Fisher Kernelized Target Projective Feature Selection based Marine Weather Prediction with Big Data

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Abstract - Weather prediction is a computer program with meteorological information to forecast atmospheric conditions for specific location. Weather prediction is carried out using different techniques for managing the big data. Consequently, the existing technique reduced the feature selection accuracy with large time consumption. To enhance accuracy with lesser time, Fisher Kernelized Target Projective Feature Selection (FKTPFS) technique is introduced for weather prediction using higher accuracy as well as lesser time. In proposed FKTPFS technique, feature selection was carried out with Fisher Kernelized Target Projective Feature Selection for identifying significant features. The objective of Fisher Kernelized Target Projective Feature Selection is to give the large separation of class means while maintaining the in-class variance small. The feature selection process of proposed FKTPFS technique minimizes time complexity of the marine weather prediction. The results and discussion shows FKTPFS increases feature selection accuracy as well as minimize the error as well as feature selection time than the existing techniques.

Keywords: Marine Weather Prediction, Bigdata, Fisher Kernelized Target Projective Feature Selection, Meteorological Information

INTRODUCTION

Weather prediction is a complex process for understanding the changes in the future. But, it gets small accuracy to weather prediction. The numerical prediction achieves several circumstances. Machine learning method has been applied to make higher prediction accuracy fluctuate in different areas. Data processing techniques was introduced in [1] to tackle data imbalance issues. Deep belief network was employed for considering short-term rainfall method. However, feature selection accuracy was not increased during marine prediction process. A deep learning method termed Multi-Layer Perceptron using HM-LSTM was designed in [2] to predict temperature, pressure, salinity as well as density. But, feature selection time was not minimized by deep learning method.

STConvS2S was introduced in [3] for learning both spatial and temporal data. However, it failed to decrease rainfall dataset error. A new multi-step prediction scheme was introduced in [4] to predict the ensemble PM2.5. Designed model was failed to enhance accuracy.

Lightweight data-driven weather prediction method was developed in [5] by using LSTM as well as TCN. But, designed method failed to develop an accurate weather prediction system. Hybrid systems that integrate machine learning models were designed in [6] to enhance the performance of sea surface temperature prediction. However, designed method was unsuccessful for enhancing accuracy.

Deep learning neural network was presented in [7] to predict sea surface temperatures. But a large amount of data was not considered for experimentation to yield successful results. Machine learning methods were introduced in [8] to reduce uncertainty of weather research and prediction. However, the designed technique failed to use spatial association for minimizing long-term predictions.

A Temporal Convolutional Network (TCN) algorithm was developed in [9] using historical weather data. The higher prediction accuracy was obtained but time of prediction was better. In [10], machine learning-based weather prediction technique was introduced. But it failed to increase the accuracy as well as competence of prediction model.

Deep Learning Weather Prediction (DLWP) approach was developed in [11]for ensemble prediction. However, the memory consumption of the prediction was not focused. Dynamic Regional Combined short-term rainfall Prediction method (DRCF) was introduced in [12] using Multi-layer Perceptron (MLP). But the weather prediction time was not improved.

A novel 2D-convolutional LSTM (convLSTM) network was introduced in [13] for Short-term temperature forecasts. But the robustness of the model was not improved for prediction. A predictable planning framework was developed in [14] for intelligent weather prediction. But the designed framework failed to improve the reliability of weather prediction.

A deep neural network (DNN) was developed in [15] for Medium-Range Weather Forecasts analyses based on training and validation. But a more accurate range of Weather Forecasts was not obtained. Hybrid method based on MLP as well as VAE was introduced in [16] for weather prediction based on Weather-related features. But the accuracy of weather prediction was not improved with minimum time consumption.

SPRINT algorithm called scalable and parallelizable decision tree algorithm was introduced in [17] for weather prediction. However, the designed algorithm did not efficiently minimize the error rate of weather prediction.

A statistical post-processing model was developed in [18]based on numerical weather prediction data for Local temperature forecasts. However, accurate weather prediction was not performed with minimum error.

