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Original Article

Kernel zed Target Feature Projection-based Implicit Indexive Bootstrap Aggregating Classifier for Marine Weather Forecasting with Big Data

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Abstract *- Weather forecasting is a computer program that offers meteorological information to forecast the atmospheric conditions for a particular location. It has been done by using enormous techniques but is still not enough for handling big data since the data consists of a more volume of data. Therefore, the techniques do not show the forecasting accuracy perfectly and take more prediction time. To improve the prediction accuracy with lesser time, A Fisher Kernelized Target Feature Projection-based Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classification (FKTFP-IMHIDSBAC) technique is introduced for forecasting higher accuracy and less time consumption of marine weather. The proposed IUMHIDSBAC technique consists of two main processes: feature selection and classification, which are carried out using Fisher Kernelized Target Feature Projection. The feature selection process of the proposed FKTFP-IMHIDSBAC technique has reduced the time complexity of the prediction. Then Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier is applied for weather forecasting with the selected features. The Bootstrap Aggregating Classifier is an ensemble technique that uses the weak learners as a Morisita-Horn Indexive Decision Stump for analyzing the testing and training data. Then the ensemble classifier combines the weak learner and applies the implicit utilitarian voting scheme to find accurate results and minimize the error. The results and discussion demonstrate that the proposed FKTFP-IMHIDSBAC technique increases the accuracy and minimizes the error as well as target tracking time than the existing techniques*

Keywords *- Marine weather forecasting, Big data, Fisher Kernelized Target Feature Projection, Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier.*

1. Introduction

Weather forecasting could be an advanced method for understanding the changes in the future. However, existing solutions perpetually get little prediction accuracy for short forecasting. The numerical prognostication models are not performing well in many circumstances. Machine learning approaches neglect has been applied to create higher prognostication accuracy fluctuate in several areas.

1.1. Contribution of Our Work

To solve the issues found in the literature study, The FKTFP-IMHIDSBAC technique is introduced with novelty as,

- To improve the weather prediction accuracy rate, an FKTFP-IMHIDSBAC method is introduced based on two different processes: Fisher Kernel zed Target Feature Projection and Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier.

- To minimize weather prediction time and space complexity, Fisher Kernel zed Target Feature Projection is handled to analyze the features and to select significant values based on the likelihood measure. The feature having maximum likelihood is selected for prediction.

- Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifiers then applied for weather data analysis and prediction. The proposed Classifier initially utilizes an Implicit Morisita-Horn Indexive Decision Stumped classifier to analyze the weather data with different observations and predict weather conditions. The cardinal voting is applied to combine the weak classifier performance to make strong results by reducing the error.

- A comprehensive method is organized to measure the implementation of the FKTFP-IMHIDSBAC technique and all existing models. The results achieved show that our FKTFP-IMHIDSBAC technique performs well.

1.2. Paper Organization

Next in this paper, Section 2 explains the FKTFP-IMHIDSBAC technique by separating it into two sections: feature selection and classification. Section 3 gives the experimental setup. Section 4 provides a detailed analysis of the experiment being conducted and the results that were achieved. Section 5 provides the conclusion of the current work.

2. Proposal Methodology

Marine weather forecasting is a promising field that predicts climatic situations in a particular placemat. Due to the development of big data technology and continuous climate changes, accurate weather prediction and the lack of handling large data volume is a complex task. Still, the weather forecast under various circumstances is inaccurate in many conditions. In this research, the model uses the FKTFP-IMHIDSBAC technique for accurate forecasting using a huge volume of data. Time Series climate data analysis in data mining risks accurate prediction. The relevant feature selection process minimizes the dimensionality; hence it reduces the time and space complexity. Based on this, the FKTFP-IMHIDSBAC model is developed.

