PREDICTION OF CYCLONE USING KALMAN SPATIO TEMPORAL AND TWO DIMENSIONAL DEEP LEARNING MODEL

K. Rajesh[1*], V. Ramaswamy[2], K. Kannan[3]

[1,2]Srinivasa Ramanujan Centre, SASTRA Deemed University, India

[3]School of Education, SASTRA Deemed University, India

Email: rajesh@src.sastra.edu[1*] (corresponding author), ramaswamyv@src.sastra.edu[2], kkannan@maths.sastra.edu[3]

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ABSTRACT

Cyclone Classification and Prediction models rely on large intensity based on the maximum speed of the wind, along with the classification of intensity. The computational constraints blended with the formation of those intensities, cyclone classification and prediction firmly depreciate the full range of optimal features required for classification and hence accurate representation is less possible. Keeping this point, our study inspects the potential of Spatio-temporal features using a machine learning algorithm as an alternative to the current study of cyclones. This method is called, Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning (SKM-2DDP) for cyclone classification and prediction. To start with, pre-processing is performed by applying the Kalman Momentum Conservation Filter mechanism based on the design of the Dvorak technique to obtain optimal estimates of state variables and reduce the computational burden involved to remove noise from input cyclone images. With the resultant denoised input cyclone images, Spatio Temporal Feature Extraction is performed. Features obtained from the inherent intrinsic properties of pre-processed cyclone images of several weather conditions result in successful classification. Followed by pre-processing, in this work, features constituting both pixel-wise intensities over time and the directional length are being considered. The dependency of autocorrelation with each pixel's intensities over time and two temporal features are helped for coarse classification of weather conditions according to their visual effects. Finally, with the inherent intrinsic features extracted, a Two Dimensional Deep Learning model is utilized to foretell the cyclone intensity. Experimental evaluation of the proposed SKM-2DDP method is accomplished using images of cyclone dataset with many factors just as peak signal to noise ratio, prediction accuracy, prediction time and false-positive rate. Our own selves have considered with several cyclone images acquired from two different cyclone image datasets namely OCKHI_DEC2017 and VARDAH_DEC2016.

Keywords: Cyclone Classification and Prediction, Spatio-Temporal, Dvorak technique, Kalman Momentum, Two Dimensional Deep Learning

1.0 INTRODUCTION

In the planetary atmosphere, cyclones are assumed to be large-scale, nonlinear, coherent, and long-lived structures which are distinguished by powerful vertical winds and robust nonlinear momentum balance in horizontal winds. One of the well-studied problems in meteorology is cyclone tracking for which several methods are available. Conventional models used for cyclone tracking depend on several factors that require distinct domain knowledge. Moreover, depression analysis is another significant concept in meteorology. In specific, the temporal evolution of cyclone detection necessitates depression analysis.

A study of temporal evolution was performed in [1] called, Cyclone identification and tracking. A channel for the search of cyclones and their temporal evolution has been reported for cyclone description and tracking. The method combined the robustness of topological approaches and detailed tracking information using optical flow analysis. In this method, first cyclones were identified based on blooming topological concepts. Followed by which, the candidate was tracked using an optical flow field. These tracks were then clustered in a moving time window to discover prominent coherent cyclone movements and forwarded to a final tracking step. With this, temporal noise was said to be removed by identifying redundant tracks and therefore improving cyclone tracking accuracy.

Estimation of cyclone intensity is considered to be the most cumbersome process because of the complicated requirement of domain knowledge like feature extraction, pre-processing and analysis based on human intervention for analysis. Due to the resulting inconsistency, extensive pre-processing and problem domain complexity, intensity estimation is considered to be a time-consuming process. Deep Convolutional Neural Network [2] architecture was designed with the objective of classifying the hurricanes based on intensity via the graphics processing unit. With this, better accuracy was said to be achieved with the lower root-mean-square error.

On the above premises, this paper applies a Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning (SKM-2DDP) for cyclone classification and prediction including a deep learning model. The significant concepts of this paper are highlighted below:

1. Unlike relying on existing cyclone images, the cyclone prediction model for disaster risk assessment is followed to figure out the impacts of a cyclone using publicly existing images, vardah and ockhi cyclone images.

2. A Kalman Momentum Conservation Filter model is developed for concerning optimal estimates of state variables involving the Dvorak technique.

3. Combining the correlation model and covariance factor, the spatial and temporal features of high events are appraised, considering both time and location.

4. A new Two Dimensional Deep Learning model is proposed, which considers probability distribution in predicting the cyclone. To layout, the applicability of the proposed method, vardah and ockhi cyclone images are considered.

The rest of the paper is organized as follows. Section 2 describes related work for cyclone prediction. In section 3, we have presented the proposed method with clear block diagrams. Section 4 is concerned with the experimental setup followed by detailed discussion. At last, Section 5 concludes the paper.

2.0 RELATED WORKS

To predict weather conditions in a significant manner, weather forecasting is considered to be one of the main solutions. Due to this, severe situations about the weather even result in loss of lives if not properly predicted. Hence, there requires a certain amount of advancements in the prevailing prediction techniques with complex background.

In [4], the optical flow was utilized to observe and develop a certain amount of visual features for predicting effective weather conditions. However, certain reliable power grids are also found to be highly susceptible to extreme occurrences. A quantitative resilience assessment mechanism was designed, in [5] which both the spatial and temporal aspects of the typhoon. It also permitted measurement of resilience by taking into consideration, the intensity of the weather, emergency, etc.

A common mechanism for sampling the area of prediction is to create an ensemble of probable outcomes. In this manner, the ensemble's distribution provides the statistical analysis for the prediction space. However, research works on sampling space has revealed that the changes in the uncertainty of the prediction, due to size or strength results in adverse effects. This problem was addressed in [6] by specifically producing the ensemble as a set of annotated trajectories, and developing a smaller representative and spatially well-formed ensemble. However, depressions were not considered. As depression play a major role in cyclone prediction, analysis of cluster and recognition of a pattern in rainfall forecast for an hourly basis was presented in [7], therefore improving the rainfall forecast accuracy. A case study on the Bay of Bengal was presented in [8].

In several scientific analysis and processes involved in decision making, effective and efficient prediction of the climate remains the major cornerstone. As far as long term is concerned, different probable climate results in several hazards. To address this issue, a deep neural network model was applied in [9] for forecasting short term climate. Yet another global modeling was designed in [10] to reduce the coastal complexity. However, due to a lack of tropical cyclone intensity, the accuracy rate was found to be reduced. The impact of microphysics systems and topography on the estimation of heavy rainfall and tropical cyclone was presented in [11].

Though CNN is best suited for recognition of objects, it necessitates several modifications as far as the estimation of intensity is concerned. In [12] domain knowledge of meteorologists was integrated with the rotation invariance to reach better performance. Yet another new software library was presented in [13] for numerical weather prediction. Yet, another zero-inflated modelling mechanism and ANN (artificial neural networks) [14] for predicting the tornadoinduced property damage utilizing available data in public. Scientific challenges related to local to regional feedback processes leading to excess causes were presented in [15].

