

Financial derivative features based integrated potential fishing zone (IPFZ) Future forecast

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Abstract. In India, around 7 million people depend on fishing for their livelihoods. They are assisted with a reliable and fast brief forecast for the areas of fish aggregations. Habitat mapping is critical in supporting strategic choices on fish usage and protection. In conjunction with techniques for machine learning, remote control has made comprehensive fish mapping on relevant scales possible. In machine learning, supervised algorithms are utilized to make forecasts from datasets, when data is accessible without relating output factors. In this research work, Ocean Surface Temperature (OST) and Satellite derived Chlorophyll material are the basic inputs to generating the information of Potential Fishing Zone (PFZ). The 16 features and additional financial derivative features are used for accurate future prediction of PFZ. The unwanted and missing data are removed using effective pre-processing techniques. Among the various methods available for forecasting nonlinear phenomena, the Neural Network is the best and the efficient method to get a forecast. Therefore, the Function Fitting Neural Network (FFNN) technique is mainly used to predicting the Integrated Potential Fishing Zone (IPFZ). The practical analyses are performed by analysing the 80%-20%, 60%-40% and future data in terms of various parameters. From the results, it is proved that the suggested FFNN achieved 90% of accuracy, where the existing neural network achieved 86% of accuracy by implementing with financial derivative features for the 80%-20% of available dataset.

Keywords: Fishing activities, function fitting neural network technique, future data prediction, machine learning, sea surface temperature

1. Introduction

Fishery development is subject on availability of natural resources, appropriate funding, adequate novel technology, fishing unit growth, fishing extension, government policies, Morden technologies, and grassroots technical information. In terms of the make-up and dynamics of its species, the marine environment is complicated. With the rises in fishing fleets, the traditionally known fishing grounds are under enormous pressure and fishing per unit effort (CPUE) decline [1] per unit effort. Through remote sensing techniques, it is therefore necessary

to distract some fishing efforts from other relevant potentially fishing regions. The prediction of structures and functions in the marine eco system requires on an in-depth appreciative of the physical and natural process that regulates organisms' great quantity distribution and output and a wide diversity of time and wide diversity of time space levels [2].

In order to study chlorophyll's link to sea surface temperature with employed Coast Zone Colour Scanner (CZCS) and (OST) [3]. The water mass classification seems to be linked to various biological and physical processes. In 1989-90, the prediction for Potential Fishing Zones (PFZs), with NOAA AVHRR OST computed in India, was launched [4] With the emergence and quick spread of satellite remote sensing that leads to the deployment of remote sensors for specific parameters, OST, CHL and PAR data col-

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lected from satellites are available as Global Area Coverage (GAC) for the previous two decades [5]. In this context it has become an important data source to explain the linkages between exploited marine animals and their habitat for the availability of world, daily, systemic images taken from satellites. To examine the distribution, abundance and migratory of fishes, continual archiving of remotely sensed satellite parameters in a particular region is necessary. Remote sensing has played an essential role in marine fisheries management and use since 1978. Neural network approaches are used [6, 7] to anticipate fishing zones.

Brain networks are simple nonlinear computing components that imitate the neural system of the human being. Brain networks are named between input and output layers as hidden layers and often called neurons [8]. When loading data into the ANN (Artificial Neural Network), it must be pre-processed into the numerical range with which the ANN can handle the efficiency of the learning results efficiently. The advantages of using PFZ advisories to the Indian fishing community were described in this research. A quantitative study of the net profit gains gained by the reduction in the time for the search and better catches and the percentage of success in PFZ-led fishing is presented.

The remains of this document are follows: The associated works for the IPFZ prediction are discussed in Section 2. The recommended methodology employed in this paper was outlined in Section 3. The study concludes with its future work in Section 4 and Section 5 to provide the outcomes and discuss the results.

2. Related works

In the most Economic Zone in the eastern coastline of Malaysia, MODIS satellite pictures with fishery catch data of 2008 have been generated by [9] in the Rastrelliger Kanagurte PAFZ, Rastrelliger Kanagurta (Cuvier 1817). The photos were classed with appropriate scores and integrated to produce a prospective map using GIS based on the selected ranges. The results showed a preferred CHL range of 0.27 ± 0.030 mg/m³ for the greatest catch and OST of 29.91 ± 0.33 °C. In the mapping of possible fishing grounds, a total accuracy of 75% was attained. This study shows how the Satellite Images and GIS can map R. Kanagurta's possible fishing areas as well as how the biophysical characteristics are related to fishing data.

In order to discover the relationships among their spatiotemporal distribution and the ecological factors, [10] developed the HSI model to identify possible fishing surroundings for sword fishes in the southern Atlantic with long-water fishery and distance sensing data for the years 1998-2007 in Taiwan. With most CPUE-defined variations explained by OST, all environmental considerations such as OST, assorted layer depth (ALD, SSHA), Ocean surface and height are abnormality and ocean Bathymetric (BAH) were extremely significant. In locations with OST 27–28 C, SSHA -0.05 - 0.05 m, CHLs 0.1-0.2 mgm⁻³ and BAH 4000 to 4500 m, the most optimal habitat has been found (i.e. hotspot). According to the calculation of numerous pragmatic HSI models in grouping with various ecological conditions, the arithmetical average model with five ecological variables was shown to be most acceptable. The biweekly maps in the projected HSI measurements were checked by the experiential catch per unit effort and suggested that this model may be utilized as a tool to trustworthy forecast for probable fishing grounds.

