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Survival study on cyclone prediction methods with remote sensing images

B. Suresh Kumar
Assistant Professor/Programmer, Department of Computer and Information Science, Annamalai University, Annamalai Nagar, Chidambaram-608002
Corresponding author email: sureshaucis@gmail.com

Dr. D. Jayaraj,
Assistant Professor/Programmer, Department of CSE, FEAT, Annamalai University, Annamalai Nagar, Chidambaram-608002
Email: jayarajvnr@gmail.com

***Abstract*---**Image classification has large interest for many decades in the remote sensing communities to reduce injure caused by cyclones. A cyclone is the leading rotating storm that includes the strong wind and rain. It included the number of interrelated features like eye, cyclone pathway, wind speed, generated storm surges, rainfall intensity and so on. Among the features, it is essential one to find in which direction cyclone travels and it influence the areas increasing the damage to life and assets. The cyclone prediction is a key issue where image intensity described the pattern characteristics at various stages. Many existing works have been designed in cyclone prediction for attaining better prediction accuracy. But, it is difficult to enhance the cyclone prediction accuracy with minimum time complexity. In order to address these issues, cyclone prediction can be carried out using deep leaning methods.

***Keywords*---**Image classification, remote sensing, image intensity, cyclones, wind speed, rainfall intensity.

Introduction

Natural disasters happen frequently around the world and their incidence as well as intensity gets improved in recent years. Disasters like cyclones and floods origin important loss of life, large-scale economic, social impacts and environmental damages. India is the one among disaster prone geographical zones of world and experience huge money loss due to different types of disasters yearly. The real-time function of satellite remote sensing has established the translation of data obtained from the space technology to the ground reality. Remote sensing methods are important one for gathering the data quickly and

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projecting the affected regions. Cyclone is a disaster ensuing from nature fury away from the human control. It experienced the damage to the agriculture, human lives, livestock and communication facilities.

This paper is arranged as follows: Section 2 reviews the cyclone prediction methods with remote sensing images. Section 3 describes the existing cyclone prediction methods. Section 4 portrays the simulation settings with possible comparison between them. Section 5 discusses the limitation of existing cyclone prediction methods. Section 6 summarizes the paper.

Literature Review

A scene classification network architecture search depending on multi-objective neural evolution (SceneNet) was designed in [1] for multi-objective neural evolution. The network architecture coding and searching were attained through evolutionary algorithm. But, the computational complexity was not minimized by scene classification network architecture framework.

A two-step scheme was designed in [2] for identifying the tropical cyclone centre with object detection for TC centres. The global and local features were obtained through network to form fusion feature map through concatenation. However, the error rate was not minimized by two-step scheme.

An attention mechanism-based deep supervision network (ADS-Net) was designed in [3] for change detection of bi-temporal remote sensing images. An encoding–decoding full convolution network was introduced with dual-stream structure. However, the pre-processing task was not carried out in efficient way.

A deep architecture with two-stage multiscale training plan was designed in [4] for semantic segmentation to develop correlation between ground objects. However, feature extraction was not carried out in an efficient manner through deep architecture.

Encoder-Decoder CNN structure SegNet with index pooling and U-net was introduced in [5] for multi-target semantic segmentation of remote sensing images. But, the feature selection was not carried out by Encoder-Decoder CNN structure. An innovative multi-level context-guided classification method with Object-based Convolutional Neural Networks (MLCG-OCNN) was introduced in [6]. The pixel-level contextual guidance was employed to increase the object classification results. But, the classification time was not reduced by MLCG-OCNN.

An end-to-end deep convolutional neural network (DeepResUnet) method was introduced in [7] to perform segmentation at pixel scale from VHR imagery. The first sub-network was cascade down-sampling network for obtaining feature maps from VHR image. The second sub-network was up-sampling network for reconstructing obtained feature maps. However, peak signal-to-noise ratio was not improved by DeepResUnet method.

Ensemble-guided cyclone track forecasting (EGCTF) method was introduced in [8] for remote tropical cyclone tracking. However, the prediction time was not reduced by EGCTF method. ResLap was introduced in [9] to attain high-resolution climate prediction. ResLap was spatial downscaling method that transformed the low spatial resolution climate data into high-resolution regional weather predict. But, the cyclone prediction time was not reduced by ResLap.