With the aid of satellite observations have resulted in an abundance of information about ocean circulation. Despite, these, the subsamples of the ocean are done by native satellite altimetry data and do not efficiently evaluate the subsurface quantities. Temporal data measurement for every orbital cycle is made twice, on the other hand, the spatial data heavily depends on the distance between tracks of the ground. To address this issue, a subgrid parameterization specific to a particular region or external forcing was designed in [16].

In [17], a case study related to trend analysis of rainfall and temperature was studied. Furthermore, long short-term memory for rainfall prediction was presented in [18] to measure the accuracy rate. Yet another adaptation of boosting ensemble mechanism to demand forecasting model by implementing a novel decision integration technique to improve the prediction accuracy was presented in [19]. A deep learning regression network was designed in [20] for moisture prediction.

The major issues in the cyclone classification and prediction are identified from the above-said literature such as less prediction accuracy, more prediction time, higher false-positive rate, minimal signals to noise ratio and so on. Such kinds of major issues are overcome by introducing a novel technique called Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning (SKM-2DDP).

This proposed work gets differentiated from the above-discussed literature studies in that optimal estimates of state variables about cyclone prediction are first presented. Unlike the literature studies, a novel deep learning model is proposed to boost the performance of cyclone prediction. In contrast to the above methods, our spatio-temporal model ensures that highly correlated features are extracted that in turn play a major role in determining the significance of a cyclone. Two-dimensional deep learning with potential predictors' efficiently predicts the intensity of the cyclone. The contents of the proposed scheme can be discussed in Section 3.

3.0 SPATIO-TEMPORAL KALMAN MOMENTUM AND TWO DIMENSIONAL DEEP LEARNING

For accurate cyclone prediction, we propose Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning (SKM-2DDP) to obtain optimal estimates of state variables and to learn effective features of cyclone trajectories for early prediction. The architecture of SKM-2DDP for cyclone classification and prediction is shown in figure 1.

The objective behind the use of the Kalman Momentum Conservation Filter mechanism lies in the fact that the performance of a forecast model changes from the cyclone to cyclone. A model works competently for a cyclone and another it does not. This event appears quite essential because each cyclone has distinct and neighborhood physical features. Hence, the Kalman Momentum Conservation Filter mechanism is applied as a pre-processing step to obtain the optimal estimates of state variables. Features acquired from the inherent characteristics of visual effects of several climatic conditions present to strong classification.

In this work, features constituting both pixel-wise intensities over time and the directional length are presented. Based on the correlation of each pixel's intensities for two different states, both spatio and features of temporal relations are used for the classification of climatic conditions in line with the visual effects. This is performed via Spatio Temporal Feature Extraction. Finally, with the extracted spatio-temporal features, early cyclone prediction is performed by applying the Two Dimensional Deep Learning model.

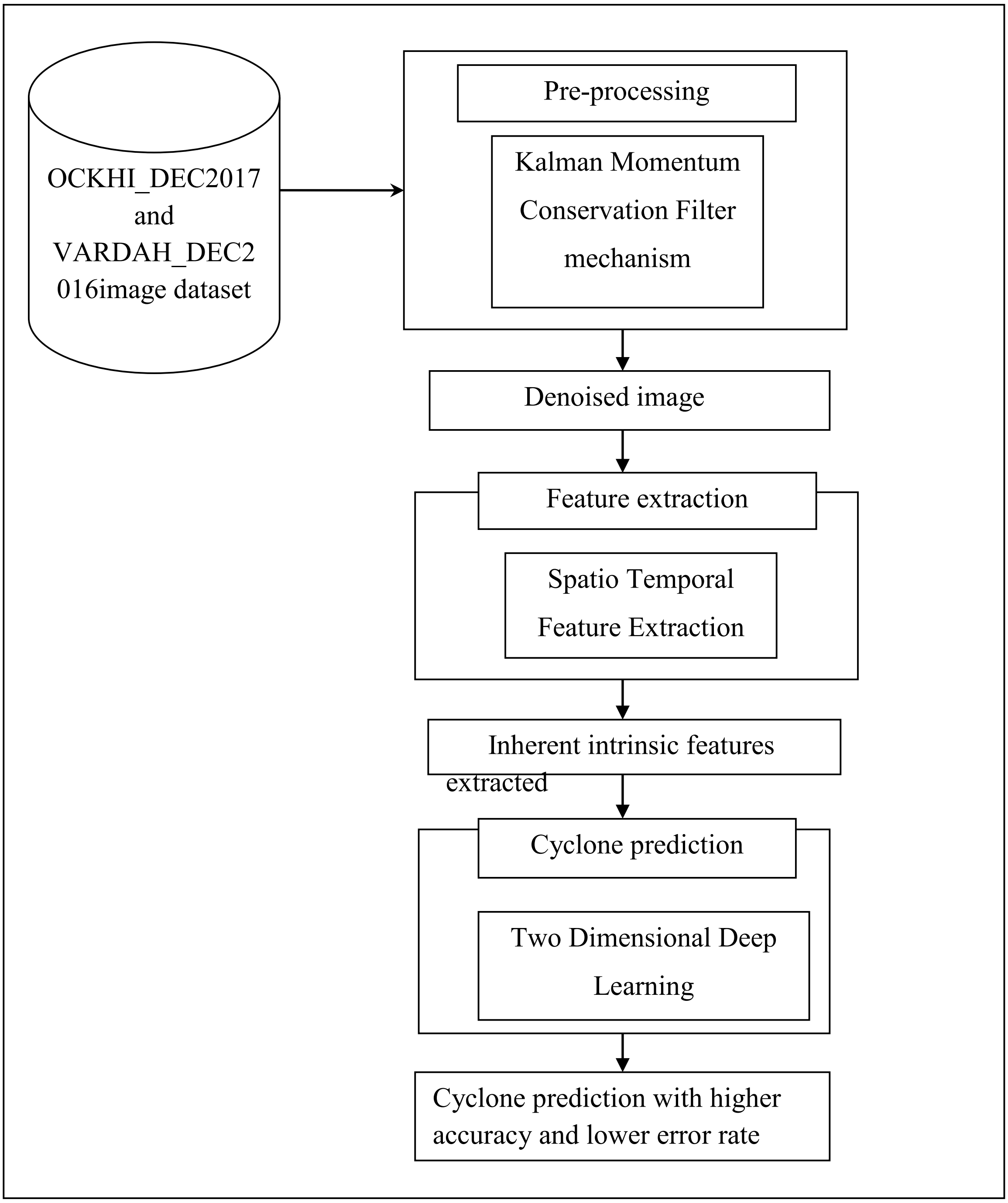

Fig. 1: Block diagram of Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning (SKM-2DDP)

3.1 System mode

In this work, the Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning (SKM-2DDP) for cyclone classification and prediction are designed based on a hypergraph model. The hypergraph model forms a generalization of a graph where an edge joins any number of vertices. The hypergraph 'HG' corresponds to a pair '$HG = (V, E)$', where 'V' denotes the number of vertices and 'E' denotes the non-empty subsets of 'V'. The input images are here represented in the form of vertices 'V' and the link between the pixels present in the input cyclone images is represented in the form of non-empty subsets.