A short period of time association between skipjack tuna and ocean surface conditions was outlined using fisheries data from [11]. The remote sensing of OST and CHL (MODIS) were used to illustrate the expected high capture zones. The highest skipjack CPUEs were recorded mostly during the 2007 and 2009 study period in the coastal regions of Palopo and Kolaka. The high tuna levels were well equivalent to 0.15-0.40 mg mg³ CHL and 29.0-31.5°C OST. OST was good. The preferred ranges are a good indicator to locate possible fishing sites for skipjacks at first.

With the use of MODIS data on periodic spatial sharing to the Ocean surface salinity (OSS), OST and CHL in sea waters off the coast of Semporna, Malaysia, [12] have shown to be projected by a potential fishery map. The OSS was evaluated with the multi-linear regression analysis and the Brown and Minnet algorithms were employed for the OST. The parameters obtained have been validated by means of in situ Hydro-Lab equipment measurement. The factors are retrieved from adequate resolution imaging spectro-radiometer (MODIS) photos indicate the monogram values establishing the links among these strictures, thus outlining the PFZ map. The R^2 was calculated at 0.93, and the larger fish catching areas correlated with the greater PFZ levels, which means the technique are ready to be used for near-real-time fish predictions.

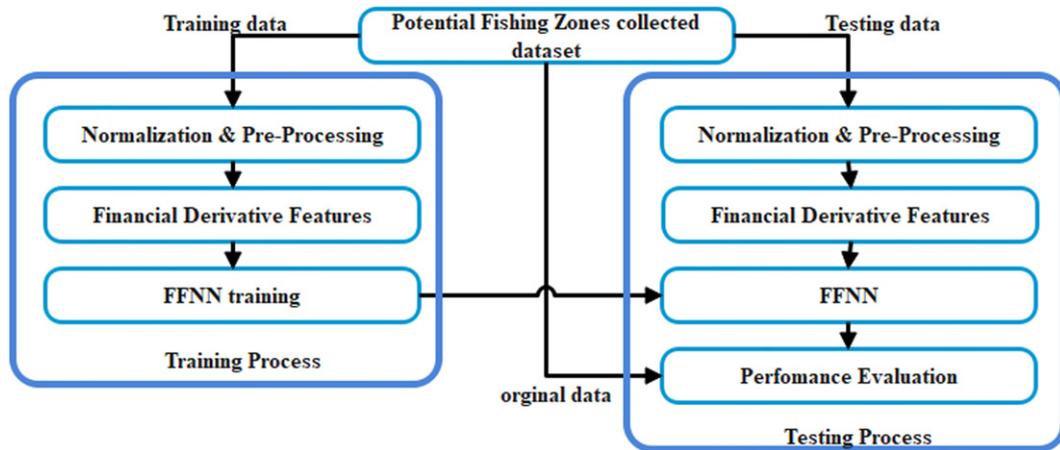


Fig. 1. Proposed Financial Derivative Features based IPFZ Future Forecast Architecture.

The Developed a Decision Support System to forecast the fishing ground of short Mackerel employing MODIS satellite images [13]. The input data for the development of Potential Fishing Zone is Sea Surface Temperature, CHL and fish catch data with fishing locations. The results displayed that OST and CHL – circulations have a nearby connection to the sharing of the fishing location of the short Mackerel to regulate the association among catcher and oceanographic parameters of linear regression. The range of Sea Surface Temperature from 26 C to 29 C and CHL - a from 1.19 mg/m³ to 1.25 mg/m³ identified as the fishing location for short Mackerel in Makassar strait.

Stimulated by artificial neural network features. This research suggested alternative IPFZ prediction approaches based on the Neural Network. As described below, our key contributions include:

- ❖ Four models for learning Neural Networks with the ability to accurately predict IPFZ were proposed.
- ❖ The accuracy of the Better classification was achieved by applying FFNN.
- ❖ Furthermore, we calculate the characteristics with the compliance of the natural time order of the data instead of selecting variables that ignore the time order.

3. Proposed system

Most of the research articles are not supporting for this Potential Fishing Zones (PFZs) future forecast, so we have referred some of the rainfall detection

related articles because of the type of the input raw data's are maximum related to this work. From that analysis we find [14] which leads improve the number of features information's based on the Financial Derivatives and geometrical features. This Economic Derivatives features and geometric structures are support the Function Fitting Neural Network to predict the future PFZs accurately. The Architecture of the proposed Financial Derivative Features based IPFZ Future Forecast is shows in the Fig. 1.

