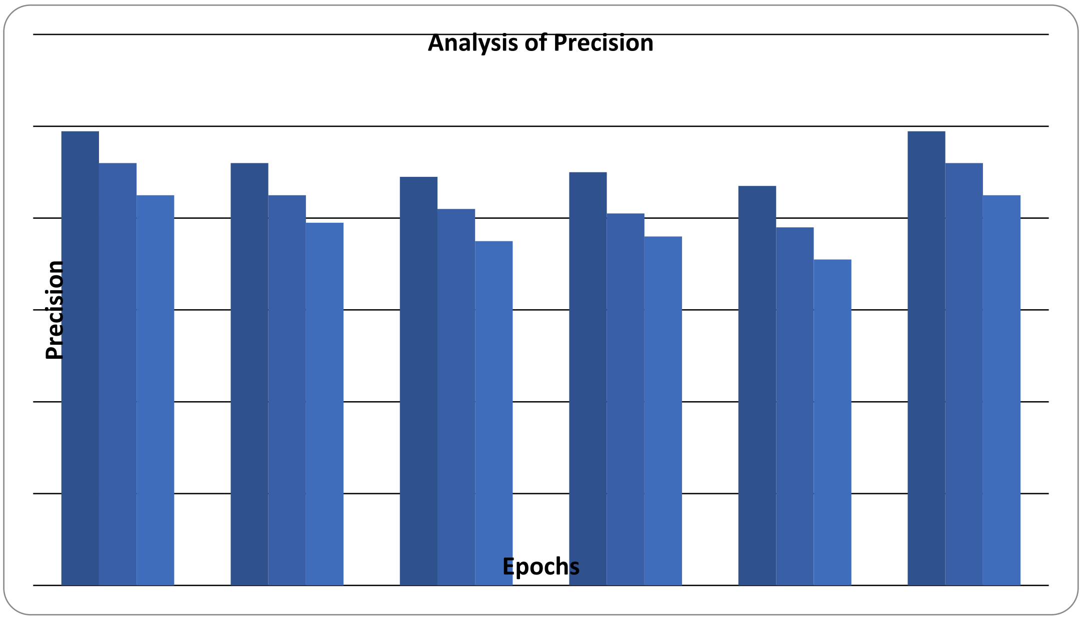

Fig. 4 Analysis of precision

The proposed method is compared with the conventional techniques such as WOA and PSO. The proposed method achieved 98.9% precision. Similarly, the WOA and PSO are achieved at 92 and 85. Based on the analysis, the projected technique achieved efficient outcomes.

Table 5. Analysis of precision

Proposed ROA	WOA	PSO
98.9	92	85
92	85	79
89	82	75
90	81	76
87	78	71
98.9	92	85

To validate the projected technique, the recall is measured and illustrated in figure 5.