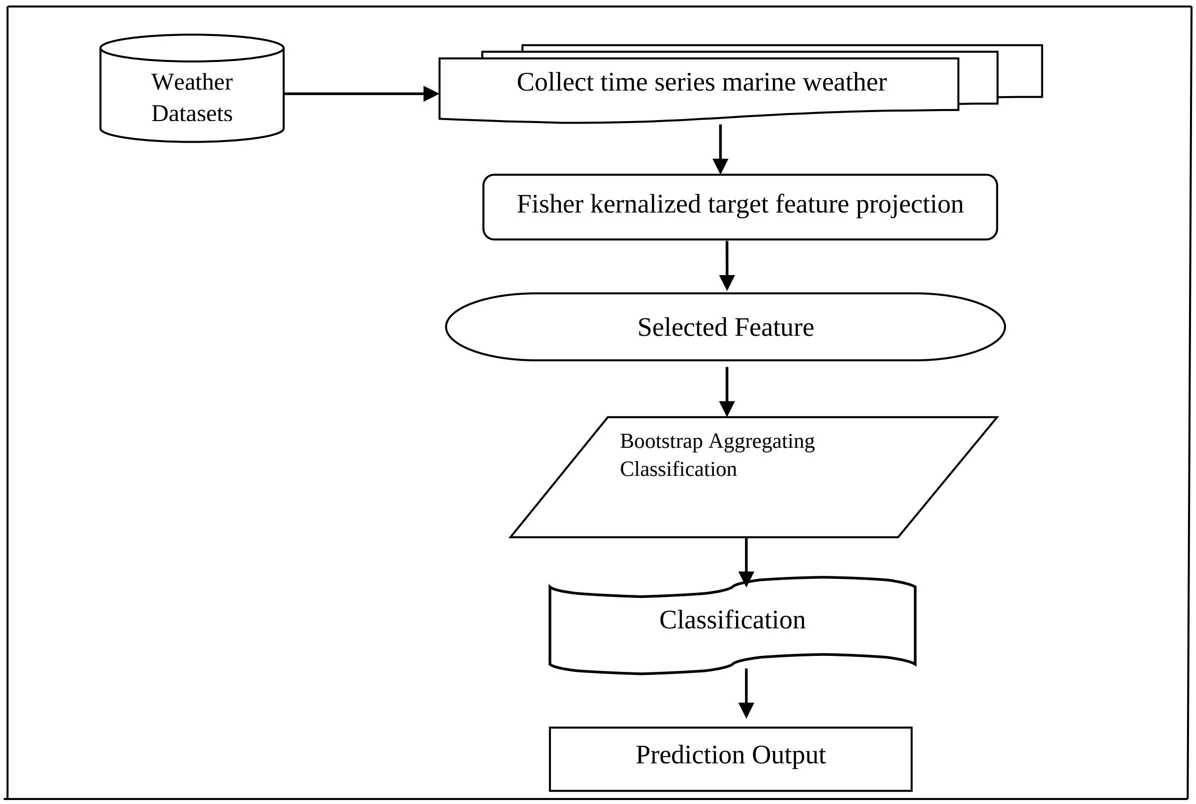

Fig. 1 architecture of FKTFP-IMHIDSBAC technique

Fig. 1 given above illustrates a block diagram of the FKTFP-IMHIDSBACtechnique. The number of time series features and records are initially stored from big weather data. Next, feature selection is said to be performed using Fisher Kernelized Target Feature Projection to identify the relevant features and remove the other features. The Bootstrap Aggregating Classification technique is applied with the relevant features for accurate classification. These two different processes of the FKTFP-IMHIDSBAC technique are described in the following sections.

2.1. Fisher Kernel zed Target Feature Projection

The proposed FKTFP-IMHIDSBAC technique performs the feature selection to minimize the dimensionality of the dataset. Massive amounts of time series data are generated regularly. This data aims to efficiently analyze the huge amounts of data generated to develop an effective early forecasting system. Due to the large volume of data, dimensionality reduction is a challenging task in the data mining community. Therefore this problem is solved by introducing a feature selection process. The main goal of feature selection is to discover the optimal subset of features. As a result, the high computational complexity of weather forecasting is minimized.

