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# Forecasting of Significant Wave Height Using Long Short-Term Memory and Multivariate Variational Mode Decomposition

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**Abstract:**

Forecasting the height of the significant wave (SWH) accurately and reliably is crucial for maritime and engineering purposes. This work designs a novel deep learning system to forecast the daily significant wave height (SWH). This work combines two techniques: Multivariate Variational Mode Decomposition (MVMD) and Long Short-Term Memory (LSTM). The oceanic time series data are decomposed into intrinsic mode (IMFs) functions using the MVMD technique. The LSTM uses the IMFs as inputs. Applying the hybrid MVMD-LSTM model to two stations Albatross Bay and Gladstone Queensland, Australia's stations. The outcome indicates that the proposed hybrid model improved the SWH forecasting. It scored acceptable performance $NS_E$=0.09999, $NS_E$=0.99999, $WI_E$=0.9999, $WI_E$= 0.999998, $LM_E$=1.7995, $LM_E$= 2.3894 for Albatross Bay and Gladstone stations respectively. This work is essential for monitoring and managing clean energy resources to maximize sustainable energy production

**Keywords:** MVMD, LSTM, wave energy, SVR, time series analysis, SWH prediction

## 1-Introduction

Accurate assessment of the height of waves in coastal waters can offer valuable data for several feasible uses in coastal construction and observation of the environment. The activities include monitoring, safeguarding against coastal erosion, and facilitating maritime transit. Significant wave height is a crucial factor in the planning and building of structures for coastal protection and sediment transfer and the selection and advancement of ports. Various factors, such as wind, waves, shoals, diffraction and reflection, gales, and sea depths, can influence the height of waves in offshore and nearshore regions [1]. Wave height prediction is based on two primary methods: Physical models and data-driven techniques [2]. The physical models primarily encompass the wave model, which simulates nearshore waves, and WAVEWATCH III [3]. Data-driven approaches mainly consist of statistical methodologies and machine learning models [4]. In recent years, Wave height prediction has been made possible by the many machine-learning algorithms being used due to the continuous growth of artificial intelligence. As an illustration, Adnan et al. [5], the researchers incorporated three machine learning algorithms (Random Forest), Gradient-boosted regression tree, Random Forest(RF) and multivariate adaptive regression spline integrated into their wave height prediction methodology.

## 2- Related Work

Sadeghifar et al.,[6] Assessed the accuracy of four machine learning models, specifically RF, adaptive neuro-fuzzy inference structure, M5P modelling tree, and artificial neural network (ANN) in predicting wave height. Ikram et al.,[7] utilized a neuro-fuzzy technique as part of their forecasting system. Fan et al., [8]The suggested model, known as long short-term memory (LSTM), aims to forecast wave height efficiently. Li et al.,[9] Suggested a wave forecasting technique employing a recurrent unit that is gated (GRU) to acquire knowledge of the interdependence among data from multivariate series. Algorithms for machine learning are experiential; they can acquire information from data and adapt to changing circumstances. This allows them to accurately anticipate nonlinear series by allowing them to collect the nonstationary features of the data. Recently, Preprocessing raw data using various decomposition methods has become a common practice before entering it into the model. This is done to gather the nonlinear properties of wave height better and enhance predict accuracy. Çelik et al., [10] employed (singular value decomposition) for decomposing the original height of wave series prior to performing the prediction.

Altun kaynak et al.,[11] Utilized the Wavelet Transform (WT) to decompose the original series into its constituent parts and made predictions for each of the resulting subseries. Mumtaz et al [12] used Multivariate Variational Mode Decomposition (MVMD) integrated with Gated Recurrent Unit (GRU)

to design the MVMD-GRU model to forecast one day ahead Hsig for the Hay Point, Townsville, and Gold Coast stations in Queensland, Australia. By decomposing the original data into a series of subsequences before prediction, the result for the model WIE =0.983, 0.918, 0.983, NSE =0.932, 0.735, 0.934, LME =0.978, 0.758, 0.752 for Hay Point ,Townsville, and Gold Coast stations. These technologies can overcome the obstacles presented by cyclic, repeated, nonlinear, and nonstationary patterns.

The study's findings (MVMD) model is a technique that decomposes the original information into various components in the frequency domains, each having different bandwidths.). MVMD is a fully nonrecursive method. MVMD has been proven to have excellent resistance to noise and precise abilities in decomposing components. It has been successfully utilized in various fields, including time series prediction[12]. This paper presents a hybrid model that combines Modeling using deep learning techniques with Multivariate Variational Mode Decomposition. The objective is to develop the MVMD-LSTM model to predict significant wave height one day in advance. Predictor lags are decomposed into functions of intrinsic mode (IMFs) by the MVMD. The IMFs are utilized as inputs for the LSTM to create the MVMD-LSTM, which is employed to forecast the major wave height one day in advance. In order to validate the designed MVMD-LSTM framework, multiple Different versions of Deep Learning algorithms were created to assess its practicality.