3.2 Kalman Momentum Conservation Filter mechanism

In this section, to start with, initial pre-processing of input cyclone images is performed by applying the Kalman Momentum Conservation Filter mechanism. The mechanism is designed based on the Dvorak technique to obtain optimal estimates of state variables and reduce the computational burden involved in removing noise from input cyclone images. Figure 2 shows the block diagram of the Kalman Momentum Conservation Filter model.

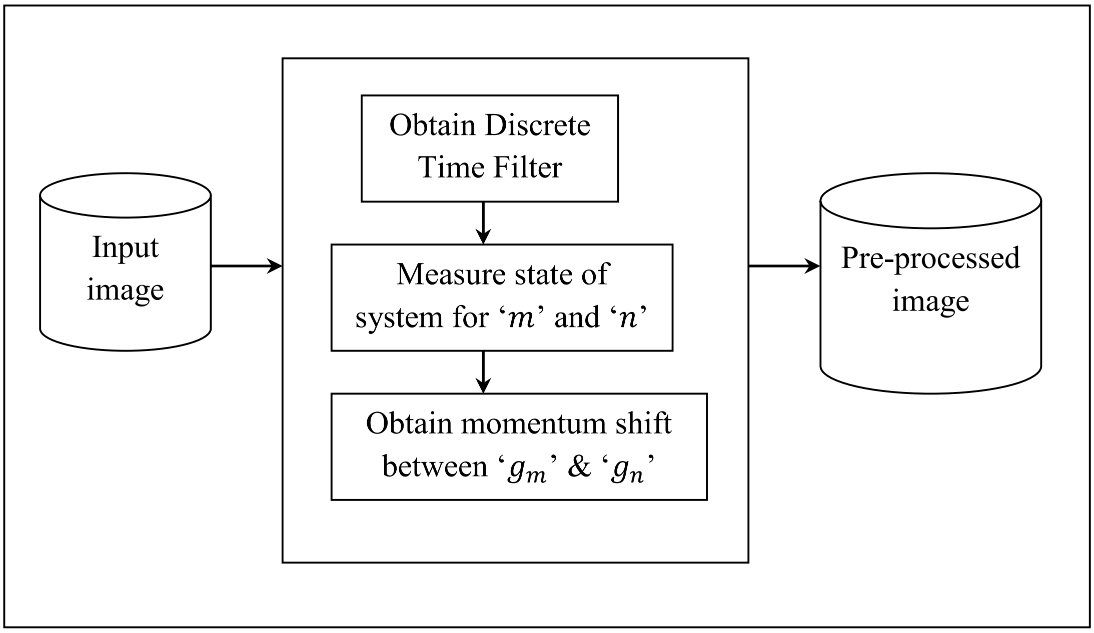

Fig. 2: Block diagram of Kalman Momentum Conservation Filter

As illustrated in the above figure 2, the discrete-time Kalman Filtering model utilized to procure the optimal estimate with a linear vector difference equation is expressed as given below.

$$p_m = STM\ (m, m-1).p_{m-1} + SI\ (m, m-1).v_{m-1} \quad (1)$$

From the above equation (1), the state of the system at the time 't_m' given by '$(n*1)$' vector for 'p_m' is obtained, '$(n*n)$' state transition matrix that corresponds the state at the time 't_{m-1}' to state at the time 't_m', '$(n*p)$' matrix that relates theoretical input at the time 't_{m-1}' to state at the time 't_m' and '$(n*p)$' theoretical random vector input at the time 't_m' respectively. Then, the states of the system for two different states 'm' and 'n' are assumed measurable through output 'q_m' and 'q_n' which is linearly related to the state distorted by a noise 'φ_m', 'φ_n' and is expressed as given below.

$$q_m = OM(m).p_m + \varphi_m \quad (2)$$
$$q_n = OM(n).p_n + \varphi_n \quad (3)$$

From above equations (2) and (3), with the aid of the observation matrices 'OM' for two different states 'm' and 'n', the momentum shift rate 'MS' of the two states '(q_m, q_n)' is equal to the sum of the forces acting on it for an input image 'x_{mn}' is expressed as given below.

$$MS(q_m, q_n) = \frac{\partial}{\partial t}(\rho q_m) + \frac{\partial}{\partial x_n}(\rho q_m q_n) \quad (4)$$

$$MS(q_m, q_n) = \frac{\partial}{\partial x_m} + \frac{\partial}{\partial x_n}\left[q\left(\frac{\partial q_m}{\partial x_n} + \frac{\partial q_n}{\partial x_m} - \frac{2}{3}\ \delta mn\ {}^{\partial q_m}/_{\partial x_m}\right)\right] + \frac{\partial}{\partial x_n}(-\rho q_m q_n) \quad (5)$$

The pseudo code representation of Kalman Momentum Conservation pre-processing algorithm is given below.

Input: Input image 'x_{mn}', time 't_m' noise 'φ_m, φ_n'
Output: Pre-processed image with optimal estimates of state variables

Begin
  For Input image 'x_{mn}'
    Measure optimal estimate with linear vector difference using equation (1)
    For each state of the system for two different states 'm' and 'n' distorted by a noise 'φ_m', 'φ_n'
      Measure output 'q_m' and 'q_n' using equation (2) and (3)
      Obtain a momentum shift rate for two states '(q_m, q_n)' using equation (4) and (5)
      Return (pre-processed image)
    End for
  End for
End

Algorithm 1: Kalman Momentum Conservation pre-processing algorithm

To start with, in the Kalman Momentum Conservation pre-processing algorithm, with the aid of satellite picture of a tropical cyclone, the input cyclone image is matched with a number of all possible pattern types [3], namely, Curved band Pattern, Shear Pattern, Eye Pattern, Central Dense Overcast (CDO) Pattern, Embedded Center Pattern or Central Cold Cover Pattern and so on. In our work, as the infrared satellite imagery is available for Eye Patterns, the difference between the temperature of the warm eye and surrounding cold cloud tops are computed. Higher the contrast, the more powerful the tropical cyclone is evaluated to be. With higher contrast images, a linear vector difference equation is obtained for each input image. Next, states of the system for two different states at different time intervals are observed. Finally, the momentum shift is extracted to obtain optimal estimates of state variables.

3.3 Correlated Spatio Temporal Feature Extraction

With the resultant denoised input cyclone images, Spatio Temporal Feature Extraction is performed. As to perform fine-tuned classification about several weather conditions, the main objective in this work remains in extracting effective and efficient features that preserve the similar weather conditions, whereas differentiating the distinct ones. This is said to be achieved by extracting the spatio and temporal features. Figure 3 shows the block diagram of the correlated spatio-temporal feature extraction model.