3.1. Dataset

Ocean Surface Temperature data (OSTs), chlorophyll, and Ocean Sat II - India (Fig. 2) Optical Communication Band, and MODIS Aqua (US) are used to detect potential fishing zones all over the place of the Indian coastline, which are regularly together by NOAA-AVHRR thermal-infrared frequencies and Eumetsat (ESA) Met-OP satellites. For each sector PFZ Announcements are produced in the form of PFZ Maps and Texts, and where PFZ are positioned (latitude and longitude data). Because of the sea's lively atmosphere, the selected place could be progressed by recognised fishing zones on the atlases. The wind speediness and route information is also incorporated into the PFZ maps to guide fisherman on the likely shifts in PFZ. This fact allows the fishermen to trace the PFZ in the maps; on the other hand after a day they will reach the site. The PFZ maps and text for the accessibility of fisherman are also obtained in each sector's with their local languages. The PFZ text gives data about exact position of (length, latitude), depth at the PFZ site and the distance from important places

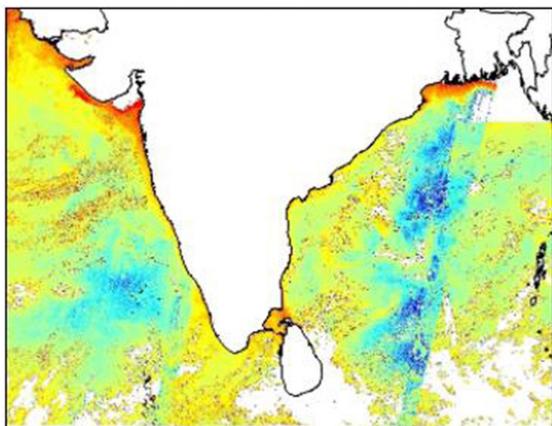


Fig. 2. Retrieved Oceansat-2 Satellite Data Chlorophyll Image.

Table 1
Feature description

Number of Features	Description
1	Landing_Center (LC)
2	UPDATED_DATE (UD)
3	DIRECTION (DIR)
4	ANGLE
5	DISTANCE_FROM (DIF)
6	DISTANCE_TO (DIT)
7	DEPTH_FROM (DEF)
8	DEPTH_TO (DET)
9	LONGITUDE_DEGREE
10	LONGITUDE_MINUTE
11	LONGITUDE_SECOND
12	LONGITUDE_DIRECTION
13	LATITUDE_DEGREE
14	LATITUDE_MINUTE
15	LATITUDE_SECOND
16	LATITUDE_DIRECTION

on the coastlines (fishing landing stage centre, light erections) clearly identifiable.

3.2. Pre-processing & normalization

The unused data and the missing datas are cleaned using pre-processing methods. In addition, the shape of the data are altered during normalization method. In the beginning, the total number of the input uncooked data is around 151031 with 16 features. The whole raw datas are taken as training data and Table 1 describes the total number of features.

Among the 16 features UPDATED_DATE is use as targeted data to training the suggested model. The input information is taken from 15-5-2013 to 18-7-2018, where the main aim of the objective is to predict the potential fishery zone by giving future

data. Hence, only 15 unique features are used in this research, however, only 13 unique features are used for training the system. The reason is that the feature LONGITUDE_DIRECTION (East) and LATITUDE_DIRECTION (North) has same information for 151031 data, which is not useful for training the proposed model. In order to training the projected network and attain improved classification precision, the “-“ between the date is removed for the period of pre-processing. The DIRECTION feature has seven directions as Southern East (SE), Southern West (SW), Northern East (NE), Southern (S), East (E), Northern (N) and Western (W). This datas are cannot be use openly to train the projected model, hence these characters are rehabilitated into variable. In addition, the Landing_Center attribute are in an floating format, which is altered into double layout for improved prediction. Hence, 13 features are known as input to the FFNN for predicting the PFZ. Moreover, in order to accurately predict the future PFZ, this research study uses more quantity of features such as Economic Derivatives and geometrical metrics, which is described as follows.

3.3. Financial derivative features

The way the dataset are deal with is another deliberation, as it is uncommon for raw data values to be give back to an algorithm to be used. The data should consequently be revised to fit our challenging domain. The aim of this research work is to predict the IPFZ over the well-defined region based on the collected fish capacity. An important factor that needs to be considered is the need to come to an end of future agreements, usually up to one year in advance, and the indenture period might take any length. In addition, given the unique character of the PFZ projections, there is an even higher need for data transformation. Therefore, we employ an Economic Derivative feature (Table 2) to give the data more understandable and more appropriate for the problem area. The result looks to be much less altered, which is why financial derivatives are applied, with adding, volatility on a daily basis appears to be lesser and a pattern is ease to recognize in PFZ predicting. This approach of predicting IPFZ is extremely flexible and may be altered to any length of interest.

3.4. Classification

The more number of features are set as input to the proposed FFNN technique for forecasting the PFZ,

Table 2
List of financial derivative and geometrical features used

S. No	Financial Derivative Features
1	Autocorrelation
2	Mean Standard
3	Contrast
4	Deviation Sum
5	Correlation
6	Difference Adjacent
7	Cluster Prominence
8	Difference Moving
9	Cluster Shade
10	Average Standard
11	Dissimilarity
12	Deviation across MA
13	Energy
14	Last Maximum
15	Entropy
16	Last Minimum
17	Homogeneity
18	Maximum probability
19	Time Last Maximum
20	Sum variance
21	Time Last Minimum
22	Magnitude of Minimum
23	Magnitude of Maximum
24	Minimum Last Contract Length
25	Maximum Last Contract Length
26	Modification of Minimum over Last Contract Length
27	Modification of Maximum over Last Contract Length

where the different types of neural networks are used to validate the presentation of the projected ideal. These neural networks include ENN, RNN and CFN are also discussed as in Comparative Techniques.