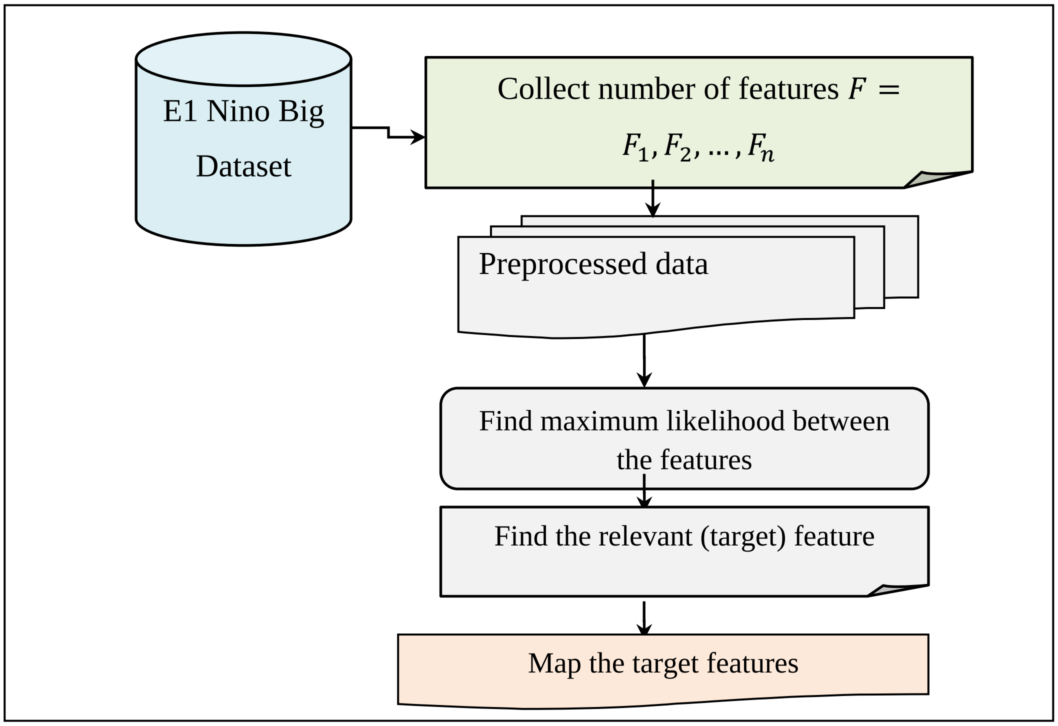

Fig. 2 Flow process of Fisher Kernelized

2.2. Target Feature Projection technique

Fig. 2 illustrates the flow process of feature selection using Fisher Kernel zed Target Feature Projection. The Fisher kernel is used to estimate the maximum likelihood of the existing features to identify a significant one.

Let us consider several features $F = F_1, F_2, \dots F_n$ Are collected from the dataset. The feature matrix is constructed as given below,

$$F = \begin{bmatrix} \mathrm{F}_{11} & \mathrm{F}_{12} & \dots & \mathrm{F}_{1n} \\ \mathrm{F}_{21} & \mathrm{F}_{22} & \dots & \mathrm{F}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{F}_{n1} & \mathrm{F}_{n2} & \dots & \mathrm{F}_{nn} \end{bmatrix} \qquad (2)$$

Where ‘ F ’ denotes a feature matrix. A maximum likelihood between the two features is estimated as follows, $F_k = \arg\max(\varphi_L)$ (3)

$$\varphi_L = \log\left[\left((2\pi d^2)^{1/2}\right) . \frac{-0.5 * |F_i - F_j|}{d^2}\right] \qquad (4)$$

Where, F_k Denotes a Fisher Kernel output, φ_L Indicates a likelihood function, arg max indicates an argument of the maximum likelihood function, F_i, F_j Denotes two feature sets in the respective columns. log Indicatesthe logarithm function, $d\, represent$ the deviation. The feature with maximum likelihood is selected for classification. The relevant (i.e. target) elements are estimated from high-dimensional space into low-dimensional space.

$$\emptyset : T_F \rightarrow F_s \qquad (5)$$

Where$\emptyset$ indicates a target projection function to map the target features (T_F) from the high dimensional space ‘into the feature subset. ‘F_s ’ in low dimensional space. This process minimizes the time complexity.