## 3. Data Description

The data is obtained from the Coastal Data System, Queensland, Australia, managed by the Environment and Science Department of the Queensland Government Gladstone, Albatross Bay. The timeframe is five years, from 1 January 2018 to 31 December 2022. Authorization was acquired to utilize the data as resources for examining the patterns, actions, and seasonal variations of notable sea wave height about a variety of marine parameters, such as Sea Surface Temperature (SST), Direction (Dir_T p), Peak Wave Energy Period (T p), Maximum Wave Height (H max), and Zero Up-Crossing Wave Period (T z), in order to create reliable forecasts for future Significant Sea Wave Height (Hsig). The main challenge associated with nonstationary time-series is the presence of ambiguity, which can hinder comprehension and lead to incorrect forecasting methods. It is essential to address the challenges posed by nonstationary time series to accurately predict future Hsig. A notable seasonal disparity in the fluctuation of major wave height has been observed recently. The significant wave heights exhibit substantial irregularity, instability, and inconsistency as a result of fluctuating magnitudes and durations[13] .The significant wave height has a high degree of randomness regarding its direction, amplitude, and frequency, contributing to its overall complexity.

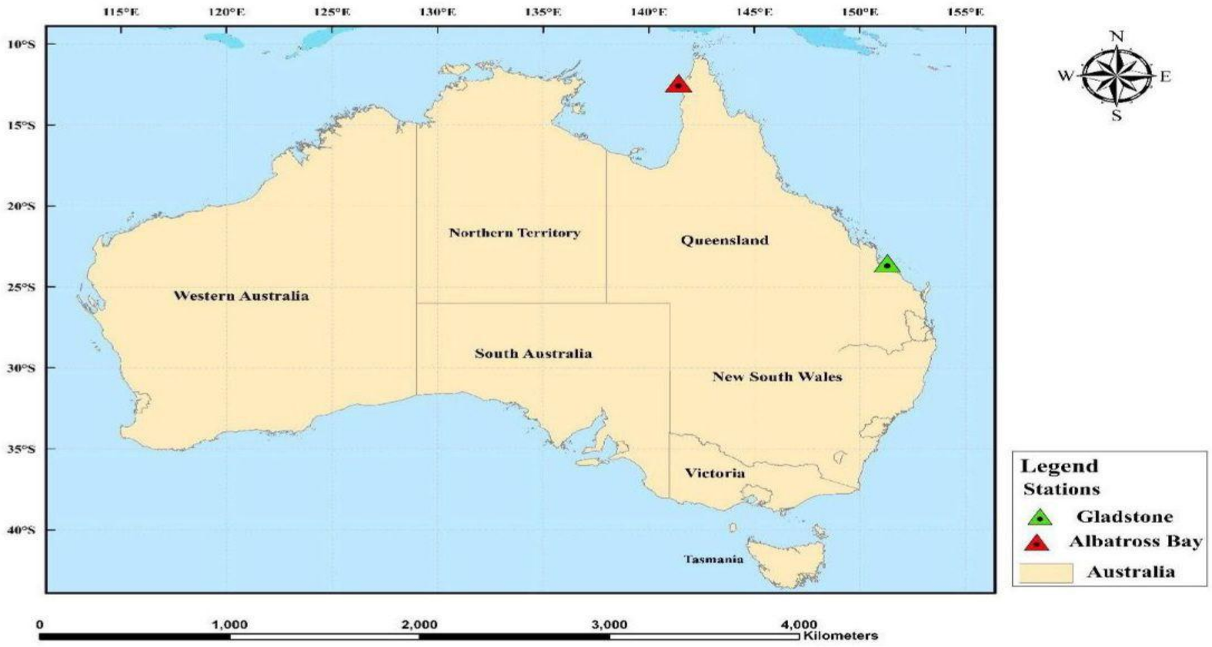


Figure 1. Map Of The Station

**4- Methodology**

The study's approach is illustrated in Figure 2.