3.4.1. Proposed Function Fitting Neural Network (FFNN)

A neural network associates a number of levels of processing, engaging basic, simultaneous and biologically nervous-inspired parts. It encompasses of a layer of input, one or numerous hidden layers and a layer of output. In every layer, the input of each layer involves of a number of nodes, or neurons, so that neurons join the different layers. Typically every neuron has weights modified during the learning process and modifies the strength of the signal of this neuron

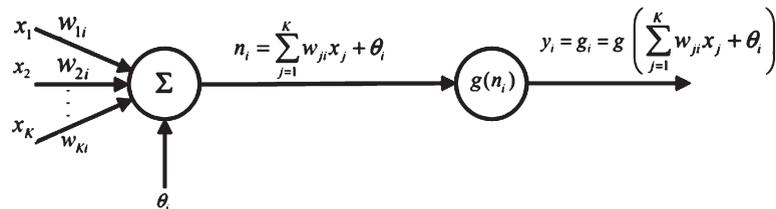


Fig. 3. Single node in a FFNN network.

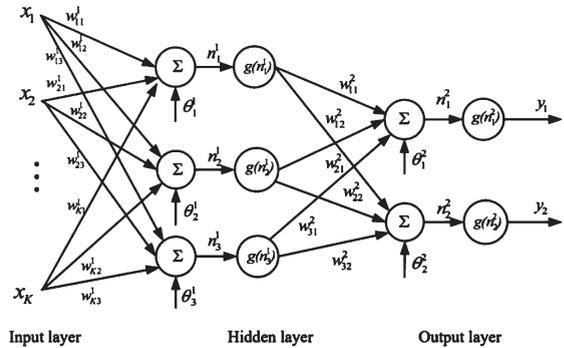


Fig. 4. FFNN with one hidden layer.

as the weight decreases or grows. The structure of a FFNN is defined in the Fig. 3.

The inputs of the neuron $x_k, k = 1, \dots, k$, and the continuous bias term θ_i are multiplying and added up. The result of n_i shall be the g -enabled input. Initially, however, a hyperbolic tangent (\tanh) or a sigmoid function is the most common activation function for the mathematical accessibility. Tangent is defined as hyperbolic

$$\tanh(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{1}$$

The node i becomes

$$y_i = g_i = g \left(\sum_{j=1}^K w_{ji} x_j + \theta_i \right) \tag{2}$$

Linking many nodes in parallel and series, a FFNN network is intended. A typical network for single hidden layer is shown in Fig. 4.

The output, $y_i, i = 1$ and 2 , of the FFNN network becomes

$$y_i = g \left(\sum_{j=1}^3 w_{ji}^2 g(n_j^1) + \theta_j^2 \right)$$

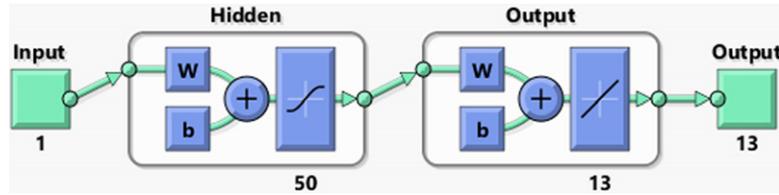


Fig. 5. The Proposed MATLAB FFNN Architecture.

$$= g \left(\sum_{j=1}^3 w_{ji}^2 g \left(\sum_{k=1}^K w_{kj}^1 + \theta_j^1 \right) + \theta_j^2 \right) \quad (3)$$

From (3) we may deem a non-linear map from the input space x to the output space ($m = 3$), the FFNN is a non-linear parameterised map (here $m = 3$). The weights of W_{ji} and biases are parameters of θ_j^k . In general, the g active functions are presumed to be the same and known in every layer beforehand. The g function is used for all layers in the figure.

When you use data $(x_i, y_i) i = 1, \dots, N$, it is a data fitting issue to discover the optimal FFNN network. The parameters (w_{ji}^k, θ_j^k) to be determined are.

This is the procedure. The designer must first f the architecture of the FFNN network: the number of layers and neurons concealed in each layer. Figure 5 shows the total architecture. At this point, too, the activation functions for each layer are expected to be known. The weights and biases (w_{ji}^k, θ_j^k) are unknown parameters to be calculated.

After procurement the results from FFNN, the post-processing is passed out. In this strategy, the twofold organize of LC include is changed over into characters. The factors of DIR are adjusted into seven directions. Subsequently, the comes about will be in an appropriate arrange, for occasion in case an client allow a future information as input, the location label name, its flow direction, latitude and longitude bearings are shown as yield of FFNN show [15].