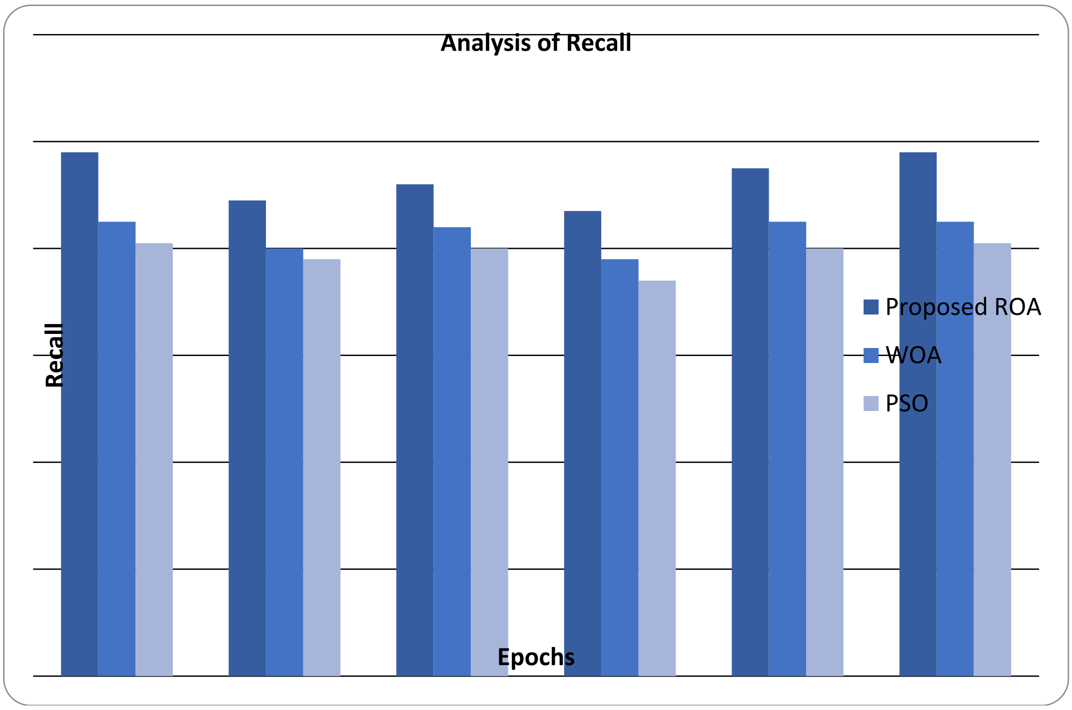

Fig. 5 Analysis of recall

The proposed method is compared with the conventional techniques such as WOA and PSO. The proposed method achieved 98% recall. Similarly, the WOA and PSO are achieved at 85 and 81. Based on the analysis, the projected technique achieved efficient outcomes.

Table 6. Analysis of Recall

Proposed ROA	WOA	PSO
98	85	81
89	80	78
92	84	80
87	78	74
95	85	80
98	85	81

To validate the projected technique, the precision is measured and illustrated in figure 6.

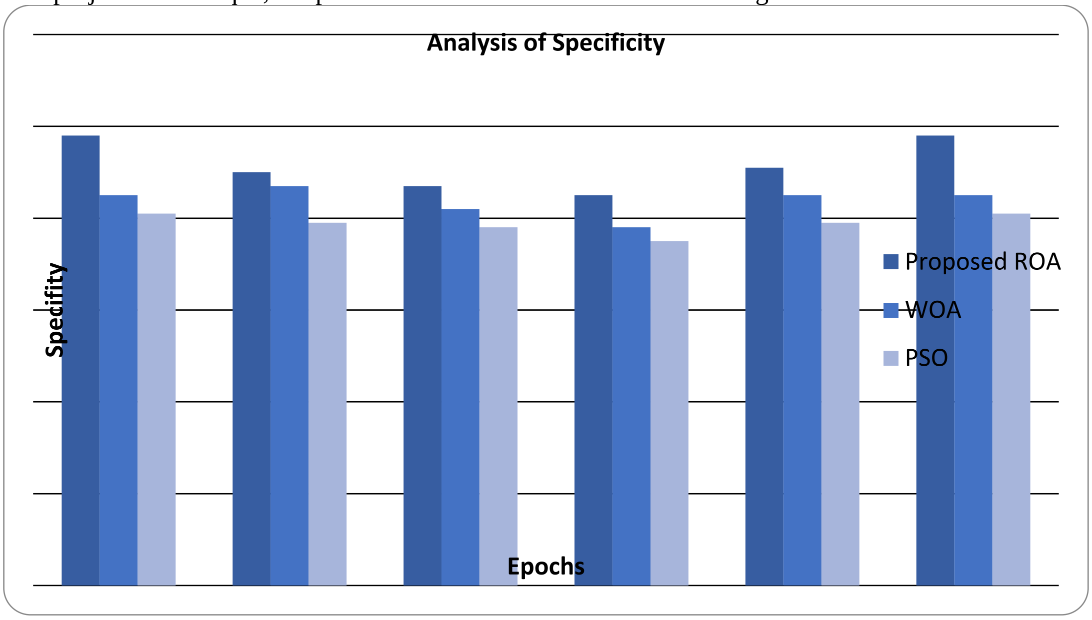

Fig. 6 Analysis of the specificity

The proposed method is compared with the conventional techniques such as WOA and PSO. The proposed method achieved 98% specificity. Similarly, the WOA and PSO are achieved at 85 and 81. Based on the analysis, the projected technique achieved efficient outcomes.