Algorithm 2: Fisher Kernelized Target Feature Projection
Input: Big time-series dataset, number of features$F = F_1, F_2, \dots F_n$ **Output:** Select target features **Begin** **1.** Collect the number of features$F = F_1, F_2, \dots F_n$ 2. **For** each featureF_i 3. Construct feature matrix F’, 4. Measure the likelihood between the features 5. **if**(arg max φ_L)**then** 6. Features are said to be a relevant 7. project the target features into low-dimensional space 8. **else** 9. Remove irrelevant features **10. End if** **11. End for** **End**

Algorithm 2 demonstrates the Fisher Kernelized Target Feature Projection. Initially, many elements are gathered from the big weather data. After that feature matrix is constructed. The forecast matrix launches the high resemblance features into two-dimensional spaces. The maximum likelihood between the features is measured. The feature with a higher likelihood is identified as the target feature. The relevant features selected are, Meridional winds, Moisture, Airborne Temperature and Ocean Surface Temperature. Feature selection in the FKTFP-IMHIDSBAC method decreases the forecast time and space complexity.

2.3. Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier

The second process of the FKTFP-IMHIDSBAC technique is to perform the data classification with the selected features using Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier. The Bootstrap Aggregating Classifier uses the decision tree methods for weak learners.

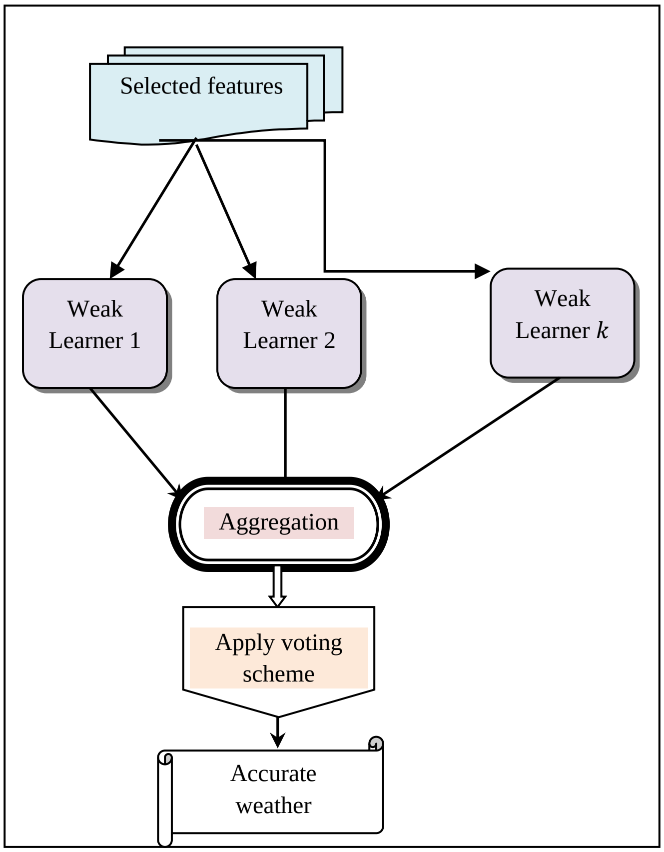

Fig. 3 schematic diagram of the bootstrap aggregating classifier

Fig. 3 illustrates the schematic diagram of the bootstrap aggregating classifier. Let us consider bootstrap aggregating classifier uses the training sets $\{x_i, z\}$ where x_i Denotes a bootstrap sample (i.e. input data), and 'Z' represents classification results. The ensemble classifier constructs an empty set of 'k' weak learners$\mathrm{R}_1, \mathrm{R}_2, \mathrm{R}_3, \ldots. \mathrm{R}_\mathrm{k}$. Here, the ImplicitMorisita-Horn Indexive Decision Stump is used as a weak learner to classify the given input data. Here, the implicit reflects previous occurrences of the time series data. The Decision Stump classifier starts with the root node directly connected to the leaf node.

