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HEFZ – RNNLSTM: An Ingenious Deep Learning Hybrid Model for Ensemble-Based Prediction of Potential Fishing Zone Areas in the Indian Ocean

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Abstract
Many millions of people call the Indian Gujarat subcontinent home, and it's famous for its long coastline (more than 1,400 kilometers long). Fishing is crucial to the survival of their ecosystem. Finding fish can be time-consuming and resource-intensive, which can drive up operational costs and reduce profits. Artificial intelligence (AI) algorithms have allowed for significant advancements in the design of advanced algorithms for the forecast of good fishing spots, both in terms of superior accuracy (Acy) and reduced time. Still, it's never an easy task to foretell where PFZs might appear. According to mitigate these issues, this study introduced a model for innovative hybrid PFZ prediction by combining remote sensing datasets with conventional dataset methodology. The proposed Model combines deep convolutional layers with recurrent neural networks based on the flitter adam optimization of long short-term memory (FA-LSTM) (RNN). Chlorophyll, sea surface temperature (SST), GPS location of last fishing location, fish living temperature, and other features are all removed using convolutional layers before FB-LTSM is used to predict future fishing spots. Extensive experiments are conducted with satellite data from NASA's Ocean colour web, and TensorFlow 1.18 with Keras API is used to implement the necessary infrastructure. The performance metrics are compared with other existing intelligent learning models, including F1-score, sensitivity, sensitivity, recall, specificity, and precision (Pscn), as well as accuracy (Acy),. Our data shows that the proposed Model (94 percent prediction Acy) outperforms the state-of-the-art algorithms, making it an ideal candidate for use in developing a smart system for improved PFZ prediction.

Keyword : RNN LSTM , Ensemble Model , PFZ , Indian Ocean ,

1. Introduction

Because of its high-quality resources, practical urban areas, and extensive biodiversity, India's coastal oceanic environment plays animportantpart in the country's financial system. Gujarat's coastal area is close to 1400 km. including islands, a large location for investigating and utilising shared 2.5 million exclusive economic zone (EEZ) assets km2. India has 7517 kilometres of coastline overall. More than 14 million people rely on employment in the marine fisheries industry, and exports from this sector bring in significant revenue for foreign markets. About 1.24 million tonnes of marine fisheries are produced annually in India, with the majority coming from the Gujarat Costal region, but there is a harvestable capacity of 4.03 million tons[1]. Nonetheless, locating the best fishing spots remains a challenge[2][3].

Both satellite data and ground truth as traditional fishing data have been used to predict fishing zones[4][5]. However, most of the research frameworks relied on chlorophyll and sea surface temperature (SST) features from ocean satellites to make their predictions[6][7]. Utilizing machine and deep learning algorithms has opened up new avenues for fishing zone prediction. Prediction of fishery area using various oceanographic parameters is accomplished using a number of algorithms, including long short-term memory (LSTM)[8][9], Linear Regression[9], K-Nearest Neighbor(KNN)[10], support vector machines (SVM)[11][12], Random Forest (RF) and Artificial neural networks (ANN)[13][14], the deep neural networks(DNN) [13][14], and Deep learning neural networks (DLN)[15]. However, a reliable forecast for PFZs is still far off in the distance of study. The authors of this study propose a novel hybrid model called HE-UISA (hybrid ensemble Using Indigenous Scientific approach) to address this issue. This model combines n-tier convolutional neural layers (NTCN) with flitter adam optimised LSTM to effectively predict PFZs (PEZs) from satellite data. This is the first work of its kind that we are aware of that has been applied to the prediction of PEZ. The paper's most significant finding is as follows:

In order to process remote sensing data and make it useful, such as the chlorophyll content and sea surface temperature, scientific convolutional layers are employed (SSC)

To improve performance, we swap out the standard FIsherman network for one that makes use of long short-term memory (LSTM).

Therefore, flitter adams is used to fine-tune the LSTM's hyperparameters for improved prediction accuracy.

2. Related Works

One of the most recent implementation of global trends for improving, finding, and expand the commercial fishing zones across the oceans is the introduction of fishery information disclosure based on help different machine learning techniques like SVM to the availability of fish. and the use of undersea technology with GPS to develop programming to fish frameworks for tests. This method is useful for PFZ long-term forecasting[16].

proposed a wavelet-based AI forecasting strategy. To predict the chlorophyll-A (C.A.) sensor simple in the upper reaches of the Arabian Indian Ocean(IASO), This interaction uses information from floats used for the IASO's upper sea perception system. It is proposed to use a model that incorporates SAE (stacked autoencoder), Bi (bidirectional) LSTM, and wavelet transformation. Compared to the baseline, experimental results show that these frameworks produce lower RMSE and MAE values[17].