3.5. Comparison neural network models

3.5.1. Elman neural network

A feedback neural system improved by Elman in 1990 can be characterized as the Elman Neural Network (ENN). ENN focuses on the training of the neural background network (BPNN). The Elman neural network architecture is usually divided into 4 layers. The undertaking layer function is to save the output of the cached layer. The output of the hidden layer connections its entrance through the delay

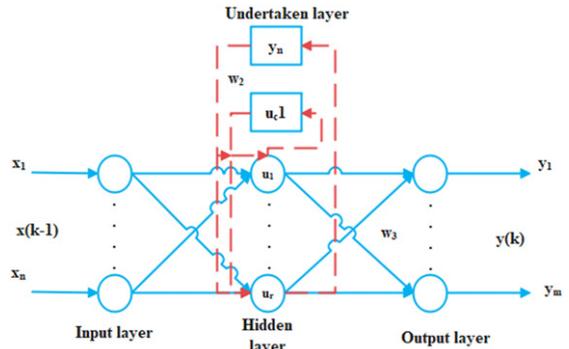


Fig. 6. Architecture of ENN.

and the storage of the undertaking layer [16] since it is focused on the background of a neural network. ENN Architecture is illustrated in Fig. 6.

The output of the hidden components of its input by delaying and storing the company layer are based on the BP network. This joining is sensitive to past information and the network for interior input can increase the dynamic data management capacity. The internal state memorization allows for a dynamic planning method, which allows the system to adapt to temporal alterations across interval. [17].

The weight of the hidden layer input is w_1 , the weight of the hidden layer in the layer is w_2 , the weight of the hidden layer to the output layer is w_3 ; $u(k - 1)$ is the input for the neural network; $x(k)$ is the output for the hidden layer; $y(k)$ is an output for a hidden layer, $x_c(k)$ is the output of the undertaken layer and $y(k)$ is the output of that hidden layer. $x_c(k)$ is the output of the undertaken layer and

$$x(k) = f(w_2 x_c(k) + w_1(u(k - 1))) \quad (4)$$

Where

$$x_c(k) = x(k - 1) \quad (5)$$

F is the transfer function hidden layer, which is usually used in S-type function; that is:

$$f(x) = (1 + e^{-x})^{-1} \quad (6)$$

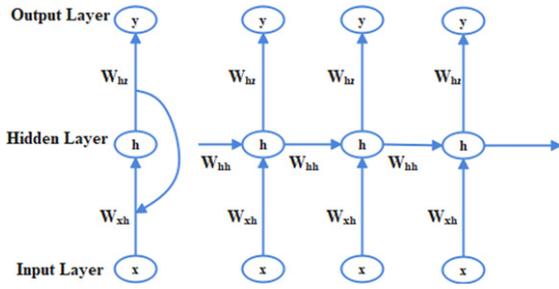


Fig. 7. RNN Architecture.

g is the output layer transfer function, which is often a linear function; that is:

$$y(k) = g(w_2x(k)) \tag{7}$$

To revise weights and the error of network is:

$$E = \sum_{k=1}^m (t_k - y_k)^2 \tag{8}$$

where t_k is represent as the output vector of the object.

3.6. Recurrent Neural Network (RNN)

Because of its extra feedback from the created layer output between input and output layers, RNN is an exclusive class of neural network. his layer is the context layer that retains data between observations [18]. In the present period, the results of the processing in the previous phase can be carried over and employed. Iparticular in real time applications, the fundamental characteristic of RNN offers an extremely large advantage. In adding to learning via all current inputs, RNN can have an unbounded memory level, and can thus learn connections over time [19]. The RNN is showed in Fig. 7.

Hidden layer of Input is stated as in (9) as:

$$h_t = g_n(W_{xh}X_t + W_{hh}h_{t-1} + b_n) \tag{9}$$

Here h_t is represented as the hidden layer at the instance t^{th} , X_t is represented as the input at instance t^{th} , moreover, g_n is represented as the function, and W_{xh} is represented as the input to hidden layer of weight matrix Equation (10) which characterizes the concealed to output layer is stated as:

$$Z_t = g_n(W_{hz}h_t + b_z) \tag{10}$$

where the output vector is signified as Z_t , and b_z is the bias or threshold, the unseen to output layer weight matrix is W_{hz} .

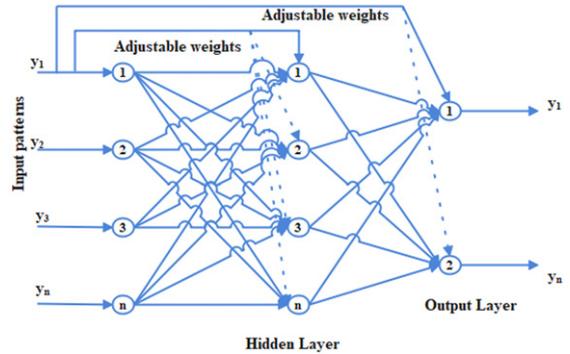


Fig. 8. Cascade FNN.

3.6.1. Cascade forward network

The Cascade Forward Network (CFN), which uses back propagation to update weights, has similarities with the FFNN. The primary distinction is that the connection between the individual level and the input at the next level is weighted [20]. In many circumstances, it has been thought that some cascade bpropagation can perform better than FFNN [21]. An important feature of this CFN is that each neuron layer is linked to the whole preceding neuron layer [22]. The pictographic representation of CFN is in Fig. 8.