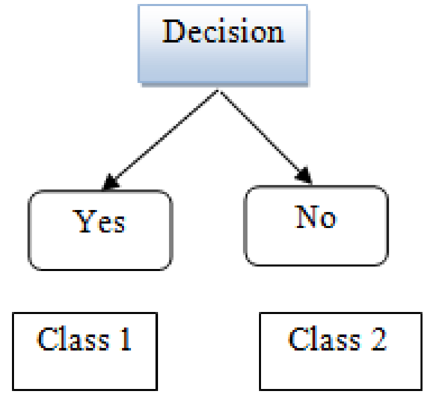

Fig. 4 process of Implicit Morisita-Horn Indexive Decision Stump

As shown in Fig. 4, Implicit Morisita-Horn Indexive Decision Stump obtains the prediction results by analyzing the patterns. The decision tree classifier analyzes the training time series data using the Implicit Morisita-Horn Index. Morisita-Horn's index measures the similarity between the time series data at different observations. The similarity is measured as follows,

$$H = 2 * \left[\frac{\sum D_i(t_i) * D_j(t_j)}{\sum D_i(t_i)^2 + \sum D_j(t_j)^2}\right] \qquad (6)$$

Where Morisita-Horn's similarity index 'H' is measured based on the sum of the product of two training time series data at different observations '$\sum D_i(t_i) * D_j(t_j)$' and $D_i(t_i)^2$signifies a squared count of dataD_i, and $D_j(t_j)^2$ denotes a squared score of data 'D_j'. Morisita-Horn's similarity index ranges between '0' and '+1'. The index with '+1' indicates a complete similarity, whereas 0' represents no similarity between the training time series data. Based on the comparison rate, the future weather conditions are correctly predicted.

$$z = \sum_{i=1}^{m} R_i \qquad (7)$$

In (7), z symbolizes the ensemble classification results, $w_i\,(x)$ represents the output of the decision tree classifier. After combining results, the error is measured based on the difference of opinion between observed and predicted results.

$$e_G = (z - z_o)^2 \qquad (8)$$

Where, e_G denotes an error, $z$symbolizes the predicted results,z_o Indicates observed results. According to the error value, the classifiers are arranged by applying Cardinal voting. The voting scheme is applied to rank. 'ϑ_r' the weak learner results 'R_i' based on the error value.

$$\vartheta_r \rightarrow \sum_{i=1}^{m} R_i \qquad (9)$$

Compared to the conventional bootstrap aggregating classifier, the proposed bootstrap aggregating classifier removes the "worst" classifiers with the largest error rates. Then the aggregating classifier finds the high-ranked classification results. Then the final output of the bootstrap aggregating classification is obtained by finding the majority votes of the results.

$$F = arg\,max\ [v\ (R_i)] \qquad (10)$$

In (10), F represents the final ensemble classification results, and arg max denotes an argument of a maximum function to find the maximum votes of sample' v' in the weak classifier results 'R_i' whose decision is known to the last classifier. As a result, the bagging classifier improves the weather prediction with minimum error. The algorithmic process of the proposed ensemble classification results is shown below,

Algorithm 3: Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier
Input: Number of training data, i.e. bootstrap samples $D_1, D_2, D_3, \dots . D_n$, **Output:** Improve prediction accuracy **Begin** **1.** **For each sample. 'D_i'** **2.** Construct 'k' decision trees with training data$D_1, D_2, D_3, \dots . D_n$ **3.** Find the **Morisita-Horn similarity** between data at different observation **4.** **If** ($H = +1$), **then** **5.** High similarity between training data **6.** **else** **7.** The low similarity between training data **8.** **end if** **9.** Combine a set of weak learners $\sum_{i=1}^{m} R_i$ **10.** **For** each R_i 11. Calculate the error. ' e_G' **12.** **end for** **13.** Rank theR_i based on out of error **14.** FinsR_i with minimum error 15. Find the output classification results $F = arg\,max\ [v\ (R_i)]$ 16. Obtain strong prediction results **End**

2.4. Algorithm 3Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier

Algorithm 3 describes the various processing of the Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier. The proposed ensemble classifier first constructs weak learners by training weather data. Weak learner measures the similarity between the training data at different observations using the Implicit Morisita-Horn index. The weak learner classifies the time series value according to the similarity value. The weak classification results are formed to construct strong classification results. The training error is calculated for each weak learner based on observed results. Then the weak learners are ranked according to the error value. The weak classifiers with the highest error are removed, and the classifiers with a lesser error are found. Finally, the majority votes of the classification results are correctly identified as prediction results. This process assists in improving weather prediction accuracy and minimising the error rate.