Hourly Rainfall Forecast (HRF) model was designed in [19] to forecast rainfall with high accuracy and time resolution. However, the model was not efficient to perform an accurate prediction. A memory graph convolutional network (MGCN) model was introduced in [20] for sea surface temperature prediction. However, it failed to select the less spatial features for minimizing the complexity.

SFPLN was developed by [21] for prediction marine information was considerably reduced. The designed SFPLN minimizes time as well as error occupied in prediction marine data. However, the prediction accuracy involved in marine prediction was not improved. A novel Dense Dilated Convolutional LSTM (D2CL) model was developed in [22] to accurately forecast the sea surface temperature based on spatial and temporal features. But it failed for forecasting long-term time data.

1.1MAJOR CONTRIBUTIONS

To address the problem, FKTPFS is developed with major contributions are shown as follows,

- To enhance weather prediction accuracy rate, an FKTPFS technique is introduced.
- To minimize time and space complexity of feature selection, Fisher Kernelized Target Projective Feature Selection is utilized to analyze features as well as for selecting significant features based on likelihood measure. The feature having maximum likelihood is selected for prediction.
- A comprehensive simulation is organized for measuring FKTPFS as well as conventional works. The results achieved demonstrate that our proposed, Fisher Kernelized Target Projective Feature Selection achieves higher performance in accuracy, feature selection time, error rate, and space complexity.

1.2 ORGANIZATION OF THE PAPER

The article is summarized by. Section 2 provides FKTPFS technique by separating it into two sections, feature selection, classification. Section 3gives the experimental setup. Section 4 provides a detailed analysis of the experiment being conducted and the results are achieved. Section 5provides the conclusion of the current work.

2.PROPOSAL METHODOLOGY

Marine weather prediction is a promising field that predicts the climate condition at a particular location at a particular time. Due to the development of big data technology and continuous climate changes, accurate weather prediction, lack of handling in large data volume is a complex task. Numerical weather prediction is the trendy method for prediction weather conditions. But, prediction of weather under various conditions was not correct. But, more accurate forecast of weather is a challenging one. In this research, weather prediction model uses the FKTPFS technique for accurate prediction using a huge volume of data. Time Series climate data analysis in data mining creates a risk for accurate prediction. Dimensionality reduction is applied for reducing the complexity of prediction by identifying relevant or redundant features in the dataset. The relevant feature selection process minimizes the dimensionality hence it reduces the time and space complexity. Based on this motivation, the FKTPFS technique is introduced.

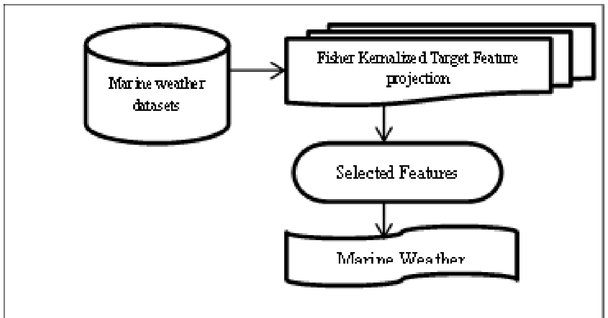

Fig: Architecture of FKTFP

Figure 1 given above illustrates an architecture diagram of the FKTPFS technique. Initially, the number of time series features and data are gathered. After collecting data and features, feature selection is said to be achieved with Fisher Kernelized Target Projective Feature Selection for identifying the relevant features as well as extract various features. The processes of FKTPFS technique are briefly described in the forthcoming sections.

3.FISHER KERNELIZED TARGET PROJECTIVE FEATURE SELECTION

Initially, FKTPFS achieves the feature selection for reducing 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 prediction 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 aim of feature selection is used for detecting optimal subset of features. As a result, high computational complexity of weather prediction is reduced.