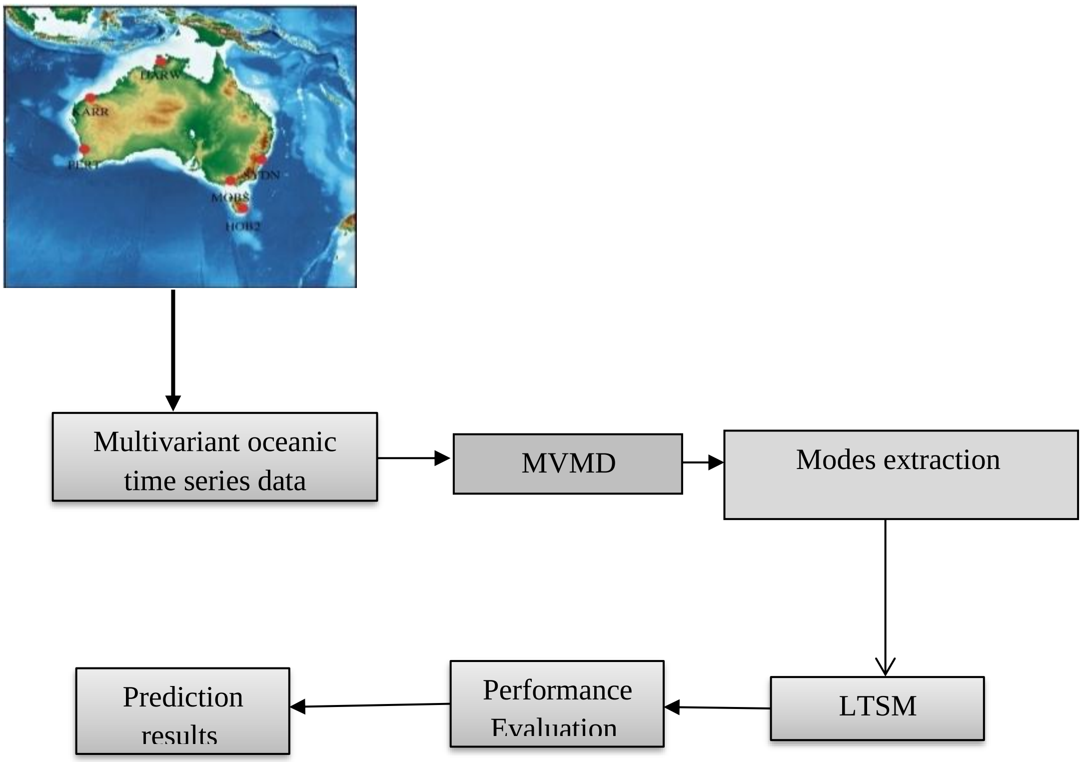


Figure 2. The Proposed Model to Wave Height Prediction

### 4.1.*(MVMD) Multivariate Variational Mode Decomposition*

The algorithm (MVMD) is a generalized form of the algorithm (VMD) variational mode decomposition designed to handle multivariate or multichannel datasets. The traditional method of Variational Mode Decomposition (VMD) involves the decomposition of a complex signal x(t) into a set of modes, or sub-signals. VMD is a univariate nonrecursive decomposition technique. Using a constant bandwidth known as intrinsic mode decomposition (IMF).

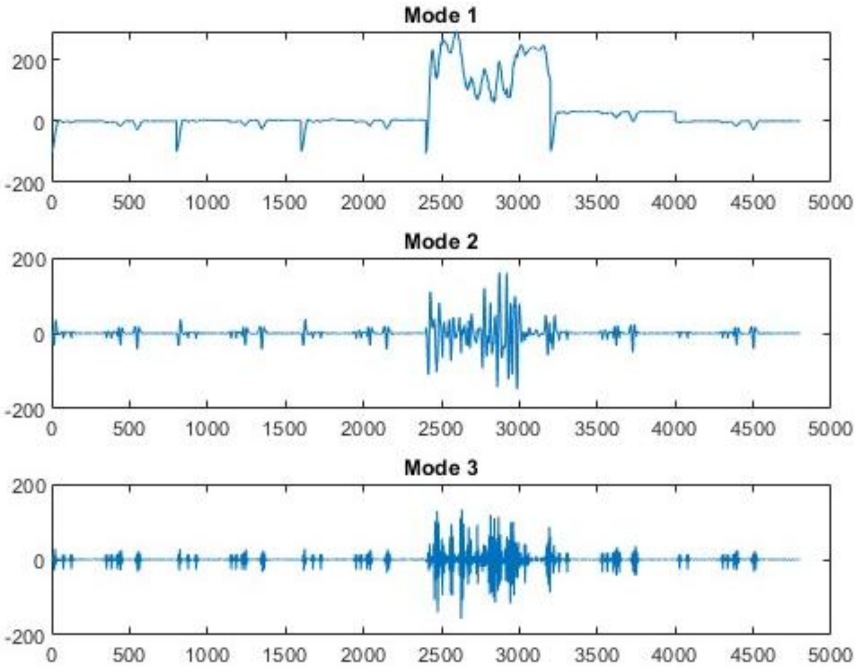


Figure 3. MVMD Decomposition Time Series into IMF

Table (1):

The MVMD design parameters are used to decompose the data into IMF for each station.

Albatross Bay and Gladstone stations.

| Albatross Bay | | | | | | | Gladstone | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| input | DC | tol | k | init | alpha | tan | DC | tol | k | init | alpha | tan |
| $H_{MAX}$ | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 |
| Tp | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 |
| Tz | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 |
| Dir-true | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 |
| SST | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 | 1 | 1e-6 | 3 | 1 | 2000 | 0.1 |

Studies indicate that( MVMD) can collect both the nonstationary and nonlinear aspects of a multichannel signal simultaneously while preventing any problems related to mode mixing [14].