3. Experimental Evaluation

Experimental evaluations of the FKTFP-IMHIDSBAC and existing SFPLN [1] STConvS2S [2] are implemented using JAVA with the E1 Nino dataset taken from https://www.kaggle.com/uciml/el-nino-dataset. The main aim of this dataset is to predict the seasonal-to-inter annual climate variations such as air temperature, surface temperatures, and Humidity for one to two years. The E1nino dataset collected for phase 1 and phase 2 journal is of spatiotemporal characteristics including integer and real type with an overall instance of 178080 and 12 attributes. Moreover, the dataset type ranges from integer (i.e., observation, year, month, day, date, latitude), categorical (i.e., zonal and meridional winds), and non-integer values, respectively.

The dataset consists of 178080 instances and 12 different attributes. Latitude and longitude indicate that buoys shifted to dissimilar locations in the equatorial Pacific Ocean. The latitude values are identified by a degree on a particular location. The longitude values are collected as five degrees off. Zonal and meridional breezes are varied between -10 m/s and 10 m/s. The relative moisture values were normally observed from 70% to 90%. The airborne warmth and the aquatic surface temperature varied from 20-30 degrees Celsius. All the meteorological analyses were collected at a similar point in time.

2.1. Performance of results analysis

The evaluation of the proposed FKTFP-IMHIDSBAC and existing SFPLN [1] D2CL[2] are provided in this section with the different performance metrics, namely prediction accuracy and mean absolute error rate, prediction time, and space complexity, with the help of table and two-dimensional graph. For each subsection, the implementation of FKTFP-IMHIDSBAC method is evaluated against the other methods.

Prediction accuracy is the ratio of predicted weather data to the total weather using the meteorological weather data. The formula for calculating the Prediction accuracy is measured as given below,

$$P_{acc} = \sum_{i=1}^{n} \frac{D_{pacc}}{D_i} * 100 \qquad (11)$$

Where, P_{acc} denotes a prediction accuracy, 'D_{pacc}' represent weather data accurately predicted, D_i Indicates whether data is involved in the simulation process for marine weather forecasting. It is measured in terms of percentage (%).

2.1.1. Mean Absolute Error (MAE)

It is evaluated to measure the difference between the real value and the forecasted value during marine weather forecasting, which is formulated as follows,

$$ER = MAE = \frac{1}{n}\sum_{i=1}^{n}(AV_i - PV_i) * 100 \qquad (12)$$

Where,AV_i Denotes real value and the expected value. 'PV_i' for 'n' samples, respectively.

Prediction time is defined as the amount of time consumed by the algorithm for marine weather forecasting using meteorological data.

$$P_{time} = \sum_{i=1}^{n} D_i * Time\ [single\ data] \quad (13)$$

Where, P_{time} Denotes a prediction time, D_i Weather data involved in the simulation process for marine weather forecasting the time consumed in weather data prediction.

2.1.2. Space complexity

It is calculated as a quantity of memory area consumed by the algorithm for weather prediction. The formula for calculating the space complexity is,

$$Com_S = \sum_{i=1}^{n} D_i * Mem\ [single\ data] \qquad (14)$$

Where, Com_S denotes a Space complexity, D_i Weather data involved in the simulation process for marine weather forecasting, Mem denotes a memory for processing the single weather data prediction.