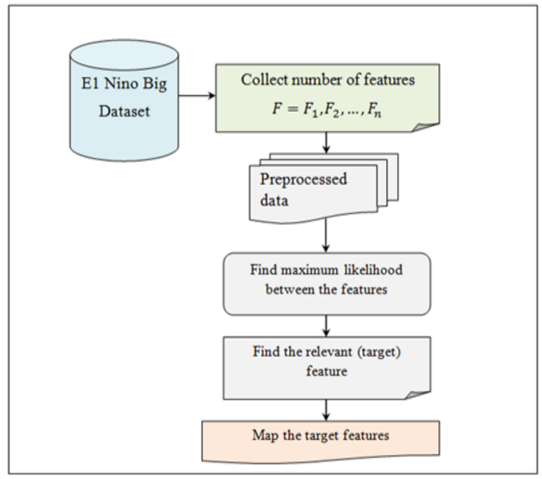

Figure 2 illustrates the flow process of feature selection using Fisher Kernelized Target Projective Feature Selection. In statistical analysis, the Fisher kernel is used to calculated relationship of objects. Fisher kernel is used for estimating the maximum likelihood between the features to find the significant features.

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

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

Where 'F' denotes a feature matrix in the form of row and column. The maximum likelihood between the two features are estimated as follows,

$$F_k = \arg\max(\varphi_L) (2)$$

$$\varphi_L = \log\left[\left((2\pi d^2)^{1/2}\right). \frac{-0.5*|F_i - F_j|}{d^2}\right] (3)$$

From (3), 'F_k' denotes a Fisher Kernel output. 'φ_L' indicates the likelihood function, arg max indicates an argument of the maximum likelihood function.'F_i' and'F_j' denotes two feature set in the respective columns. 'log' indicate the logarithm function, 'd' symbolizes the deviation. The feature with maximum likelihood is selected for classification. The relevant (i.e., target) features are proposed over high-dimensional space within lesser dimensional space. It is given as,

$$\emptyset : T_F \rightarrow F_s (4)$$

From (4), '$\emptyset$'indicates the target projection function to map the target features '(T_F)' from the high dimensional space into the feature subset 'F_s' in the low dimensional space. This process minimizes the time complexity. The algorithmic process of FKTPFS is given as,

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 feature F_i
3. Construct feature matrix F',
4. Measure the likelihood between the features
5. if $(arg \max \varphi_L)$ 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 1 explains Fisher Kernelized Target Projective Feature Selection. Initially, the features are gathered. Next, feature matrix is constructed. The projection matrix scheme the better relationship features within two-dimensional spaces. Maximum likelihood between the features is measured. The feature with a higher likelihood is identified as the target feature for time series data prediction. The feature selection process in the FKTPFS technique reduces the time as well as the space complexity for performing big weather dataset.

4.EXPERIMENTAL EVALUATION

Experimental evaluations of the FKTPFS technique and existing data processing method [1] and deep learning method [2] are implemented using JAVA with E1 Nino dataset taken from https://www.kaggle.com/uciml/el-nino-dataset. It includes oceanographic as well as surface meteorological readings over sequence of buoys located through Pacific Ocean. Main aim of the dataset is to predict the seasonal-to-inter annual climate variations such as air temperature, surface temperatures, Humidity, for one to two years. It includes 178080 as well as 12 different attributes such as observation, year, month, day, etc to intensity of 500 meters. The latitude as well as longitude indicates that buoys shifted around to dissimilar locations of the equatorial Pacific Ocean. The latitude values are identified by degree over estimated location. The longitude values are collected with five degrees of estimated location. The zonal and meridional winds were varied among -10 m/s and 10 m/s. The relative humidity is normally observed among 70% and 90%. Air temperature, as well as sea surface, varied among 20 and 30 degrees Celsius. Every meteorological reading was collected by similar time. With helps of less number of features, marine weather prediction is carried out by using FKTPFS technique in efficient and accurate manner. With help of FKTPFS technique, five features of data instances

5.PERFORMANCE OF RESULTS ANALYSIS

In this section, simulation of FKTPFS, data processing method [1] and deep learning method [2] are discussed in this section with the different performance metrics namely feature selection accuracy, error rate, feature selection time and space complexity with the help of table and two-dimensional graph. For each subsection, FKTPFS technique is evaluated against other conventional methods.