3. Proposed Framework An Overview of the System The proposed framework, the Hybrid Ensemble Fishing Zone (HEFZ) with Recurrent Neural Network Based on LSTM (RNNLSTM), is depicted in detail in Figure 1. There are three stages to the proposed HEFZ - RNNLSTM Model's operation. The method of gathering data includes segmented, Convolutional layers are used to extract feature data, followed by LSTM networks that have been flitter adam optimised.

3.1.Materials and Methods (DataCollection Unit).

SST, SSC, FLT, and GPS coordinates were compiled into a database of environmental variables (latitudes and longitudes). The proposed Model relies heavily on three variables because of their significance as environmental predictors of fishing zones. According to[18][19], SSC data provides information on the sea's usefulness and are important for recognising the temperature that are typically obvious in SST.

Downloads of satellite data spanning nearly 13 years (from January 1, 2009, to April 30, 2021) were used to educate the proposed Model.

3.2. Satellite dataPreprocessing.

To improve prediction accuracy, the pre-preprocessing method is used to filter out invalid observations caused by bad weather or instances where satellites failed to detect the sst.

In order to prevent overfitting, we throw out the null value and consider only cases in which the satellite-based sst and chl are known to be inaccurate. We have downloaded 13 years of remote sensing data, but there isn't enough of it to properly train the network. So, we use data augmentation to fix this issue. A large amount of newly corrected training data samples are generated by applying offline transformations [20] to the series of each fishing location data with fish living data in order to perform the data augmentation. In order to avoid overfitting issues, as depicted in Figure 1, it is common practise to obtain augmented samples that correlate similarly to the original data.

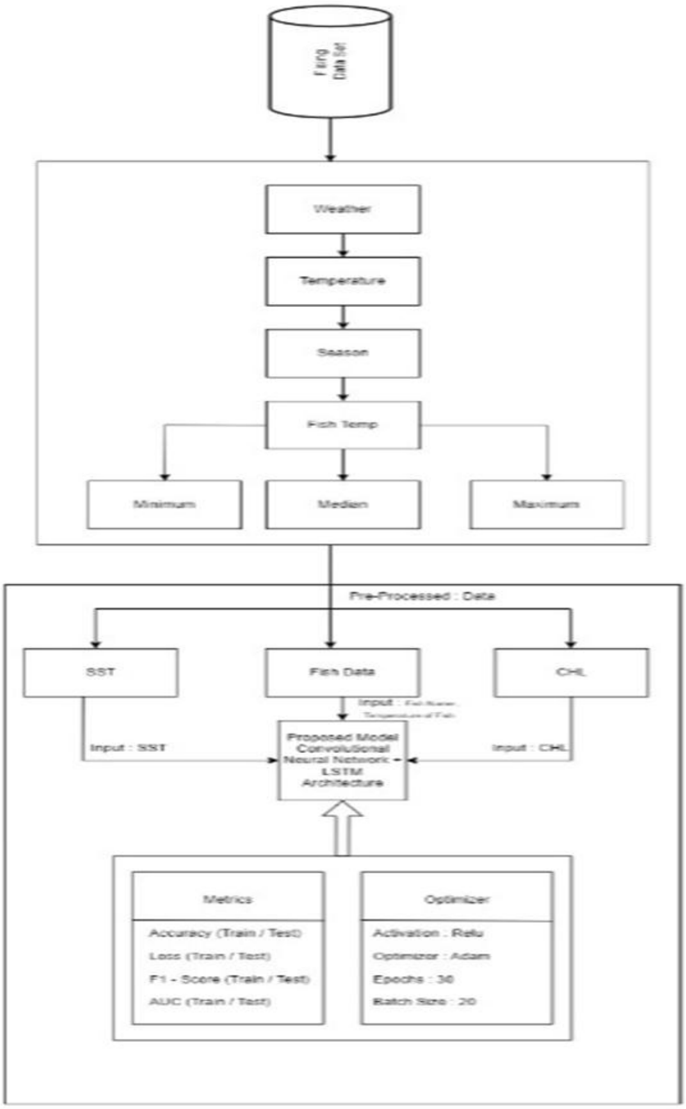

Figure 1: Proposed Fishing Model for the HEFZ – RNNLSTM.

3.3. Proposed Fishing Network Training Model. This section describes the working criteria for the two-tier layers and flitter adam-optimized LSTM suggested in this paper.

3.3.1. Proposed Fishing a group of convolutional layers. Figure 2 shows the results of using an bunch of convolutional neural networks for segmentation and feature extraction, as described in [21]. The SST and CHL are extracted in the first-stage convolutional layers, as shown in Tables 1 & 2 and 2, respectively. Features are extracted from remote sensing data and saved in their own files. The feature from the FTDS file of fish temperatures is extracted using a similar fashion of convolutional layers Table 3.