The CFN mathematical equation is specified as:

$$y = \sum_{i=1}^n f^i(w_i x_i) + f^o \left(\sum_{j=1}^K w_j^o f_j^h \left(\sum_{i=1}^n w_{ji}^h x_i \right) \right) \tag{11}$$

Input layer activation function is provided in the output layer as a f^i , whereas input layer weight to output layer is w_i^i . In the event of the combination of bias and an input layer, the activation function of each neuron within the covered up level is written as f^h , in order to express equation (11) as

$$y = \sum_{i=1}^n f^i(w_i x_i) + f^o \left(w^b + \sum_{j=1}^k w_j^o f_j^h \left(w_j^b + \sum_{i=1}^n w_{ji}^h x_i \right) \right) \tag{12}$$

The next section will show the performance analysis of proposed model.

4. Results and discussion

MLAB R2021a and Intel i5 processor, with 1Tera Byte hard disk and 8GB of RAM, is being explored with the projected system.

4.1. Evaluation metrics

The challenge evaluation measurements are utilized to survey our method's execution in division and classification. The assessment criteria for division incorporate sensitivity (SE), specificity (SP), accuracy (AC), and false measures. The presentation requirements are as follows:

$$accuracy = (tp + tn) / N \tag{13}$$

$$sensitivity = tp_rate \tag{14}$$

$$specificity = tn_rate \tag{15}$$

$$precision = tp / (tp + fp) \tag{16}$$

$$recall = \frac{tp}{tp + fn} \tag{17}$$

$$f_measure = 2 * ((precision * recall) / (precision + recall)) \tag{18}$$

$$gmean = sqrt(tp_rate * tn_rate) \tag{19}$$

Where *tp*, *tn*, *fp* and *fn* signify the true negative, false positive, number of a true positive TP, and false negative FN, *N* describes the total number of elements.

4.2. Performance study of proposed FFNN model for 80%-20% of dataset

In this section, two different types of analysis are carried out by considering with and without financial derivative features to validate the performance of proposed FFNN model with various neural networks.

Table 4
Evaluation of FFNN model Without Having Financial Derivative Features

Classification Models	Accuracy	F Measure
ENN	0.8381	0.1100
RNN	0.8178	0.0989
CFNN	0.8008	0.0912
FFNN	0.8586	0.1239

Initially, the available data is split into 80%-20%, i.e. 80% of data is used for training procedure and remaining 20% of data is used for testing process. Table 3 provides the experimental value of different neural networks without financial derivative features for the analysis of 80%-20% in available dataset.

The above Table 3 validates the performance of projected model in terms of precision, specificity, recall, sensitivity and gmean. The sensitivity and recall are same for all techniques, i.e. the ENN model achieved 1.000 of sensitivity and recall, where the proposed FFNN model achieved 1.000 of sensitivity and recall. In the specificity experiments, the ENN, RNN, CFNN and FFNN achieved 83%, 81%, 79% and 85%, which proves that the proposed FFNN achieved better performance than other neural networks. The ENN and RNN achieved nearly 91% of gmean, CFNN achieved 89% of gmean, but the proposed FFNN achieved 92% of gmean and high value of precision (i.e.0.0660). However, the existing neural network achieved only 0.0550 of precision value. From this study, the proposed FFNN model attained better presentation even without financial derivative features. Table 4 and Fig. 9 shows the performance of FFNN model in terms of accurateness and F-measure.

In the accuracy analysis of without having the financial derivative features, the ENN, RNN, CFNN and proposed FFNN achieved the 83%, 81%, 80% and 85%. As well as, these techniques achieved the f-measure of 0.11, 0.09, 0.09 and 0.12. From these analysis, it is clearly proved that without financial derivative features also, the proposed FFNN model achieved better performance for 80%-20% of available dataset. The next Table 5 shows the validation

Table 3
Performance evaluation without financial derivative features

Classification Technique	Sensitivity	Specificity	Precision	Recall	Gmean
ENN	1.0000	0.8365	0.0582	1.0000	0.9146
RNN	1.0000	0.8160	0.0520	1.0000	0.9033
CFNN	1.0000	0.7988	0.0478	1.0000	0.8937
FFNN	1.0000	0.8572	0.0660	1.0000	0.9258

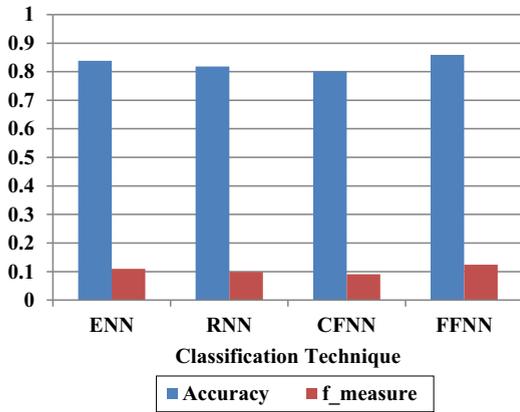


Fig. 9. Accuracy and F-measure Evaluation of FFNN Without Having Financial Derivative Features.

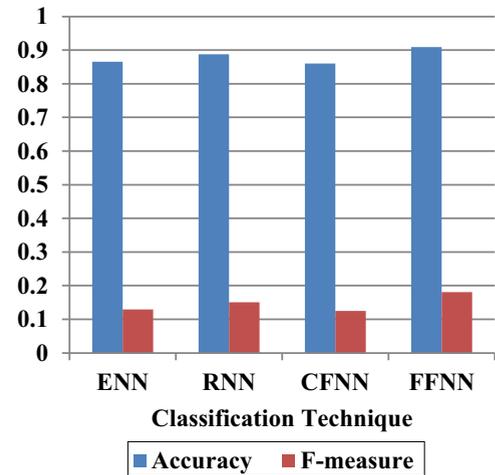


Fig. 10. Performance Evaluation of Proposed FFNN With Financial Derivative Features for 80%-20% of available dataset.

of proposed FFNN model with existing models by considering the financial derivative features for the 80%-20% of available dataset.