Feature Selection Accuracy: It is defined as the ratio of the weather data accurately predicted to the total weather using the meteorological weather data. The feature selection accuracy is measured as,

$$FS_{acc} = \sum_{i=1}^{n} \frac{N_{df}}{ND_i} * 100 \quad (5)$$

From (5), 'FS_{acc}' represent thefeature selection accuracy. 'N_{df}' represent the number of data where features are correctly selected.'ND_i'Represents the number of data instances involved in the simulation process for marine weather prediction. It is measured in terms of percentage (%).

Mean Absolute Error (MAE): It is evaluated for calculating difference among actual value as well as predicted value. It is expressed by,

$$MAE = \frac{1}{n} \sum_{i=1}^{n} (AV_i - PV_i) * 100 \quad (6)$$

From (6), 'AV_i' denotes the actual value. 'PV_i' indicates predicted value. It is calculated by percentage (%).

Feature Selection Time: It is referred by number of time consumed for marine weather prediction using meteorological data.

$$FS_{time} = \sum_{i=1}^{n} ND_i * Time\ [single\ data\ instance] \quad (7)$$

From (7), 'FS_{time}' denotes the feature selection time.'ND_i'represents the number of data instances involved in the simulation process for marine weather prediction. It is calculated by milliseconds (ms).

Space complexity: It is calculated by number of memory space taken for performing the weather prediction. Formula for calculating the space complexity is measured as follows,

$$Com_S = \sum_{i=1}^{n} ND_i * Mem\ [single\ data\ instance] \quad (8)$$

From (8), 'Com_S' represent thespace complexity. 'ND_i'Symbolizes the data instances involved in the simulation process for marine weather prediction. 'Mem'portrays the memory for performing weather prediction. It is computed by megabytes (MB).

Table 1 Tabulation of Feature Selection Accuracy

Number of Instances (Number)	Feature Selection Accuracy (%)		
	FKTPFS Technique	Data Processing Method [1]	Deep Learning Method [2]
10000	98	93	91
20000	91	87	84
30000	94	92	91
40000	94	86	81
50000	94	89	88
60000	91	84	83
70000	89	84	83
80000	97	82	80
90000	98	81	81
100000	97	83	81

Table 1 reports feature selection accuracy with amount of time series data collected from dataset in the range from 10000 to 100000. The performance of different feature selection accuracy of FKTPFS as well as Data Processing Method [1] and Deep Learning Method [2]are given in the table 1. The table values reveal that feature selection accuracy of the FKTPFS technique is noticeably enhanced than the existing techniques. Let us consider that the 10000time series weather data in the first iteration. Consequently, the feature selection accuracy of the proposed FKTPFS technique is observed as98% and the feature selection accuracy of existing Data Processing Method [1] and Deep Learning Method [2] is 93% and91% respectively. Correspondingly, ten varieties of feature selection accuracy results of the proposed FKTPFS technique with conventional techniques. Feature selection accuracy of the FKTPFS technique is enhanced as 10% and 12% compared with [1] [2].