Parameter Explanation

Sr No	**Parameter Name**	**Description**
1	**Sensor**	Aqua & Terra Are Both Surface Sensor Aqua = 1 Tera = 2
2	**Month**	Taken Value of That Date of Month

3	**Season**	Fishing Season
4	**Time**	Morning = 1 Afternoon = 2
5	**Lat**	Latitude
6	**Lon**	Longitude
7	**Sst**	Sea Surface Temperature

Table 1 SST remote sensing data extract in csv file

Sr No	Parameter Name	Description
1	**Sensor**	Aqua & Terra Are Both Surface Sensor Aqua = 1 Tera = 2
2	**Month**	Taken Value of That Date of Month
3	**Season**	Fishing Season
4	**Time**	Morning = 1 Afternoon = 2
5	**Lat**	Latitude
6	**Lon**	Longitude
7	**chl**	chlorophyll the material in plants that is green and absorbs sunlight to aid in growth

Table 2 chlorophyll remote sensing data extract in csv file

Sr No	Parameter Name	Description
1	**Sr.No**	This is Just a Serial Number
2	**Species Category**	This Field Show the Category of Fish
3	**Scientific Name**	This is Scientific Language Name of The Fish
4	**English Name**	This is the Original English Language Name of The Fish
5	**Local Name**	This is the Local Language Name of The Fish (Mother Tongue)

6	**Min Temp**	minimum temperature for Fish leaving
7	**Max Temp**	maximum temperature for Fish leaving
8	**Mean Temp**	Mean temperature for Fish leaving
9	**Fish Temp In Category**	Divide Fish category based on the some range of temperature Group 1 : 30 To 40 Group 2 : 29 To 26 Group 3 : 21 To 25 Group 4 : 16 To 20 Group 5 : 11 To 15 Group 6 : 01 To 10

Table 3 extract the feature from SST & CHL to the fish temperature data set

Using the newest approaches such as "LSTM and deep learning," primarily concentrate on the assumption of temperature increase in the water. Consequently, it is possible to stop the extinction of all marine species.

3.4.LSTM Training that has been improved for prediction. The network is trained by first extracting and ensemble-ing feature data. In place of the standard neural network training network, the proposed system makes use of the flitter adam optimised long short-term memory. The preceding section detailed the operational mechanism of the proposed LSTM training network.

3.4.1. Hyperparameter Optimized LSTM Network. Although LSTM plays a remarkable role in the prediction, as mentioned in [15], the network's performance degrades when it deals with larger datasets[20]. The computational complexity of the existing frameworks grows with the size of the dataset. As a result of this shortcoming, the proposed LSTM training must take into account the computational complexity of its hyperparameters, which include hidden layers, learning rate, and epochs. The rate of accuracy achieved in predictions will be higher using this method than with a conventional network.

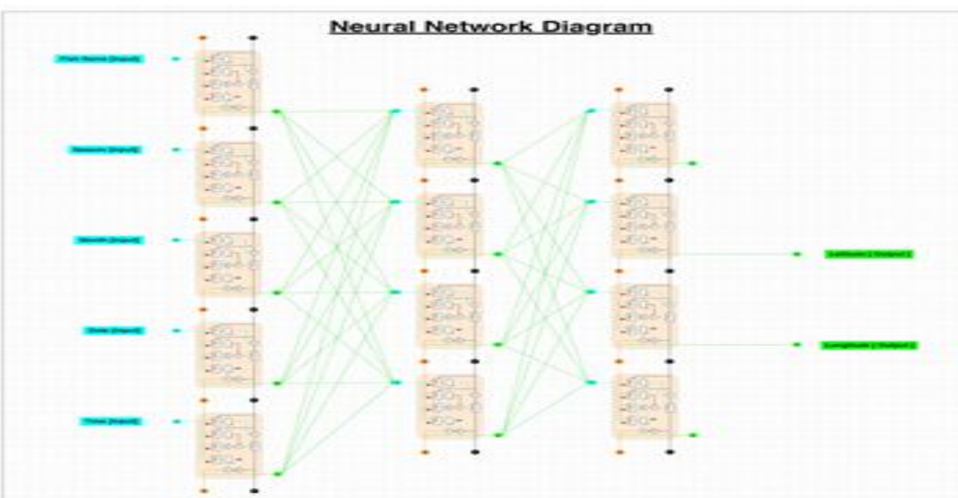

Figure 2: CNN layers utilize a double-tier ensemble for faster classification and feature extraction.