In the specificity analysis, the ENN, RNN, CFNN and FFNN achieved 86%, 88%, 85% and 90%, where the sensitivity and recall of all techniques are 1.000, when implementing with financial derivative features. In the precision experiments, the FFNN achieved high performance (i.e. 0.0994), where the ENN and CFNN achieved nearly 0.0670. The ENN, RNN, CFNN and FFNN achieved gmeans of 92%, 94%, 92% and 95% that shows that the projected FFNN model achieved better presentation than other techniques. However, the FFNN achieved less performance, when it is not implemented with Financial Derivative features. This proves that these added features plays a major role for predicting the future IPEZ accurately. Table 6 and Fig. 10 shows the experimental investigation of proposed FFNN model in terms of accuracy and F-measure for the 80%-20% of available dataset.

In the accuracy analysis, the ENN and CFNN achieved low accuracy (i.e. nearly 86%), RNN achieved 88% and proposed FFNN achieved 90%. The ENN, RNN, CFNN and FFNN achieved the f-measure of 0.12, 0.15, 0.12 and 0.18 that proves

Table 6
Performance evaluation of proposed FFNN with financial derivative features

Classification Models	Accuracy	F-measure
ENN	0.8652	0.1292
RNN	0.8875	0.1509
CFNN	0.8600	0.1250
FFNN	0.9094	0.1808

FFNN achieved better performance than other neural techniques. Without financial derivative features, the proposed FFNN achieved less performance, which is proven in Tables 3 and 4. The next section will explain the experimental analysis for 60%-40% of existing dataset.

4.3. Performance study of proposed FFNN model for 60%-40% of dataset

Here, the performance of projected FFNN technique is validated with the 60% of training data and 40% of testing statistics. Table 7 shows the analysis of FFNN in terms of several metrics without considering the financial derivative features.

Table 5
Performance evaluation with financial derivative features

Classification Technique	Sensitivity	Specificity	Precision	Recall	Gmean
ENN	1.0000	0.8638	0.0690	1.0000	0.9294
RNN	1.0000	0.8864	0.0816	1.0000	0.9415
CFNN	1.0000	0.8586	0.0667	1.0000	0.9266
FFNN	1.0000	0.9085	0.0994	1.0000	0.9531

Table 7
Performance evaluation of proposed FFNN with financial derivative features

Classification Models	Sensitivity	Specificity	Precision	Recall	Gmean
ENN	1.0000	0.8027	0.0487	1.0000	0.8959
RNN	1.0000	0.8217	0.0536	1.0000	0.9065
CFNN	1.0000	0.7443	0.0380	1.0000	0.8627
FFNN	1.0000	0.8674	0.0708	1.0000	0.9314

Table 8
Performance evaluation of proposed FFNN with financial derivative features

Classification technique	Accuracy	F-measure
ENN	0.8047	0.0929
RNN	0.8234	0.1017
CFNN	0.7469	0.0732
FFNN	0.8688	0.1322

The above table validate the performance of proposed model in terms of sensitivity, specificity, precision, recall and gmean. The sensitivity and recall are same for the all techniques, i.e. the RNN, CFNN model achieved 1.000 of sensitivity and recall, where the proposed FFNN model achieved 1.000 of sensitivity and recall. In the specificity experiments, the ENN, RNN, CFNN and FFNN achieved 80%, 82%, 74% and 86%, which proves that the proposed FFNN achieved better performance than other neural networks. The ENN and RNN achieved nearly 90% of gmean, CFNN achieved 86% of gmean, but the proposed FFNN achieved 93% of gmean and high value of precision (i.e.0.0708). However, the existing neural network achieved only 0.0450 of precision value. From this analysis, the proposed FFNN model achieved improved performance with financial derivative features. Table 8 and Fig. 11 shows the performance of FFNN model in terms of accurateness and F-measure with additional financial derivative features.

In the accurateness analysis of with the financial derivative features, the ENN, RNN, CFNN and proposed FFNN achieved the 80%, 82%, 74% and 86%. As well as, these techniques achieved the f-measure of 0.09, 0.10, 0.07 and 0.13. From these analysis, it is clearly proved that with financial derivative features also, the proposed FFNN model achieved higher performance for 60%-40% of available dataset. The next section will presents the analysis of future data prediction using proposed FFNN with other neural networks.

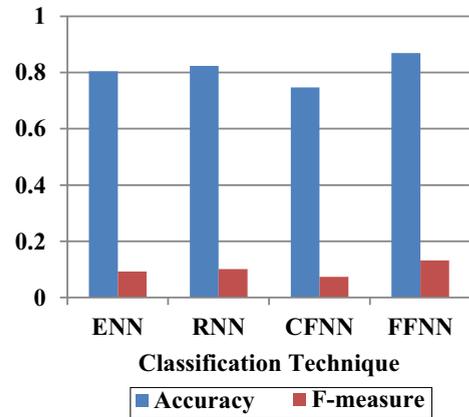


Fig. 11. Evaluation of FFNN With Financial Derivative Features in terms of accurateness and F-measure.