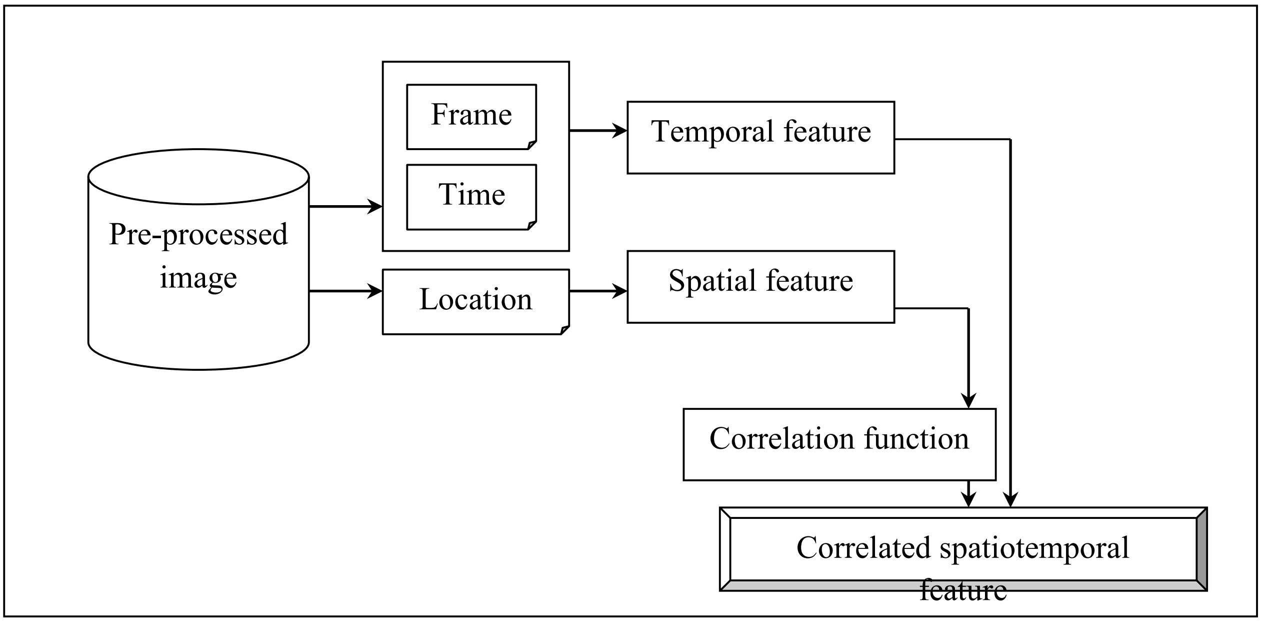

Fig.3: Block diagram of Correlated Spatio Temporal Feature Extraction model

As illustrated in the above figure, concentrating on each pixel, intensities of image sequences representing different states with respect to time are evolved as temporal features and is expressed as given below.

$$TF = \frac{COV(PI_{CF+DF}, PI_{DF})}{COV(PI_{DF}, PI_{DF})} \tag{6}$$

From the above equation (6), the temporal factors for the corresponding pre-processed images 'PI' are arrived based on the covariance factor. In the high dimensional setting, though optimal estimates of state variables are obtained via pre-processing, the number of variables in pre-processed image 'PI' is found to be greater than the sample size 'n'. This dimensionality poses a challenge in extracting potential predictors. To address this issue, a covariance factor is evolved in the above equation (6), that determines the current frame 'CF' and displace frame 'DF' number of time series '$PI_t, t \in T$'. Followed by this, a correlation function 'C_{fun}' is expressed as given below that includes the pre-processed images for current frame 'PI_{CF}', pre-processed images including both current and displaced frame 'PI_{CF+DF}' and the average pixels of the pre-processed images '$AVG(PI)$' respectively. This is expressed as given below.

$$C_{fun} = \frac{(PI_{CF} - AVG(PI))(PI_{CF+DF} - AVG(PI))}{(PI_{CF} - PI)} \tag{7}$$

Based on the correlated function, the spatio features are extracted and observed at location 'loc' and is mathematically expressed as given below.

$$SP = C_{fun}.AVG \left[\frac{PI_{loc}(k)}{T}\right] \tag{8}$$

The pseudo-code representation of correlated feature extraction is given below.

Input: pre-processed image 'PI'
Output: Spatio-temporal feature 'ST' extraction with potential predictor
1: **Begin** 2: **For** each pre-processed image 'PI' 3: Extract temporal factors using (6) 4: Obtain the correlation function using equation (7) 5: Extract spatio factors based on correlation using equation (8) 6: **Return** (spatio-temporal features) 7: **End for** 8: **End**

Algorithm 2: Correlated feature extraction

As given in the above-correlated feature extraction algorithm with the pre-processed cyclone images given as input, the objective remains in extracting potential predictors that later serve for significant prediction. This is achieved by extracting both the temporal and spatio features. A correlation function over time and location is then used to extract spatio features, resulting in a potential predictor extractor model.

3.4 Two Dimensional Deep Classification model

Finally, with the inherent intrinsic features extracted, a Two Dimensional Deep Learning model is incorporated to predict the cyclone intensity. With the heavy complication and increasing quantity of data being collected, a single-dimensional model is limiting. A two-dimensional deep learning model with the potentiality of any complex nonlinear spatio and temporal behaviors of a cyclone might increase the accuracy of prediction of future cyclone trajectories. Each Two Dimensional Deep Learning (2DDL) pattern involves a visible layer, 'VL', a hidden layer 'HL', linked by weights 'W'. The parameter involved in the design of 2DDL involves three factors, representing weights 'W', and two bias factors 'u' and 'v' expressed as given below.

$$\theta = (W, u, v) \tag{9}$$

From the above equation (9), the probability pattern 'PP' mapping between the visible and hidden layer is expressed as given below.

$$PP = -\sum_i a_i VL_i - \sum_j b_j HL_j - \sum_i \sum_j W_{ij} VL_i HL_j \tag{10}$$

From the above equation (10), the probability pattern is measured based on the weight 'W_{ij}' between visible layer 'VL_i' and hidden layer 'HL_j', bias 'a_i' and 'b_j' respectively. Then, the probability distribution which is utilized to predict the output vector with respect to the visible layer 'VL' is expressed as given below.

$$Prob(VL \mid \theta) = \frac{PP\ (VL \mid \theta)}{PP(VL, HL \mid \theta)} \tag{11}$$

The pseudo-code representation of Two Dimensional Deep Classification is given below.

Input: Spatio-temporal feature 'ST', visible layer 'VL', a hidden layer 'HL'
Output: Significant cyclone prediction

```
Begin
    For each Spatio-temporal feature 'ST'
        Obtain probability pattern 'PP' mapping between the visible and hidden layer using equation (10)
        Measure probability distribution to predict output vector to visible layer 'VL' using equation (11)
        If 'Prob(VL |θ)' = 1 then
            Possible occurrence of cyclone
        End if
        If 'Prob(VL |θ)' <> 1 then
            No possible occurrence of cyclone
        End if
    End for
End
```

Algorithm 3: Two Dimensional Deep Classification algorithm

As given in the above Two Dimensional Deep Classification algorithm, the objective remains in predicting the intensity of cyclone through a probability distribution. Here, the hidden states first extract and provide notable hidden dynamic features from the extracted spatio-temporal features and permit the visible layer to accordingly weight these patterns. Making the two-dimensional deep learning models appropriate and effective, it makes forecasting the complex atmospheric systems of cyclones in a significant manner.

The Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning algorithm is given below:

Input: Input image 'x_{mn}', time 't_m' noise 'φ_m, φ_n'
Output: Efficient cyclone prediction with a minimum error rate

```
// Pre-processing Phase
Begin
    For Input image 'x_mn'
        Measure optimal estimate with linear vector difference using equation (1)
        For each state of the system for two different states 'm' and 'n' distorted by a noise 'φ_m', 'φ_n'
            Measure output 'q_m' and 'q_n' using equation (2) and (3)
            Obtain a momentum shift rate for two states '(q_m, q_n)' using equation (4) and (5)
            Obtain a pre-processed image
        End for
    End for
// Feature Extraction
For each pre-processed image 'PI'
        Extract temporal factors using (6)
        Obtain correlation function using equation (7)
        Extract spatio factors based on correlation using equation (8)
        Extracted spatio-temporal features
    End for
// Classification Phase
    For each Spatio-temporal feature 'ST'
        Obtain probability pattern 'PP' mapping between the visible and hidden layer using equation (10)
        Measure probability distribution to predict output vector to visible layer 'VL' using equation (11)
        If 'Prob(VL |θ)' = 1 then
            Possible occurrence of cyclone
```

End if
If ‘$Prob(VL\ |\theta)$’ <> 1 **then**
No possible occurrence of cyclone
End if
End for
End

Algorithm 4: Spatio-Temporal KalmanMomentumand Two Dimensional Deep Learning algorithm (SKM-2DDP)

Algorithm 4 represents the processing steps of the SKM-2DDP algorithm for predicting cyclone with higher accuracy and minimum error. At first, the input image is taken from the dataset. The input image is denoised by using the Kalman momentum conservation filter mechanism. With the pre-processed image, a correlated spatio- temporal feature extraction process is performed for extracting different features. Then, the correlated spatio extracted features are given to the input of two-dimensional deep learning models. In this model, the prediction of the cyclone with a lower error rate is achieved by measuring the probability distribution function.

4.0 EXPERIMENTAL EVALUATION

This section describes the process of evaluating the Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning (SKM-2DDP) for cyclone classification and prediction. The SKM-2DDP is evaluated in different aspects, Peak signal to noise ratio, cyclone prediction accuracy, cyclone prediction time, false-positive rate with respect to different images extracted from two image datasets, namely, OCKHI_DEC2017 and VARDAH_DEC2016 gathered at the different time and same images are applied to comparison with the existing methods for a fair comparison. This is performed using MATLAB. The data set used in SKM-2DDP is obtained from National Central Satellite Meteorological Centre (Cyclone Image) via http://satellite.imd.gov.in/dynamic/insat_3DR.htm

4.1 Impact of PSNR

Peak signal to noise ratio is defined as the ratio of the original cyclone image and the distorted images. The Peak signal to noise ratio is measured as follows,

$$PSNR = 10 * log_{10} \left[\frac{R^2}{MSE}\right] \quad (12)$$

$$MSE = (I - I')^2 \quad (13)$$

From the above equation (12) and (13), the peak signal to noise ratio corresponds to the ratio of the logarithmic value of the maximum possible pixel value of the image ‘R’ and the mean square error ‘MSE’ respectively. Mean square error ‘MSE’ refers to the square difference between the original image ‘I’ and noisy image ‘I'’ respectively. Here the value of the maximum possible pixel is assigned as ‘dB’.

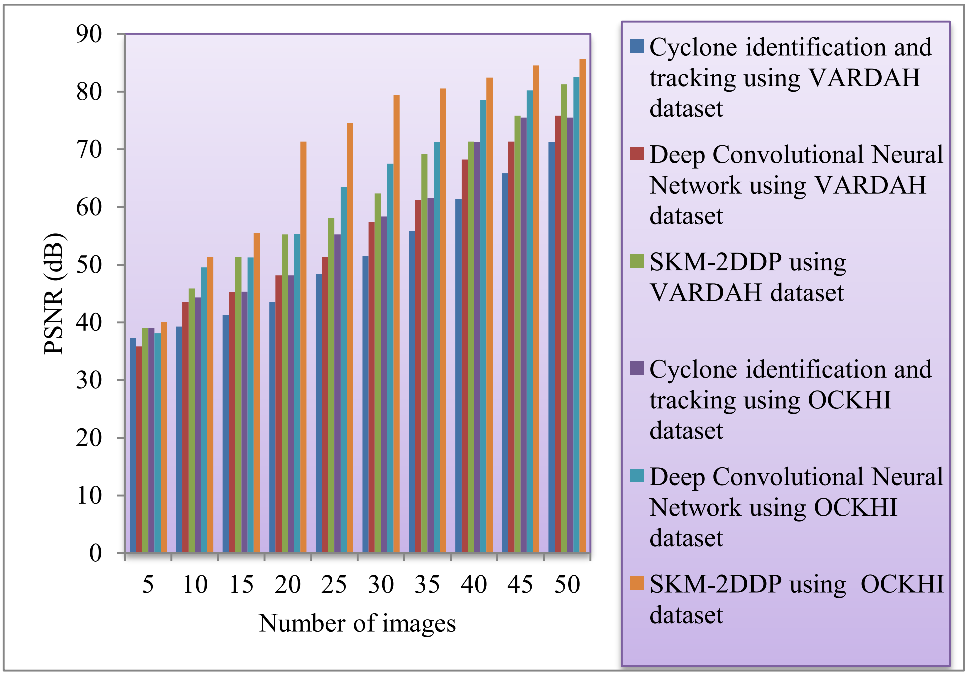

Fig. 4: Performance graph of PSNR using vardah cyclone images and ockhi cyclone images

Figure 4 given above shows the graphical representation of the PSNR. Here, in the above figure, the x-axis represents the different numbers of images obtained from two different image sets, namely vardah cyclone images and ockhi cyclone images collected at different time intervals of varying sizes. On the other hand, the y-axis represents the PSNR measured in terms of decibels (dB). With the increase in the number of cyclone images provided as input, the peak signal to noise ratio also increases. Higher the PSNR rate, the more efficient the method is said to be. From the figure, it is inferred that the PSNR is found to be improved by applying both the vardah cyclone images and ockhi cyclone images. For simulation purpose, with 5 numbers of images given as input, the MSE using vardah cyclone images for the existing Cyclone identification and tracking [1] and Deep Convolutional Neural Network [2] was observed to be 121 and 169, similarly, for the proposed SKM-2DDP method it was observed to be 81. Therefore, the PSNR with vardah cyclone images using existing Cyclone identification and tracking [1] and Deep Convolutional Neural Network [2]was found to be '37.30dB', '35.85dB' and '39.04' using SKM-2DDP method. Similarly, the PSNR, when applied with the ockhi cyclone images using the existing Cyclone identification and tracking [1] and Deep Convolutional Neural Network [2], was found to be '30.04dB', '38.13dB' and '40.06dB' using SKM-2DDP method. This was due to the application of the Kalman Momentum Conservation Filter model. By applying the Kalman Momentum Conservation Filter model, higher contrast images were obtained using the Dvorak technique. With the higher contrast images, by applying the momentum conservation optimal estimates of state variables are said to form. Therefore, the PSNR using the SKM-2DDP method is improved by 18% and 10% when compared with [1] and [2] using vardah cyclone images. Similarly, the PSNR using the SKM-2DDP method is improved by 23% and 11% when compared with [1] and [2] using ockhi cyclone images.