This pre-processing approach has the ability to decompose a subset of signals, that involve a number of series of times $y(t) = \sum_{n=1}^{n} imf \;\; c(t) = [y_1(t); y_2(t); \ldots; y_n]$ into predefined n number of multi variate $imf_n(t) = imf_1(t); imf_2(t); \ldots.; imf_n$ . To optimize the (MVMD), The mode value (n) can be chosen by :

$$mininise \; \{y_n^k\}\{wt\} \left\{\sum_t \sum_k ||\partial_t \left[e^{-jw_n t} \bar{u}_t^n(n)\right]||\right\} \qquad (1)$$

$$\sum_t \bar{u}_t^k(K) = y^k(n), \quad k = 1,1, \ldots., k \qquad (2)$$

## 4.2. Long Short-Term Memory (LSTM)

(LSTM) efficiently addresses the commonly encountered issue of long- and short-term dependence and overcomes the gradients that vanish in RNNs [15]. LSTM networks consist of memory blocks connected in successive layers [16]. Each block of the LSTM consists of three gates, which can be summarized as follows :

- The( Forget gate) determines which information to exclude from the block.

$$f_t = \sigma\left(U_f \; * [H_{t-1}, X_t] + b_f\right) \qquad (3)$$

- The( input gate) identifies a specific input values that will be used to change the memory's state.

$$i_t = \sigma\left(U_i \; * [H_{t-1}, X_t] + b_i\right) \qquad (4)$$

- The (output gate) acquires the ability to generate an output based on the block's input and memory.

$$o_t = \sigma\left(U_o \; * [H_{t-1}, X_t] + b_o\right) \qquad \mathbf{(5)}$$

An (LSTM) unit comprises a cell that is regulated by the input gate, which is a sigmoidal gate, is followed by the forget gate and the output gate., which control its reading and modification. The LSTM unit receives inputs from four outside sources, the three gates and the input, at each of its four terminals. The two outside sources are as follows [17] :

- The present instance

- The values of every (LSTM) unit in the same layer that were previously hidden

The structure of the( LSTM) unit is depicted in Figure 3.

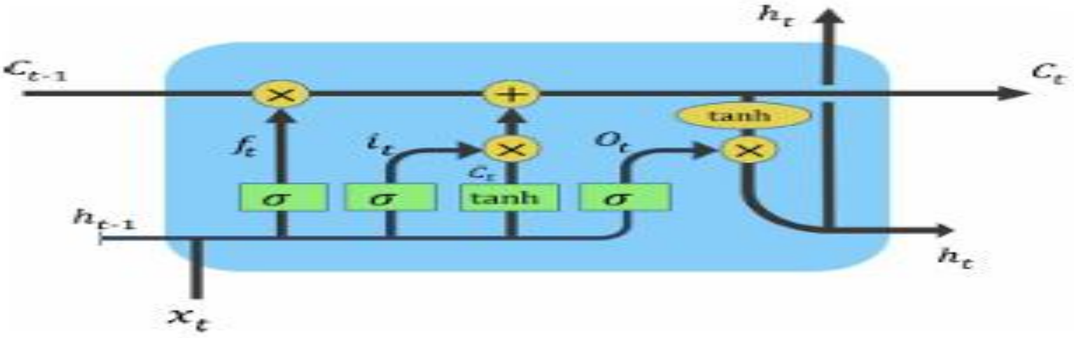


Figure 4. Structure of the LSTM

## 4.3. Support Vector Regression

A highly efficient machine learning methodology for classification and prediction tasks. Support Vector Regression (SVR) is an analysis of regression technique that utilizes Support Vector Machines (SVMs) for performing both linear and nonlinear regression. Similar to SVMs for classification, (SVR) is a machine learning algorithm that determines the optimal hyperplane to match the training data by maximizing the distance between the hyperplane and the data points. However, instead of finding a hyperplane that splits the data into different classes., SVR finds a hyperplane that predicts the continuous output variable (i.e., the target variable) given the input variables.

In SVR, The objective is to fulfill a given margin of error (epsilon) while minimizing the difference between the expected to and actual values. The margin of error allows some data points to be within a certain distance from the predicted values, which can be useful for dealing with noisy data or outliers [18]. The parameter C determines the balance between maximizing the margin and reducing the error.

To resolve the optimization issue in SVR, quadratic programming is often used. The optimization problem involves finding the values of alpha, which are Lagrange multipliers that determine the support vectors (i.e., the data points that lie on or within the margin). Once alpha is obtained, the weights and bias terms can be calculated to predict new output values for unseen input values.