Table 9
Performance evaluation with financial derivative features

Classification models	Sensitivity	Specificity	Precision	Recall	Gmean
ENN	1.0000	0.5833	0.0237	1.0000	0.7638
RNN	1.0000	0.5423	0.0216	1.0000	0.7364
CFNN	1.0000	0.5013	0.0199	1.0000	0.7080
FFNN	1.0000	0.6449	0.0277	1.0000	0.8030

4.4. Performance analysis of future data prediction

By using the available datasets, the proposed FFNN tries to predict the future IPFZ accurately in terms of exactness, recollection, sensitivity, specificity and gmean. This analysis is taken for 80% of training data and 20% of testing data and the experimental values are given in Table 9.

The sensitivity and recall are same for the all techniques, i.e. the ENN, RNN, CFNN model achieved 1.000 of sensitivity and recall, where the proposed FFNN model achieved 1.000 of sensitivity and recall. In the specificity experiments, the ENN, RNN, CFNN and FFNN achieved 58%, 54%, 50% and 64%, which proves that the proposed FFNN achieved better performance than other neural networks. The ENN, RNN and CFNN achieved nearly 75% of gmean, but the

Table 10
Evaluation of proposed FFNN with financial derivative features for future data

Classification modules	Accuracy	F-measure
ENN	0.5875	0.0462
RNN	0.5469	0.0423
CFNN	0.5062	0.0389
FFNN	0.6484	0.0538

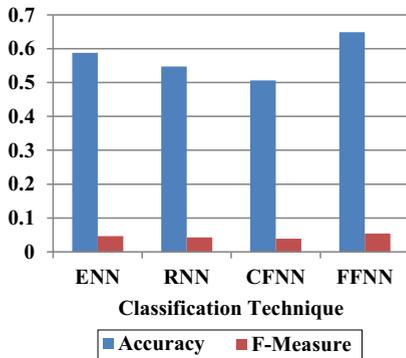


Fig. 12. Evaluation of proposed FFNN With Financial Derivative Features for future data.

proposed FFNN achieved 80% of gmean and high value of precision (i.e.0.0277) than other neural networks (i.e.0.022 of precision). However, the CFNN achieved only 0.0199 of precision value. From this analysis, the projected FFNN model attained better performance with financial derivative features. Table 10 and Fig. 12 shows the performance of FFNN model in terms of accurateness and F-measure with additional financial derivative features.

In the accuracy analysis of with the financial derivative features, the ENN, RNN, CFNN and proposed FFNN achieved the 58%, 54%, 50% and 64%. As well as, these techniques achieved the f-measure of 0.04, 0.04, 0.03 and 0.05. From this analysis, it is clearly proved that with financial derivative features

also, the proposed FFNN model achieved higher performance for future data. However, the performance is less when compared with the analysis of 80%-20% and 60%-40% of data. The reason is that the layers of FFNN model is needs to improve for the prediction of future data.

4.5. Comparative analysis of Proposed FFNN with various Existing approach

The above table clearly proves that the proposed FFNN model achieved better accuracy than various existing techniques. For example, the data mining approach [23] and HMM [24] achieved nearly 83% of accuracy, where SVM [25], RF [26] achieved nearly 79% of accuracy. But, the FFNN model achieved 90.94% of accuracy due to the usage of additional financial derivative features as input for predicting the future IPFZ accurately [27]. However, the performance needs improvement by modifying the layers of FFNN.

5. Conclusion

Satellites assist detect environmental elements that affect fish habitat. Satellite observations Surface temperature, water colour, wind and current data comprise environmental characteristics that are well measured using satellite sensor data. Fern sensing data are used to obtain information on chlorophyll content, primary productivity, coastal and estuarine bio optical qualities and ocean traffic characteristics. In this research study, OST dataset is used for future prediction. Initially, 13 features are used as input and after that financial derivative features are added with those 13 features for accurate future prediction of IPFZ. These more number of features are given as input to FFNN and compared with ELN, RNN and CFNN. The validation results proves that

Table 11
Comparative analysis of with various existing approach

Author Year	Approach	Data used	Accuracy averaged
Natteshan et al [22] 2016 ¹	Data mining approach	Fishery, SSC, OST data from 2000-2004	87.11
Natteshan et al [22] 2016 ²	Heuristic Rule approach	SSC, OST and turbidity	84.71
de Souza et al 2016 [23]	A Hidden Markov Model (HMM)	S-AIS	83
da Silveira et al 2021 [24]	SVM	—	79
Naghibi et al. 2016 [25]	Regression tree, and random forest machine learning models	—	78.03
Proposed 2021	FFNN with Financial Derivative Features	OST	90.94

the FFNN achieved better performance than other neural network techniques and less performance for future data analysis. From this analysis, it is proved that more of the research articles are not supporting for this PFZs future forecast (Table 11). In this work we are major concentrated on the PFZs future forecast, which leads the average accuracy of FFNN model. In future, the performance can be improved by implementing the ensemble classifiers with financial derivative features.

Note

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Not available for this Research Article.

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