An interpolation and data augmentation technique was introduced in [10] for temporal resolution development and character diversification. The designed technique required the classical approach during the pre-processing movement. However, complexity level was not reduced by interpolation and data augmentation method.

A feature extraction method called as multilayer feature fusion network (MF2Net) was introduced in [11] for scene classification. VGGNet-16 model was used as feature extractor to attain the multilayer convolutional feature. But, the feature extraction accuracy was not increased by MF2Net.

A new data-driven deep learning model was designed in [12] to predict the tropical cyclone track through spatial location and multiple meteorological factors. But, the prediction time was not minimized by data-driven deep learning model.

Cyclone prediction methods with remote sensing images

Tropical cyclones are the natural disasters for generating high winds, huge rainfall, global flooding and storm surges. The coastal regions are concerned by the disasters. The intensity and frequency of tropical cyclones get improved considerably. The impacts of tropical cyclones were high in different coastal areas of the world. The disasters cause significant loss of life, large scale property and environmental damage. Cyclone hazard modelling is an efficient management process under attentiveness stage of cyclone disaster.

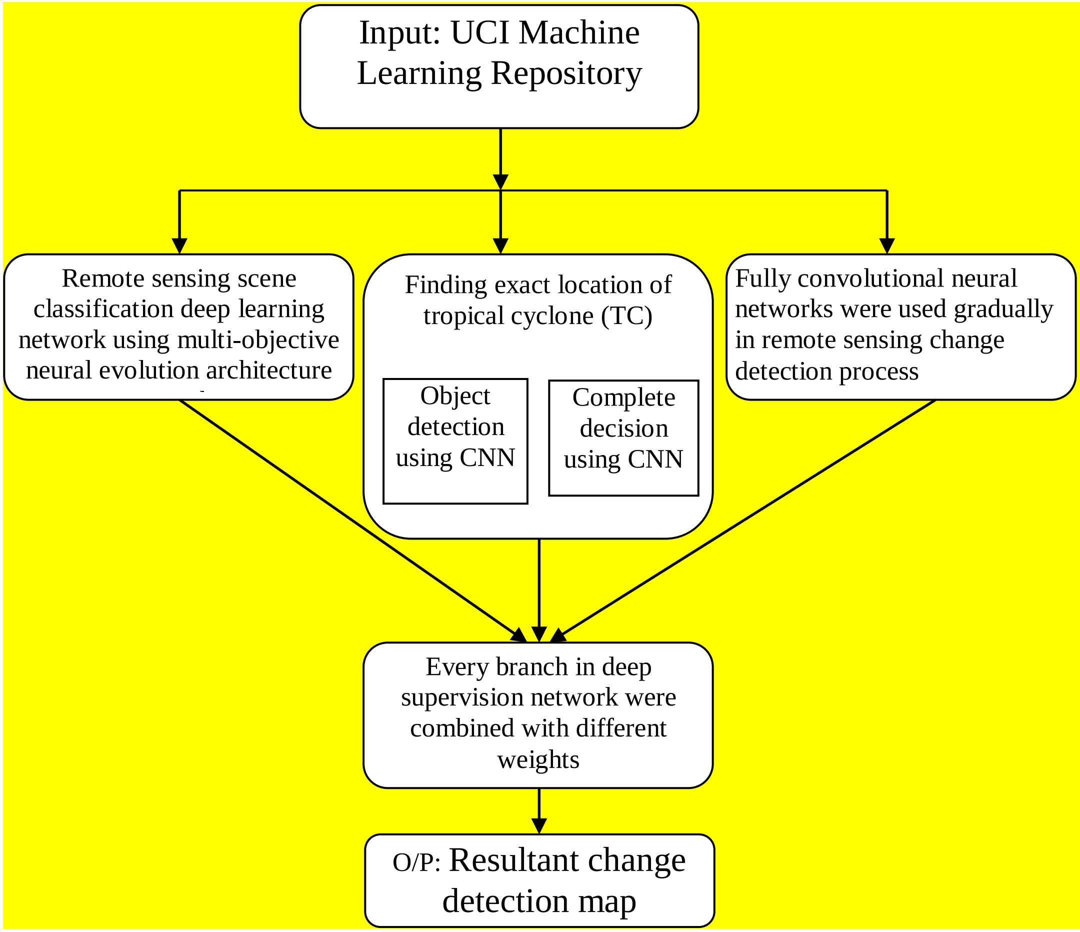

Figure 1: Proposed Flow Diagram

SceneNet: Remote sensing scene classification deep learning network using multi-objective neural evolution architecture search

Deep learning based scene classification received large interest for remote sensing imagery. Deep learning networks were introduced with fixed architecture for natural image processing because of intricate geometric structural features. Scene classification denotes the diverse semantic features of remote sensing images. The semantic label information was highlighted in the remote sensing scene classification and social semantic attributes like airport, industrial area, commercial area, golf course. The scene classification classified into three classes of low-level, middle-level, and high-level techniques. The low-level features in scene classification comprise color histogram, local binary patterns (LBP) and the gray-level cooccurrence matrix (GLCM). The different features and spatial distributions were reflected in remote sensing images.

A scene classification network architecture search depending on multi-objective neural evolution (SceneNet) was introduced. The scene classification network architecture search was performed depending on multi-objective neural evolution.

SceneNet was an EA-based NAS approach for remote sensing image scene classification task. In SceneNet, the appropriate network robotically searched without the handcrafted design and computational complexity. In SceneNet, connection modes of network architecture were determined through binary coding form in EA. The exploitation and exploration search capabilities of network architecture was recognized to the global search potentiality of EA and local search ability of Bayesian optimization algorithm (BOA).

A center location algorithm for tropical cyclone in satellite infrared images