4.2 Impact of Cyclone prediction accuracy

Cyclone prediction accuracy is determined based on the percentage ratio of the number of cyclone images correctly predicted to the overall samples used as input for experimentation. The cyclone prediction accuracy is calculated as specified below.

$$PA = \frac{Number\ of\ cyclone\ images\ correctly\ predicted}{n} * 100 \quad (14)$$

From the above equation (14), the cyclone prediction accuracy 'PA' is measured in terms of percentage (%) with 'n' corresponding to the input images provided as a sample. Higher the cyclone prediction accuracy more efficient the method is said to be.

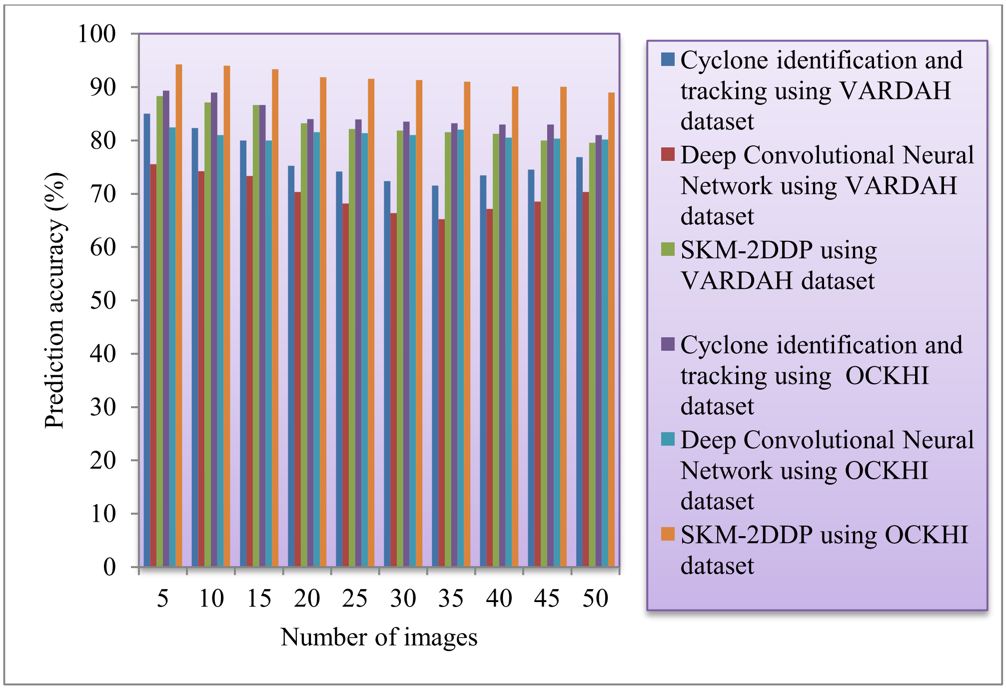

Fig.5: Performance graph of Cyclone prediction accuracy using vardah cyclone images and ockhi cyclone images

Figure 5 illustrates the convergence graph of cyclone prediction accuracy utilizing vardah cyclone and ockhi cyclone images. As shown in the above figure, the cyclone prediction accuracy is directly proportional to the number of varied images provided as input for the simulation setup. This is because, with the increase in the number of images, the sizes of images also vary according to the two different cyclone images and hence, the prediction rate also differs. However, from the figure, it is inferred that the cyclone prediction accuracy seems to be better using the SKM-2DDP scheme when compared to the two existing methods [1] and [2] for both the vardah cyclone images and ockhi cyclone images. This is evident from the mathematical calculations for sample images 15. When '15' sample images were used, the overall prediction accuracy using SKM-2DDP was observed to be '86.66%', using Cyclone identification and tracking was observed to be '80%' and using Deep Convolutional Neural Network it was observed to be '73.33%' when applied with vardah cyclone images. Similarly, when applied with ockhi cyclone images, the overall cyclone prediction accuracy using SKM-2DDP was observed to be '93.33%', using Cyclone identification and tracking was observed to be '86.66%' and using Deep Convolutional Neural Network it was observed to be '80%'. This is due to the application of a correlated spatio-temporal feature extraction model. By applying the correlated spatio-temporal feature extraction model, only potential predictors were extracted based on the correlation measurement. This was done by obtaining the covariance factor for both the current frame and the displaced frame. With these resultant values, both the temporal and spatial features were obtained. Therefore, the cyclone prediction accuracy is said to be improved using SKM-2DDP by 9% and 19% when compared to [1] and [2] using vardah cyclone images and improved using SKM-2DDP by 8% and 12% when compared to [1] and [2] using ockhi cyclone images respectively.

4.3 Impact of Cyclone prediction time

Cyclone prediction time indicates the time consumed in predicting the cyclones correctly and the overall samples which is specified as input for experimentation. The cyclone prediction time is formulated as below.

$$PT = n * Time\ [Cyclone\ prediction\ ] \quad (15)$$

From the equation (15), the cyclone prediction time 'PT' is calculated in terms of milliseconds (ms) with 'n' corresponding to the input images given as the sample. Lower the cyclone prediction time more efficient the method is said to be. Figure 6 given below illustrates the cyclone prediction time using vardah cyclone images and ockhi cyclone images. With the x-axis corresponding to the different numbers of images provided as input using vardah cyclone images and ockhi cyclone images collected at different periods, the y-axis represents the cyclone prediction time. It is measured in terms of milliseconds (ms). From the convergence plot it is inferred that with higher numbers of images provided as input, the size of the images differs and hence the cyclone prediction time is also found to be higher with the increasing number of images. However, another fact to be observed that the cyclone prediction time using the SKM-2DDP scheme is found to be better and wise than the existing methods [1] and [2] for both the vardah cyclone images and ockhi cyclone images.

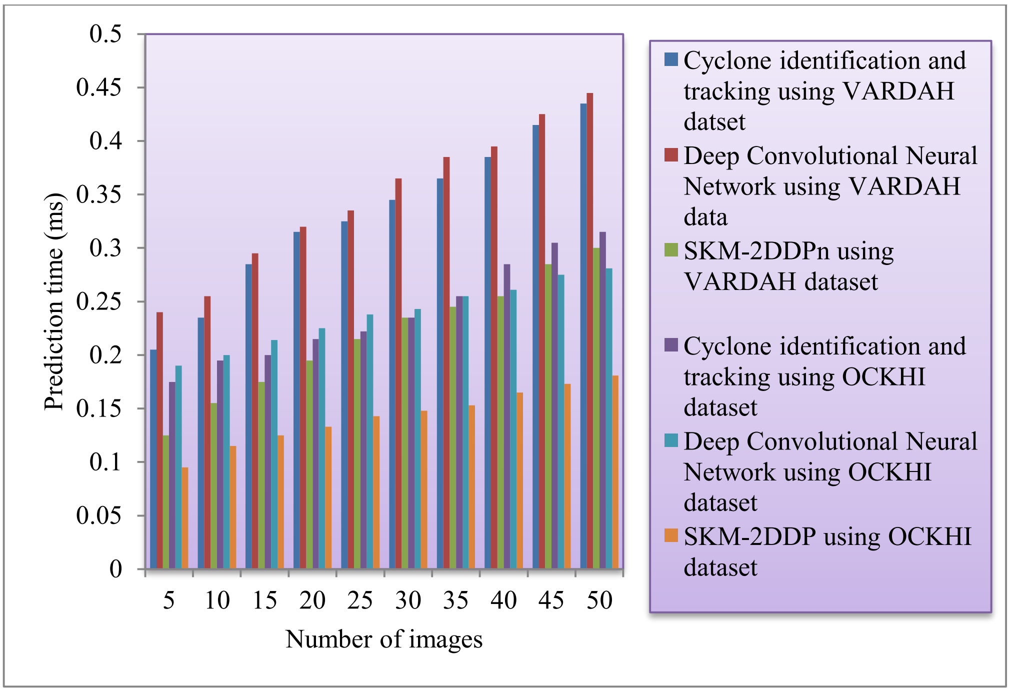

Fig.6: Performance graph of Cyclone prediction time using vardah cyclone images and ockhi cyclone images