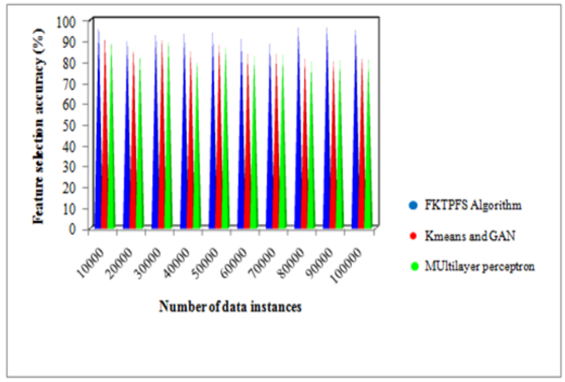

Figure 5 Comparative analysis of the feature selection accuracy

Figure 5 shows feature selection accuracy versus the number of data instances. As shown in figure 5, the blue colour denotes feature selection accuracy of the FKTPFS technique whereas red color as well as green colour denotes the feature selection accuracy of existing Data Processing Method [1] and Deep Learning Method [2]. According to the obtained results, the accuracy of FKTPFS is increased. This enhancement is achieved by applying the Fisher Kernelized Target Projective Feature Selection for identifying significant features .Fisher Kernelized Target Projective Feature Selection is to give the large separation of class means while maintaining the in-class variance small. The feature selection of FKTPFS technique is used for enhancing accuracy of the marine weather prediction.

Table 2 Tabulation of mean absolute error

Number of Data Instances	Mean absolute error (%)		
	FKTPFS Technique	Data Processing Method [1]	Deep Learning Method [2]
10000	2	7	9
20000	9	13	16
30000	6	8	9
40000	6	14	19
50000	6	11	12
60000	9	16	17
70000	11	16	17
80000	3	18	20
90000	2	19	19
100000	3	17	19

Table 2 given above explains the mean absolute error rate for three prediction methods, namely proposed FKTPFS Technique, existing Data Processing Method [1] and Deep Learning Method [2]. The objective is to identify that the mean absolute error rate using the FKTPFS Technique is found to be minimized. For every technique, totally ten different outcomes are obtained with various time series data taken from the dataset. For example, 10000 data are taken as input and the percentage of mean absolute error rate is 2% whereas the mean absolute error rate of the existing techniques namely Data Processing Method [1] and Deep Learning Method [2] is 7% and 9% respectively. Likewise, the nine iterations are conducted with various input weather data to attain ten results. The output of the FKTPFS Technique is compared with conventional techniques. Finally, mean absolute error rate is found to be significantly decreased by 56% and 61% compared with Data Processing Method [1] as well as Deep Learning Method [2].

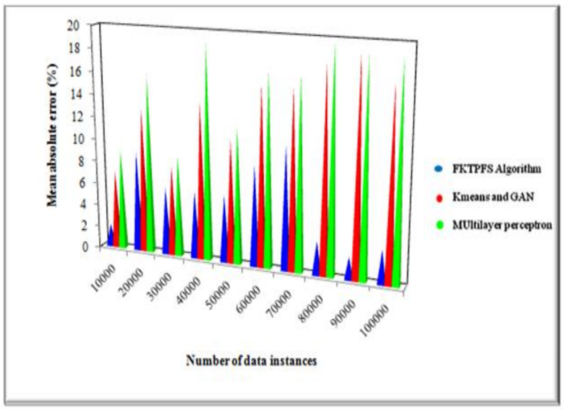

Figure 6 Comparative analysis of the mean absolute error

Figure 6 shows a comparison of the processed and two existing methods using number of weather data. In the above graphical illustration, different numbers of weather sample data and therefore a significant error rate is also observed for all three methods. From the figure, the error rate is said to be comparatively lesser using the FKTPFS Technique upon comparison with existing Data Processing Method [1] and Deep Learning Method [2]. The lesser mean absolute error rate using the FKTPFS Technique is due to the application of Fisher Kernelized Target Projective Feature Selection to identify the significant features. FKTPFS Technique is to give the large separation of class means while maintaining the in-class variance small. The feature selection of FKTPFS helps to enhance accuracy of the marine weather prediction. This helps to minimize the error rate.