Overall, SVR is a powerful technique for regression analysis that can handle linear and nonlinear relationships between variables and can incorporate different types of kernels to capture complex patterns in the data.

## 4.4. Gated Recurrent Units

There are just two gates in this model, and they utilize activation functions to decide if the previously hidden states ought to be carried over or disregarded and When the hidden states should be updated by reducing the chance of a vanishing gradient and solves the issue by allowing the structure is designed to enhance the learning process by efficiently determining when to retain or discard information, ensuring a continuous flow of relevant knowledge through recurrent iterations., Compared to LSTM, GRU can be trained more quickly due to its straightforward nature . It addresses the issue that long-distance information acquisition presents with RNN. The following formulas regulate the primary functions of GRU [19].

Up data gate $Y_t = \sigma(w_Y * [h_{t-1}, c_t]$ (6)

Reset gate $x_t = \sigma(w_x * [h_{t-1}, c_t]$ (7)

input ($c_t$) and previous output ($h_{t-1}$), update gate($Y_t$) and reset gate($x_t$)

## 5- Results Section

The suggest model was compared with other models. The oceanic time series were utilized as inputs for both the model suggested and the benchmarked models. Tables 3, 4, show the simulation outcomes of the suggested model in addition to GRU and SVR for two stations named Albatross, and Gladstone stations. From the results in( Table3 and Fig.5), we can observe that the proposed MVMD coupled with LSTM performed very well with most models for example, in Table3 the LSTM model gained the lowest RMSE=0.009, MAE=0.007, and RMAE=0.001 for SWH prediction for albatross station. Similarly, the MVMD-LSTM model (Table 4 and Fig. 6) achieved significantly better predictions for the station Gladstone .Fig.7 demonstrates the forecasted and the measured( SWH )using the scatter diagram representation in combination with the correlation equation. The MVMD-LSTM approach is certainly showing well preciseness and accurateness with respect to the benchmark comparing models MVMD-SVR, MVMD-GRU for albatross station. Similarly, the proposed hybrid MVMD-LSTM model for the Gladstone station is also significantly better against the benchmark models (Fig. 8).

Table 3: Performance evaluation of the proposed model for albatross station

| Model | GRU | LSTM | SVR |
|---|---|---|---|
| RMSE | 1.9061049 | 0.0097874440 | 0.056843229 |
| MAE | 0.28715485 | 0.0077114357 | 0.035874683 |
| RRMSE | 0.024068724 | 0.00058010052 | 0.0027298830 |

| | | | |
|---|---|---|---|
| **RMAE** | 0.0076191411 | 0.0011488791 | 0.0042561758 |
| $WI_E$ | 0.99982595 | 0.99999994 | 0.99999815 |
| $NS_E$ | 0.99930906 | 0.99999964 | 0.99999255 |
| $LM_E$ | 0.0077554616 | 1.7995890 | 1.5503231 |

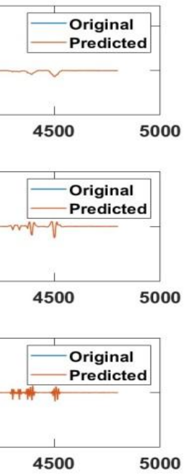


Figure5. Outputs For Wave Height in Albatross Station

Table4: Performance evaluation of the proposed model for Gladstone station

| model | GRU | LSTM | SVR |
|---|---|---|---|
| **RMSE** | 1.7864505 | 0.027444374 | 0.031504732 |
| **MAE** | 0.66610020 | 0.020072021 | 0.020361628 |
| **RRMSE** | 0.022509951 | 0.0013124447 | 0.0018716984 |
| **RMAE** | 0.017494872 | 0.0025749367 | 0.0030075461 |
| $WI_E$ | 0.99984658 | 0.99999958 | 0.99999911 |
| $NS_E$ | 0.99939883 | 0.99999827 | 0.99999648 |
| $LM_E$ | 0.019753462 | 2.38943461 | 1.2693977 |