4. Methodology

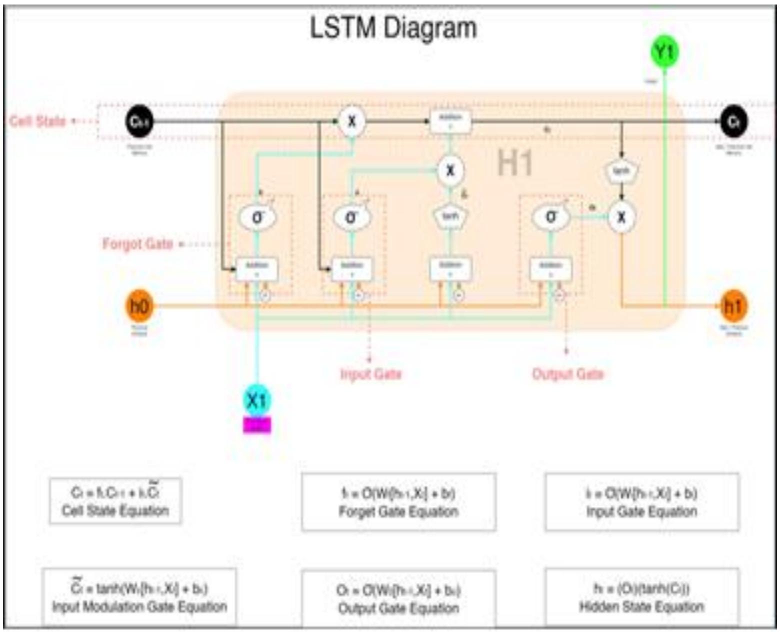

Figure 3 : LSTM Diagram

Sr. no.	Layer (type)	Activation Used	epochs	batch_size / Output Shape	Parameter
1	Convolution Layer (LSTM)	Relu		64 (None, 5, 64)	16896
2	Dropout(0.2)	-		(None, 5, 64)	0
3	Convolution Layer (LSTM)	Relu	20	32 (None, 32)	12416
4	Dropout (0.2)	-		(None, 32)	0
5	Dense	linear		2 (None, 2)	66

Table 4 : SST and CHL feature extraction and classification were done using CNN (Tier 1) parameters.

Sr. No	Fishing Data	Trained Data %	Tested Data %
1	3,92,500	80	20

Table 5: Proposed model for testing and training using SST and CHL dataset

Finally, the above Table 4 & Table 5 Show the effective prediction of the various PFZs is achieved LSTM's refined hyperparameters are used.

4.1 Setup for an experiment: The proposed HEFZ – RNNLSTM are implemented in TensorFlow 3.18 with Keras API which runs on "Windows PC10 with i7 CPU, 4 GB NVIDIA Geo-force GPU, 16 GB RAM and 2.5 GHZ"

4.2. Comparative data analytics: Figure 4 compares the proposed Model to other state-of-the-art learning of algorithms.

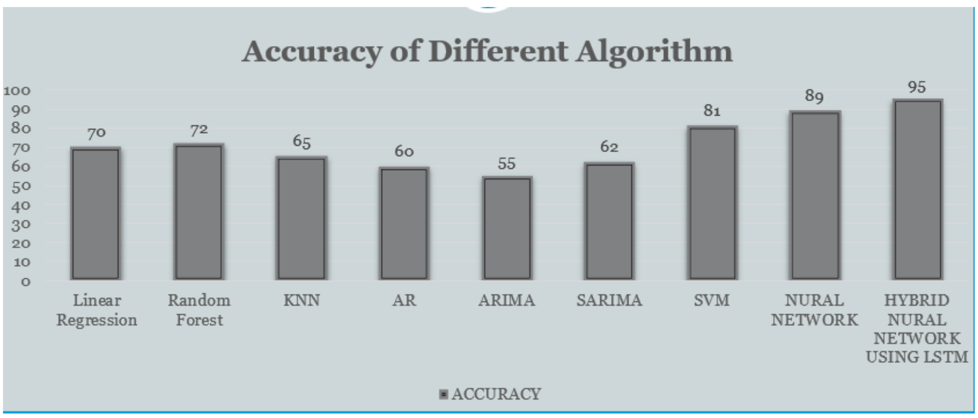

Figure 4: Accuracy of Different Algorithms

5. Conclusion

The paper proposes a new HEFZ - RNNLSTM for predicting PFZs that can be put to use by the fishing community. The proposed algorithm uses an optimised LSTM network in place of the conventional neural network training, which operates on the principle of two tiers embedded layers. The proposed framework utilises the flitter adam optimization method to fine-tune the hyper parameters. SST and SSC, as well as GPS coordinates and fish-living temperature data, are included in the datasets, which also include traditional data. The data sets were obtained by visiting the website https://oceancolor.gsfc.nasa.gov/. The aforementioned datasets were used to conduct extensive experiments, and validation metrics were calculated for a multitude of environments. Validation of the proposed Model's performance occurs at random between January and May of 2023. Acy is consistently more accurate than other state-of-the-art learning models, with a monthly prediction accuracy of 94%. The above findings demonstrate the potential utility of the proposed Model in predicting the PFZs for the benefit of the fishing community.

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