Table 1. prediction accuracy

Number of weather data	Prediction accuracy (%)		
	FKTEP-IMHIDSBAC	SFPLN	D2CL
10000	98.3	94.5	96.3
20000	96.25	91.5	93.75
30000	94.33	89	91.66
40000	93.75	88	90.75
50000	92.4	87	89
60000	90.83	85.83	87.5
70000	89.28	85.42	86.42
80000	88.75	82.75	85.62

Table 1 shows the implementation results of weather prediction accuracy with the dataset from 10000 to 100000. The performance of different weather calculation accuracy of three methods, namely FKTFP-IMHIDSBAC and SFPLN [1] D2CL [2], are reported in table 1. The table values demonstrate that the accuracy of the FKTFP-IMHIDSBAC model is noticeably enhanced than the existing techniques. Let us consider the 10000-time series weather data in the first iteration. Therefore, the accuracy of the proposedFKTFP-IMHIDSBAC technique is observed as98.3%, and the prediction accuracy of existing SFPLN [1] D2CL [2]is94.5%, and 96.3%, respectively. Correspondingly, ten varieties of prediction accuracy results of the proposed FKTFP-IMHIDSBAC technique are compared to the conventional methods. The overall value of the ten comparison results provides evidence that the prediction accuracy of the FKTFP-IMHIDSBAC technique is increased by 6% when compared to [1] and 3% when compared to [2], respectively.

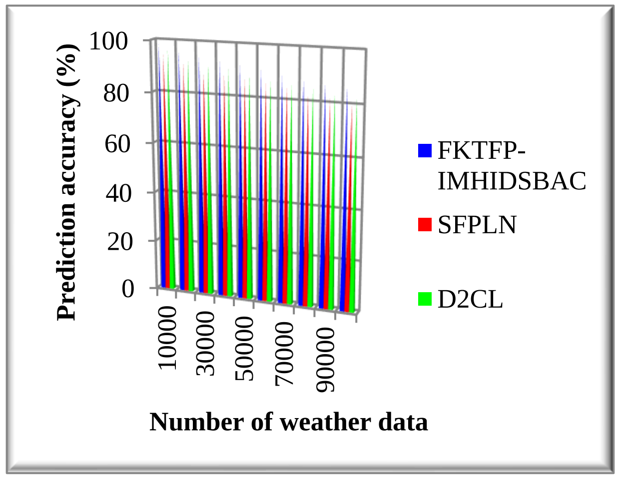

Fig. 1 Comparative analysis of the prediction accuracy

Fig. 1 shows the prediction accuracy. As shown in Fig. 5, the blue colour cone indicates the prediction accuracy of the FKTFP-IMHIDSBAC technique. According to the visualization, the proposed technique's accuracy is increased. This enhancement is achieved by applying the Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier. The ensemble classifier initially constructs the empty set of decision stump classifiers to analyze the time series data based on different observations. The weak classification results are combined and obtain the final results of different temperature prediction accuracy in the Atlantic Ocean.

Table 2. Tabulation of prediction time

Number of weather data	Prediction time (ms)		
	FKTFP-IMHIDSBAC	SFPLN	D2CL
10000	2200	2700	2500
20000	2600	3000	2800
30000	3300	4200	3750
40000	4000	4800	4400
50000	4500	5500	5000
60000	4800	5820	5400
70000	5250	6160	5600
80000	6240	7040	6560
90000	6570	7380	7020
100000	6800	7500	7200