Table 7. Analysis of Specificity

Proposed ROA	WOA	PSO
98	85	81
90	87	79
87	82	78
85	78	75
91	85	79
98	85	81

To validate the projected technique, the precision is measured and illustrated in figure 7.

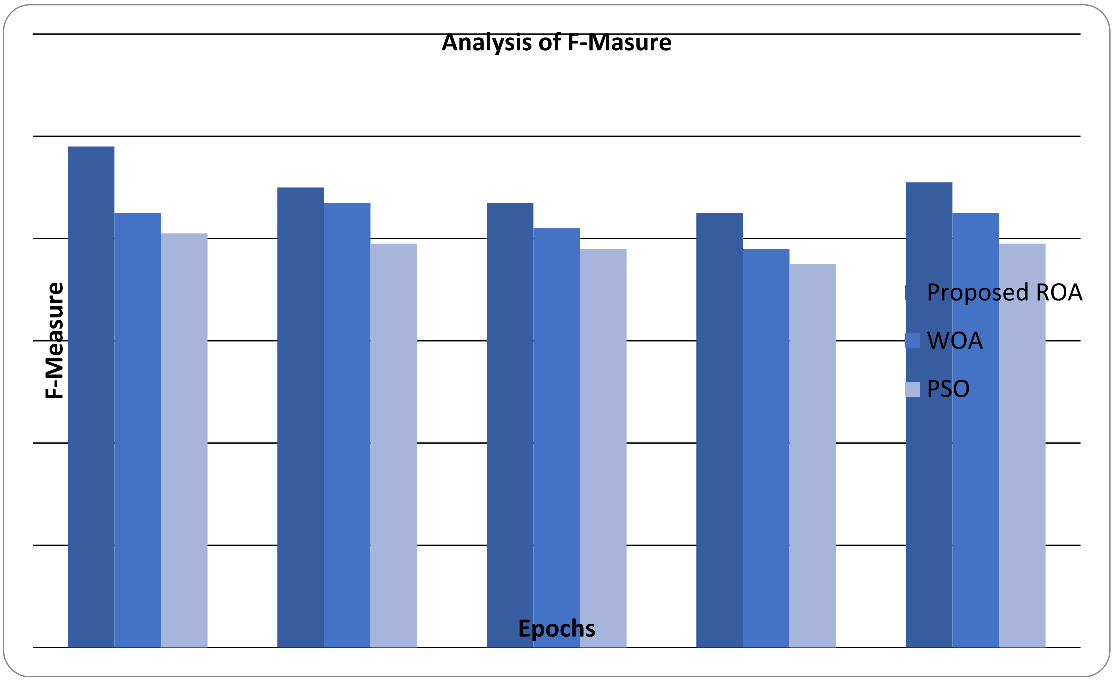

Fig. 7 Analysis of F_Measure

The proposed method is compared with the conventional techniques such as WOA and PSO. The proposed method achieved 98% F-Measure. Similarly, the WOA and PSO are achieved at 85 and 81. Based on the analysis, the projected technique achieved efficient outcomes.

Table 8. Analysis of F- measure

Proposed ROA	WOA	PSO
98	85	81
90	87	79
87	82	78
85	78	75
91	85	79

5. Conclusion

This paper has developed an HRNN with PCA for efficient weather forecasting. Initially, the databases are collected from the open-source system. After that, PCA is utilized to reduce the dimension of the input collected data. The huge amount of data reduces the forecasting accuracy with the repeated values and attributes. Hence, PCA is utilized for reducing the similar dimension of attributes. The reduction data is utilized to propose a weather forecasting model. The HRNN is a combination of RNN and ROA. The proposed HRNN is working with two phases such as training and testing. The collected data is divided into two parts as80% and 20%. 80% of the data is utilized for the training phase of the proposed technique. The remaining 20% is utilized for the testing phase of the proposed technique. The proposed technique is implemented, and performance metrics evaluate performance. It is compared with the conventional techniques such as WOA and PSO to validate the proposed technique.

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