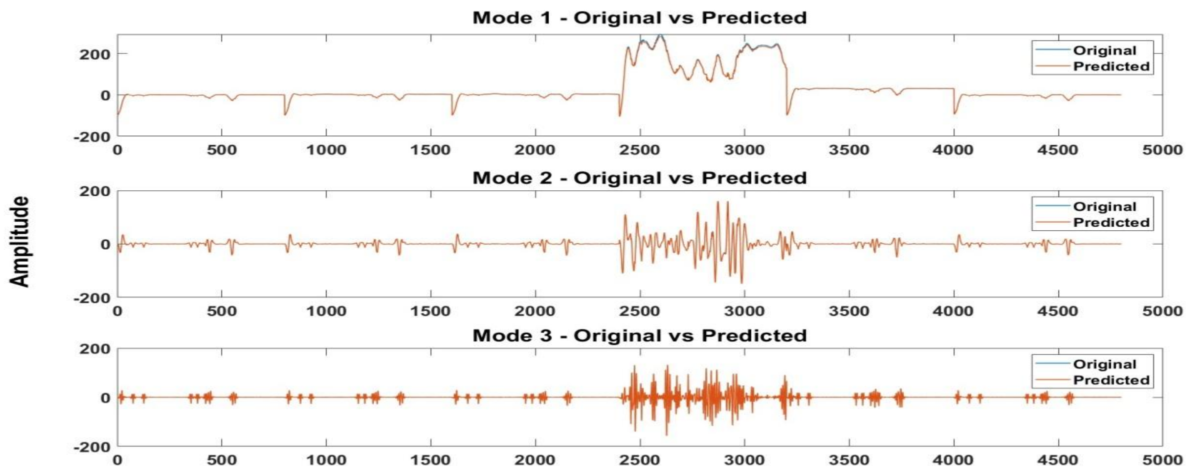

Figure 6. Outputs For Wave Height in Gladstone Station

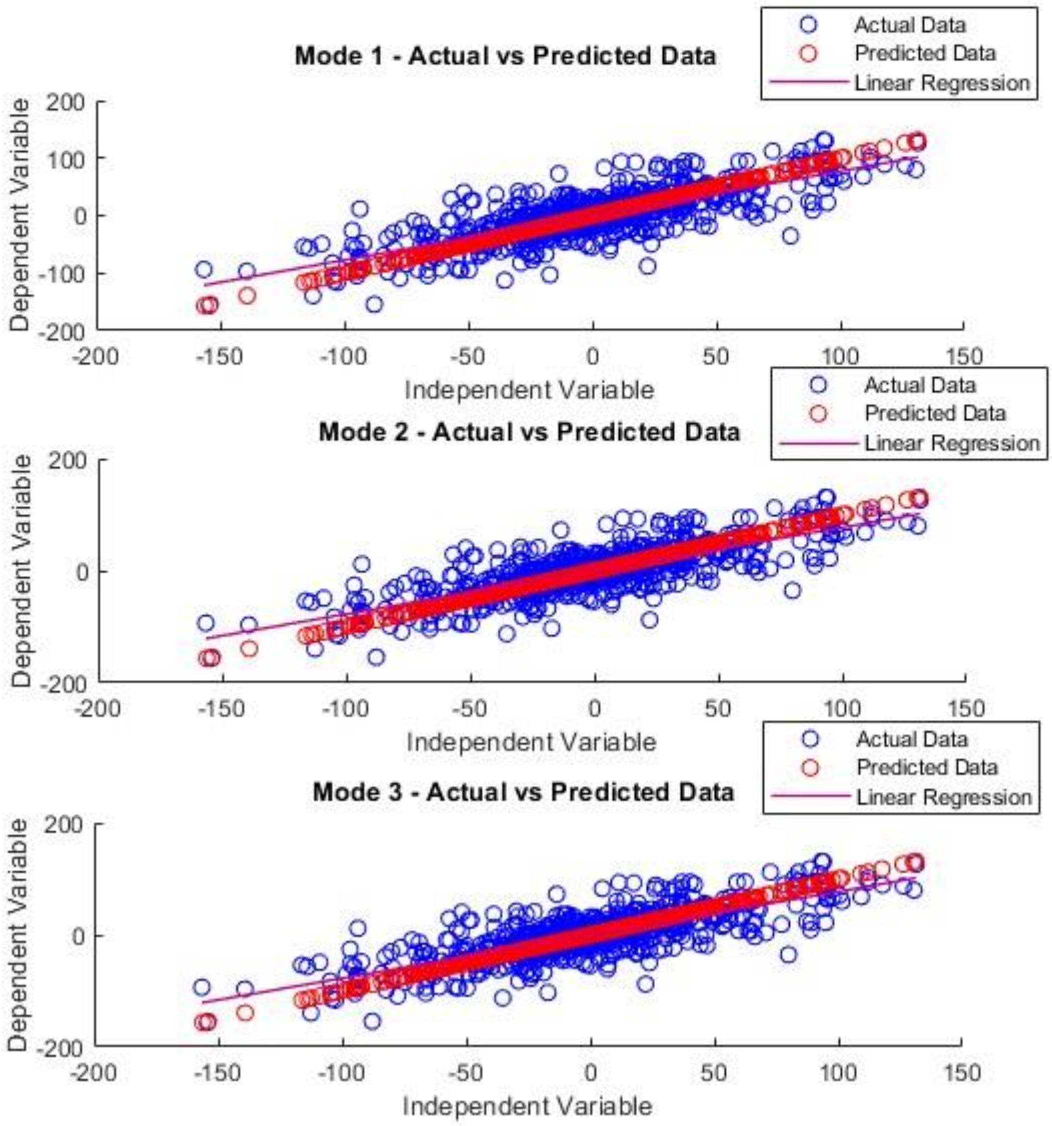


Figure 7. Regression Plots of Albatross Station

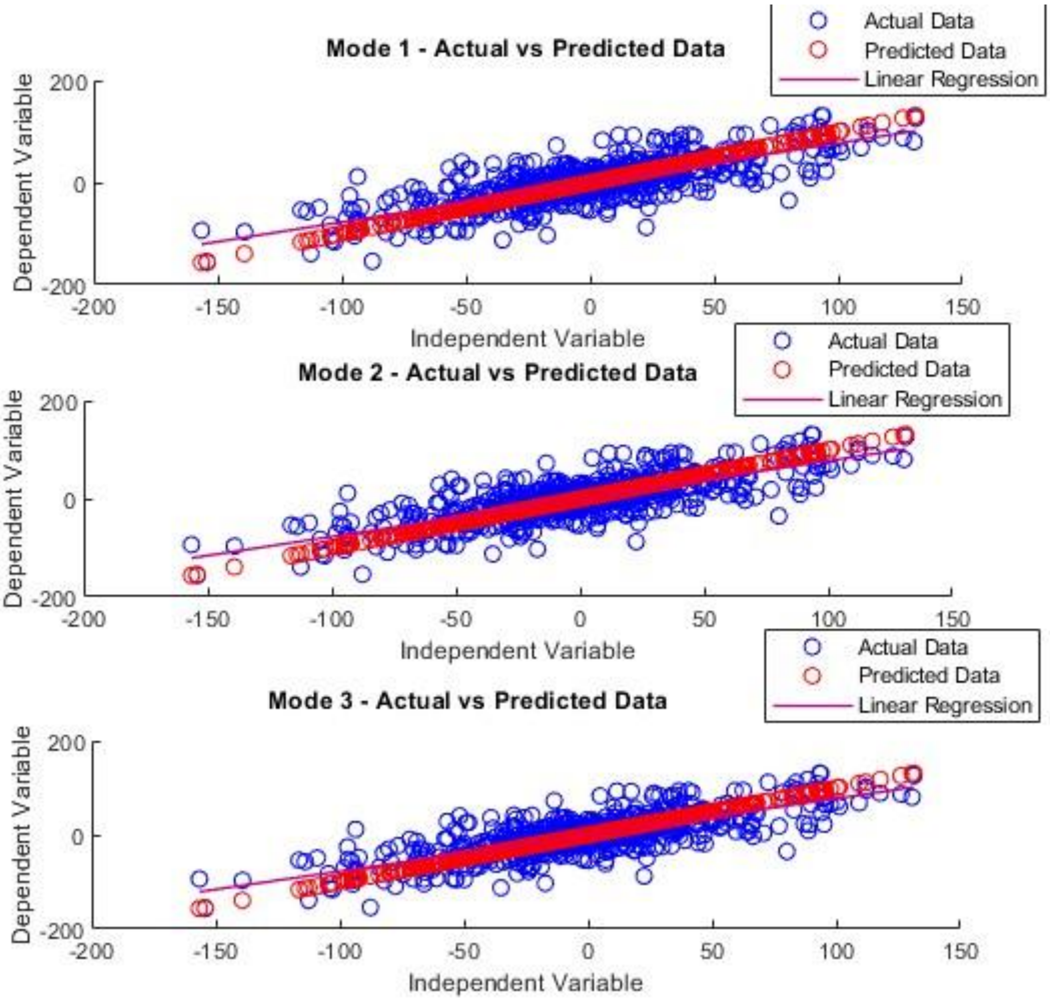


Figure 8.Regression Plots of Gladstone Station

## 6- Evaluation Metrics

This study assesses the prediction performance by employing commonly used assessment measures [20]. It involves the evaluation of forecasted values of algorithms by comparing them to their actual values using statistical metrics. To assess the degree to which the suggested model accurately replicates the actual output by the following measurements described in Table2.

Table 2: The equations used for these measurements

| Metrics | equations |
|---|---|
| Mean absolute error(MAE) | MAE=$\frac{1}{N}\sum_{K=1}^{N}\lvert A-P\rvert$ |
| Root Mean square error(RMSE) | RMSE=$\sqrt{\frac{1}{N}\sum_{K=1}^{N}\lvert A-P\rvert^2}$ |