Table 3 Tabulation of Feature Selection Time

Number of data instances	Feature Selection Time (ms)		
	FKTPFS technique	Data Processing Method [1]	Deep Learning Method [2]
10000	2100	2300	2600
20000	3800	4200	4600
30000	4500	5100	6000
40000	4400	5200	6000
50000	5000	6000	6500
60000	5400	6600	7200
70000	5950	7000	7700
80000	6400	7600	8000
90000	6750	8100	8550
100000	7000	8500	9000

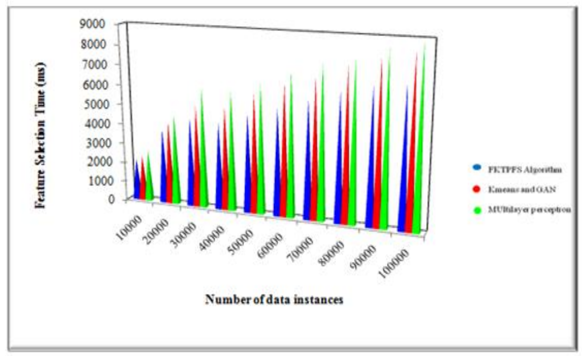

Figure 7 Comparative analysis of the feature selection time

Figure 7 given above shows the graphical representation of feature selection time using the proposed FKTPFS Technique, Data Processing Method [1] and Deep Learning Method [2]. From figure 5, prediction time is enhanced as amount of weather data. Prediction time of using the proposed FKTPFS Technique is comparatively minimized than [1] and [2]. This is owing to the application of geometric projection of the feature selection with Fisher Kernelized Target Projective Feature Selection. At first, projection matrix project the high similarity features. The maximum likelihood between the features is measured. The feature with a higher likelihood is identified as the target feature for accurate marine weather prediction. The feature selection process of the FKTPFS Technique reduces the feature selection time. Experimentation of '10000' amount of data instances and time consumed for feature selection using FKTPFS technique is '2200ms', and '2300ms' and2600ms' using Data Processing Method [1] and Deep Learning Method [2]. In experimentation, prediction time using the FKTPFS technique was comparatively smaller than [1] and [2]. With obtained results, the feature selection time of FKTPFS technique is compared with existing results. This helps to minimize the feature selection time of FKTPFS technique by 15% and 22% compared to [1] and [2].

Table 4 Tabulation of space complexity

Number of data instances	Space complexity (MB)		
	FKTPFS technique	Data Processing Method [1]	Deep Learning Method [2]
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

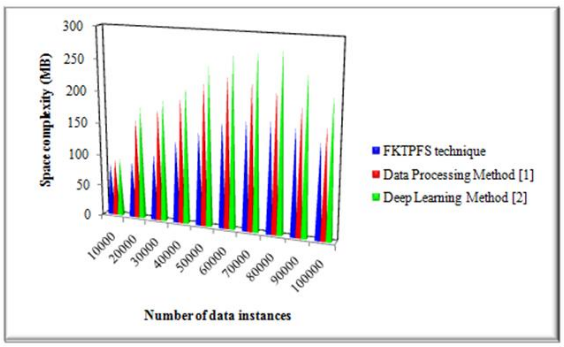

Figure 8 Comparative analysis of the space complexity

Table 4 and figure 8given above illustrate the comparative analysis of the space complexity with number of weather data. Figure 7 illustrates the comparison graphical illustration of space complexity using the FKTPFS technique, Data Processing Method [1] and Deep Learning Method [2]. The graphical results are inferred that the space complexity is comparatively smaller using the FKTPFS technique when 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. Space complexity of the FKTPFS is reduced as 26% than the Data Processing Method [1] and 36% when compared to Deep Learning Method [2].

CONCLUSION

A new marine weather prediction technique called FKTPFS which simultaneously analyzes the spatial and temporal features via feature selection and classification. The FKTPFS technique uses Fisher Kernelized Target Projective Feature Selection to analyze the features and selects the target features to minimize the dimensionality of the dataset hence reduce time and space complexity. The performance of the FKTPFS technique and existing classification techniques is estimated with different metrics such as feature selection accuracy, mean absolute error rate, feature selection time, and space complexity. The observed outcomes demonstrate higher feature selection accuracy is achieved using the FKTPFS technique and minimize the time, space complexity as well as error rate when compared to conventional classification methods.

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