This is evident from the sample calculations. With '15' sample images provided as input using the SKM-2DDP method, the overall cyclone prediction was observed to be '$0.125ms$', using [1] it was observed to be '$0.205ms$' and using [2] it was observed to be '$0.24ms$' when applied with vardah cyclone images. Similarly, by applying ockhi cyclone images, the overall cyclone prediction was observed to be '$0.095ms$' using the SKM-2DDP method, using [1] it was observed to be '$0.175ms$' and using [2] it was observed to be '$0.19ms$'. From this sample mathematical calculation, it is evident that the cyclone prediction time was found to be lesser using the SKM-2DDP method when compared to [1] and [2]. This is because of the application of the correlated feature extraction algorithm. By applying the correlated feature extraction algorithm, only highly correlated features were extracted. With this highly correlated feature, the cyclone prediction time was found to be lesser using the SKM-2DDP method by 34% and 38% compared to [1] and [2] using vardah cyclone images. Similarly, by applying the ockhi cyclone images, the cyclone prediction time was found to be lesser using the SKM-2DDP method by 40% and 41% compared to [1] and [2] respectively.

4.4 Impact of False positive rate

The false-positive rate is mentioned as the percentage ratio of the number of satellite cyclone images incorrectly predicted as the probability of occurrences of cyclone images to the total number of sample images provided as input. The mathematical representation of the false-positive rate is measured using the following equations,

$$FPR = \frac{No.of\ images\ incorrectly\ predicted}{n} * 100 \tag{16}$$

From the above equation (16), the false-positive rate 'FPR', is measured based on the sample images 'n' provided as input. It is measured in terms of percentage (%).

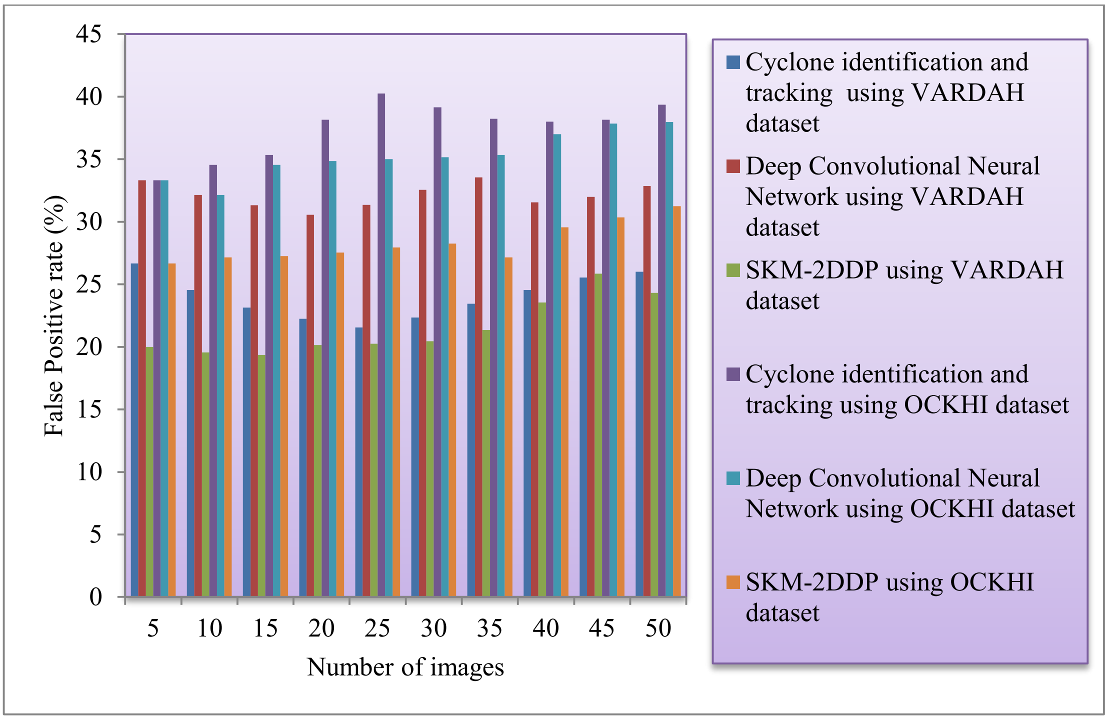

Fig.7: Performance graph of false-positive rate using vardah cyclone images and ockhi cyclone images

Figure 7 given above shows the convergence graph of the false-positive rate using vardah cyclone images and ockhi cyclone images. From the figure, it is inferred that by applying both the images, the false positive rate is found to be lesser using the SKM-2DDP method when compared to [1] and [2]. Let us consider, '5' sample images provided as input the false positive rate of proposed SKM-2DDP method is '20%', whereas the false-positive rate of existing [1] & [2] is 27% and 33% when applied with vardah cyclone images. Similarly, by applying ockhi cyclone images, the false positive rate is observed as 27% using the SKM-2DDP method, using [1] it was observed to be '33%' and using [2] it was observed to be '33%'. This is because of the incorporation of Two Dimensional Deep Classification algorithm. By implementing this algorithm, the probability distribution is applied to predict the intensity of the cyclone. Besides, the hidden states are initially extracted and in turn, ensure notable hidden dynamic features via correlated spatio-temporal features. In this way, it provides a visible layer to accordingly weight the patterns according to the possible occurrence of the non-occurrence of the cyclone. With this classification, the false positive rate is said to be minimized using SKM-2DDP method by 10% and 33% compared to [1] and [2] for vardah cyclone images and similarly by 24% and 20% compared to [1] and [2] for ockhi cyclone images. From this analysis, the false-positive rate of the proposed SKM-2DDP method is lesser when compared to other existing methods.

The proposed SKM-2DDP method enhances the performance of the cyclone prediction with the help of a deep learning model. In this method, the peak signal to noise ratio is enhanced by applying the Kalman Momentum Conservation Filter model and higher image quality is obtained using the Dvorak technique. Then, with the help of correlated spatio-temporal feature extraction model cyclone prediction accuracy is increased and reduces the prediction time efficiently. Finally, Two Dimensional Deep Classification algorithm is applied to predict the cyclone intensity with minimum false positive rate.