| | |
|---|---|
| Correlation coefficient(coRR) | $\mathrm{CORR}=\frac{\sum_{K=1}^{N}(A-\bar{A})(P-\bar{P})}{\sqrt{\sum_{K=1}^{N}(A-\bar{A})^2\sum_{K=1}^{N}(P-\bar{P})^2}}$ |
| (Willmott's Index (WI) | $\mathrm{WI}=1-\frac{\sum_{K=1}^{N}(A-P)^2}{\sum_{K=1}^{N}(\lvert A-\bar{A}\rvert+\lvert A-\bar{A}\rvert)^2}$ |
| Nash-Scuttle estimator (NSE) | $\mathrm{NS_E}=1-\frac{\sum_{K=1}^{N}(A-P)^2}{\sum_{K=1}^{N}(A-\bar{P})^2}$ |
| Legates and MacCabe's (LME) | $\mathrm{LM_E}=\left[\frac{\sum_{K=1}^{N}\lvert A-P\rvert}{\sum_{K=1}^{N}\lvert A-\bar{A}\rvert}\right]$ |
| Relative mean absolute percentage error(RMAE) | $\mathrm{RMAE}=\frac{1}{N}\sum_{K=1}^{N}\left\lvert\frac{(P-A)}{A}\right\rvert \mathrm{x}100$ |
| Relative root mean squared percentage error (RRMSE) | $\mathrm{RRMSE}=\frac{1}{N}\sum_{K=1}^{N}\left\lvert\frac{(P-A)}{A}\right\rvert \mathrm{x}100$ |

Where A represents the actual value, and P represents the projected value. N represents the entire number of samples. The (WI) Shows the discrepancies between A and P, and .In actual data, the means and variances show how sensitive the data is to outliers. the( $LM_E$) and( WI) values range from 0 to +1, with +1 being the optimal number. The Nash-Scuttle estimator is employed to assess model performance (values ranging from ($-\infty to+1$).

## 7. Discussion

A novel approach for modelling, based on a hybrid combination of MVMD-LSTM has been developed. To estimate the height of the waves (Hsig) for the Albatross, Gladstone stations in Queensland, Australia, one day ahead. The effectiveness of the suggested MVMD-LSTM model is evaluated in comparison to the hybrid MVMD-GRU, and MVMD-SVR models. The MVMD-LSTM model had superior performance compared to all other models in accurately predicting one-day ahead daily Hsig. This was determined by evaluating numerous goodness-of-fit test criteria such as MAE, R , LME, WIE, NSE, RMSE and RMAE.

The( MVMD) approach is beneficial for enhancing the predictive precision of the LSTM algorithm, as it possesses a greater capacity to address both the characteristics' nonstationarity and nonlinearity effectively. In addition to the complexities of mode mixing [21], relative to other techniques for data decomposition like (MEMD) multivariate empirical mode decomposition approach, The results confirm that the MVMD-LSTM model achieves significantly higher accuracy in both stations. This is because Deep Learning approaches rely on historical predictors that might have a profound impact on the results. The multivariate variational mode decomposition (MVMD) has been employed in this study to analyze and decompose various climatic and oceanic input predictions for the first time. Parameters of interest include the sea surface temperature, maximum wave height, direction, peak wave energy period and zero up-crossing wave period. In previous searches[22], only basic baseline models were utilized to predict significant wave height. Moreover, the present study expands the range of constructing models for deep learning (LSTM, SVR, GRU) while Previous research relied on conventional machine learning methods such as extreme learning machines. Random forest learning, and multivariate linear regression. Several recommendations can be implemented in future work. For instance, Predictors obtained from satellite data can function as a substitute technique for ground data, the hybrid MVMD-GRU model has been greatly improved, , leading to a substantial improvement in precision of one-day ahead Hsig predictions.

## 8. Conclusion

This paper develops a new framework called MVMD-LSTM, which combines multivariate data decomposition and deep learning techniques to accurately predict significant wave height one day ahead. The MVMD-LSTM model, which has been suggested, has been utilized in the Albatross, Gladstone& Queensland, Australia stations for the next day Forecasting a significant wave height. The MVMD-LSTM model was compared with GRU, SVR The results indicate that the MVMD-LSTM model had superior accuracy, as measured by goodness-of-fit metrics, in predicting the major wave height for all stations one day ahead. The MVMD-LSTM modelling method is unique in two ways: it utilizes the MVMD method in the initial stage and then incorporates the LSTM model. The MVMD technique enhances accuracy by efficiently handling the unpredictable characteristics of predictor data, which gives rise to non-stationarity and non-linearity. The MVMD-LSTM model achieved better results. [RMSE=0.0097874 ,MAE=0.00771, RRMSE=0.000580 , RMAE=0.001148 ,$WI_E$ =0.99999994, $NS_E$=0.999999 $LM_E$= 1.79958] Albatross and [RMSE= 0.02744437 ,MAE=0.02007202, RRMSE=0.001312444**,** RMAE=0.0025749367 **,** $WI_E$= 0.99999958 , $NS_E$ = 0.99999827, $LM_E$ =2.38943461] Gladstone stations.

The MVMD-LSTM modelling framework can be utilized for analyzing droughts, precipitation patterns, and agricultural systems. The purpose of these areas is to provide support to policymakers and government officials to facilitate more effective and prompt decision-making about future climate change, energy, and agriculture-related matters.

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