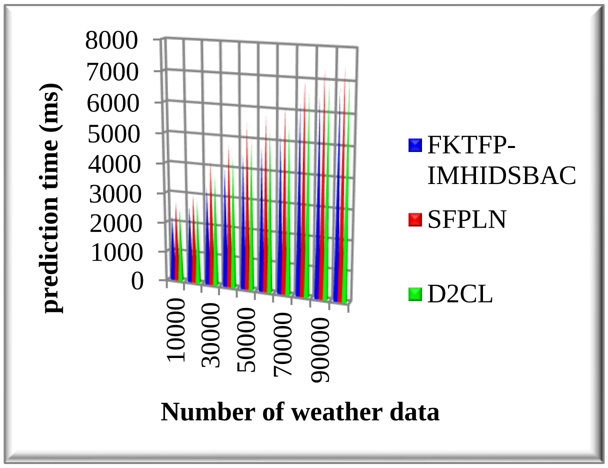

Fig. 2 Comparative analysis of the prediction time

Fig. 2 shows the graphical representation of the FKTFP-IMHIDSBAC technique and SFPLN [1] and D2CL [2]. As shown, the performance of prediction time using all the methods increases while increasing the number of weather data. Prediction time using the proposed FKTFP-IMHIDSBAC method is comparatively minimized than [1] and [2]. This is owing to the geometric projection of the feature selection using Fisher Kernelized Target Feature Projection. The maximum likelihood between the features is measured. The feature with a higher likelihood is identified as the target feature for accurate prediction. FKTFP-IMHIDSBAC technique reduces the prediction time. Let us consider the experimentation of the '10000' number of weather data, and the time consumed for predicting weather data using the IMHIDSBAC technique is '$2200ms$', and '$2700ms$' and $2500ms$' using SFPLN [1] and D2CL [2]. Since it is assumed that the weather prediction time using the FKTFP-IMHIDSBAC method is relatively smaller than [1] and [2]. The obtained results compared the performance of the recommended method is compared to existing results. This helps to minimize the weather prediction time FKTFP-IMHIDSBAC technique by 15% [1] and 8% [2], respectively.

Table 3. Tabulation of space complexity

Number of weather data	Space complexity (MB)		
	FKTFP-IMHIDSBAC	SFPLN	D2CL
10000	83	110	96
20000	100	140	120
30000	114	150	135
40000	144	176	160
50000	170	210	190
60000	192	234	210
70000	210	252	238
80000	224	288	256
90000	261	306	279
100000	300	340	320

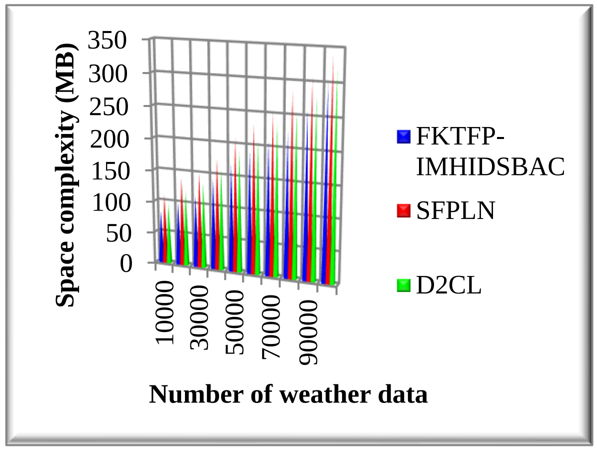

Fig. 3 Comparative analysis of the space complexity

Table 3 and Fig. 8 given above illustrate the comparative analysis. Fig. 3 illustrates the comparison graphical illustration of space complexity using the FKTFP-IMHIDSBAC technique, SFPLN [1], and D2CL [2]. The graphical results infer that the space complexity is comparatively smaller using the FKTFP-IMHIDSBAC technique compared to existing techniques. The reason for this improvement is the application of the feature selection process. By applying this dimensionality reduction algorithm, the size of the dataset is minimized. The lesser relevant features and the data are used for the prediction process rather than the other features in the dataset. This process is said to be minimized the space complexity. The average of ten results demonstrates that the FKTFP-IMHIDSBAC technique is minimized by 20% more than the SFPLN [1] and 11% compared to D2CL[2].

3. Conclusion

The proposed marine weather forecasting technique, FKTFP-IMHIDSBAC, simultaneously analyzes the spatial and temporal feature selection and classification. The FKTFP-IMHIDSBACtechnique is Fisher Kernelized Target Feature Projection to analyze the features and selects the target features to minimize the dimensionality of the dataset. In the next phase, computationally efficient, robust and accurate weather forecasting is performed through Implicit Morisita-Horn Indexive Decision Stumped Bootstrap Aggregating Classifier. Here, the Implicit Morisita-Horn Indexive Decision Stump classifier is used as a weak learner applied to the input features by evaluating the selected target features and combining their results using cardinal voting. The performance of the FKTFP-IMHIDSBACtechnique and existing classification techniques is estimated with prediction accuracy, mean absolute error rate, and prediction time and space complexity. The observed results demonstrate that higher weather prediction accuracy is achieved using the FKTFP-IMHIDSBACtechnique and minimises the time, space complexity and error rate compared to conventional classification methods.

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