5.0 CONCLUSION

In this paper, Spatio-Temporal Kalman Momentum and Two Dimensional Deep Learning (SKM-2DDP) for cyclone classification and prediction with higher cyclone prediction accuracy and the lower error rate is proposed. Three novel models have been proposed. The first model called, Kalman Momentum Conservation Filter model aims to select optimal estimates of state variables at each round for different images. It's done by obtaining the momentum shift rate and applying the Dvorak technique. The second model, called, Correlated Spatio Temporal Feature Extraction has targeted to extract the potential predictor. Correlated feature extraction is used to get highly correlated features. Finally, the Two Dimensional Deep Learning model performs the cyclone prediction through a probability distribution. Following the procedures of the three proposed methods will not only improve the cyclone prediction accuracy but also reduces the false positive rate and cyclone prediction time. So, the error rate is found to be comparatively lesser with the state-of-the-art methods. The performance results of the proposed method have confirmed using MATLAB simulation with two datasets such as vardah and ockhi dataset. Through the implementation, the proposed method is compared with the state-of-the-art method in terms of cyclone prediction accuracy, cyclone prediction time, PSNR and false positive rate that yields better outcomes than others. From the experimental results, 91% of prediction accuracy is increased, 28% of the false positive rate is reduced, 21% of prediction time is reduced and 71% of peak signal to noise ratio is increased by the proposed SKM-2DDP method. However, the proposed method does not consider the accuracy of feature selection. In future work, the effective ensemble classification model is used to enhance the performance of feature selection accuracy and prediction accuracy of cyclone data.

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REFERENCES

[1] Akash Anil Valsangkar, Joy Merwin Monteiro, Vidya Narayanan, Ingrid Hotz, Member, IEEE and Vijay Natarajan, “An Exploratory Framework for Cyclone Identification and Tracking”, IEEE Transactions on Visualization and Computer Graphics. Vol. 25, Issue: 3, March 1 2019

[2] Ritesh Pradhan, Ramazan S. Aygun, ManilMaskey, Rahul Ramachandran, and Daniel J. Cecil, “Tropical Cyclone Intensity Estimation Using a Deep Convolutional Neural Network”, IEEE Transactions on Image Processing, Vol. 27, Issue: 2, February 2018

[3] Xiao-Yong Zhuge, Jian Guan, Fan Yu, and YuanWang, “A New Satellite-Based Indicator for Estimation of the Western North Pacific Tropical Cyclone Current Intensity”, IEEE Transactions on Geo Science and Remote Sensing, Vol. 53, No. 10, OCTOBER 2015

[4] SnehlataShakya, Sanjeev Kumar, “Characterizing and predicting the movement of clouds using fractional-order optical flow”, The Institution of Engineering and Technology, Vol 13 Iss 8, pp. 1375-1381, Jun 2019

[5] Yihao Yang, Wenhu Tang, Yang Liu, Yanli Xin, Qinghua Wu, “Quantitative Resilience Assessment for Power Transmission Systems Under Typhoon Weather”, IEEE Translations and content mining, Jun 2018

[6] Le Liu, Lace Padilla, Sarah H. Creem-Regehr, Donald H. House, “Visualizing Uncertain Tropical Cyclone Predictions using Representative Samples from Ensembles of Forecast Tracks”, IEEE Transactions on Visualization and Computer Graphics, Jun 2018

[7] Fu-Ru Lin,1 Nan-Jing Wu,2 and Ting-Kuei Tsay1,” Applications of Cluster Analysis and Pattern Recognition for Typhoon Hourly Rainfall Forecast”, Advances in Meteorology, Hindawi, Mar 2017

[8] Mir Kashem, MdKawser Ahmed, FangliQiao, M A E Akhter, K M Azam Chowdhury, “The response of the upper ocean to tropical cyclone Viyaru over the Bay of Bengal”, ActaOceanologicaSinica – Springer, Jun 2019

[9] Theodore Weber, Austin Corotan, Brian Hutchinson, Ben Kravitz, and Robert Link, "Technical Note: Deep Learning for Creating Surrogate Models of Precipitation in Earth System Models", Atmospheric Chemistry and Physics, Discussions, Apr 2019

[10] Nadia Bloemendaal, SanneMuis, Reindert J. Haarsma, Martin Verlaan, MaialenIrazoquiApecechea, Hans de Moel, Philip J. Ward, Jeroen C. J. H. Aerts, "Global modeling of tropical cyclone storm surges using highresolution forecasts", Climate Dynamics, Springer, Sep 2018

[11] Khin Win Maw1,2 and Jinzhong Min3," Impacts of Microphysics Schemes and Topography on the Prediction of the Heavy Rainfall in Western Myanmar Associated with Tropical Cyclone ROANU", Hindawi, Sep 2017

[12] Boyo Chen, Buo-Fu Chen, Hsuan-Tien Lin, "Rotation-blended CNNs on a New Open Dataset for Tropical Cyclone Image-to-intensity Regression", ACM, Aug 2018

[13] Willem Deconinck, Peter Bauer, MichailDiamantakis, Mats Hamrud, Christian Kühnlein, Pedro Maciel, GianmarcoMengaldo, Tiago Quintino, BaudouinRaoult, Piotr K. Smolarkiewicz, Nils P. Wedi, "Atlas: A library for numerical weather prediction and climate modeling", Computer Physics Communication, Elsevier, Jul 2017

[14] Jeremy Diaz, Maxwell B. Joseph, "Predicting property damage from tornadoes with zero-inflated neural networks", Weather and Climate Extremes, Elsevier, Jan 2019

[15] Jana Sillmann, ThordisThorarinsdottir, Noel Keenlyside, Nathalie Schaller, Lisa V. Alexander, Gabriele Hegerl, Sonia I. Seneviratne, Robert Vautard, Xuebin Zhang, Francis W. Zwiers, "Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities", Weather and Climate Extremes, Elsevier, Sep 2017

[16] Thomas Bolton, Laure Zanna, "Applications of Deep Learning to Ocean Data Inference and Subgrid Parameterization", Journal of Advances in Modeling Earth Systems, Feb 2019

[17] AmogneAsfaw, Belay Simane, Ali Hassen, Amare Bantider, "Variability and time series trend analysis of rainfall and temperature in north central Ethiopia: A case study in Woleka sub-basin", Weather and Climate Extremes, Elsevier, Aug 2018

[18] Zeyi Chao, Fangling Pu, Yuke Yin, Bin Han, Xiaoling Chen, "Research on Real-Time Local Rainfall Prediction Based on MEMS Sensors", Journal of Sensors, Hindawi, Jun 2018

[19] ZeynepHilalKilimci, A. Okay Akyuz, MitatUysal, SelimAkyokus, M. OzanUysal, Berna Atak Bulbul, Mehmet Ali Ekmis, "An Improved Demand Forecasting Model Using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain", Complexity, Hindawi, Mar 2019

[20] Yu Cai, Wengang Zheng, Xin Zhang, Lili Zhangzhong, XuzhangXue, "Research on soil moisture prediction model based on deep learning", PLOS ONE | https://doi.org/10.1371/journal.pone.0214508 April 3, 2019