The exact location of tropical cyclone (TC) was essential one for intensity assessment and trajectory prediction. The deep convolutional network was designed to collect the multilevel structural image features. A two-step scheme was designed for locating the TC centre for deep learning based object detection and complete decision. In object detection, statistical scale distribution of TCs, global and local features obtained by network were joined to form feature map fusion by upsampling and concatenation. The variation in TC scale was accommodated by different scale outputs. A high detection rate and low false alarm rate were attained with object detection to give the initial position for TC centre. The final position of centre was attained by means of segmentation, edge detection, circle fitting and decision.

A multiscale feature fusion network integrated through computer vision technology to calculate the TC centre in the satellite IR images. The initial part was depending on the OS model to establish the TC and attain the preliminary position of the TC centre from multiple clouds. In second part, image processing (IP) methods were built in candidate region of interest to attain the precise location of TC centers. The position of TC centre with average error was attained through comprehensive decision of first and second parts. Deep learning was designed for TC detection. CNN extract the cloud features with powerful feature learning capabilities. IP algorithms estimated the centre position depending on TC morphology. The precise TC centre was positioned with threshold segmentation, edge detection, and circle detection to increase the accuracy.

ADS-Net: An attention-based deeply supervised network for remote sensing image change detection

Change detection technology is an essential one to observe the remote sensing data for exact comprehension of earth surface changes. With the continuous growth and deep learning technology evolution, fully convolutional neural networks were used gradually in remote sensing change detection process. The present techniques mainly encounter network structure problems, poor identification of small change areas and poor robustness since they cannot completely obtain the relationship and difference between the features of bi-temporal images. An attention mechanism-based deep supervision network (ADS-Net) was introduced for change identification of bi-temporal remote sensing images. An encoding–decoding full convolution network was designed with dual-stream structure. The feature level of bi-temporal images was obtained in the encoding phase. In decoding stage, feature maps of diverse levels were inserted into the deep supervision network with branches to reconstruct change map. The prediction outcomes of every branch in deep supervision network were combined with different weights to attain the resultant change detection map.

Performance analysis of cyclone prediction techniques

In order to compare thecyclone prediction techniques, number of data points is considered as an input to perform the experiment. Experimental evaluation of three methods namely two-step scheme, scene classification network architecture framework and attention mechanism-based deep supervision network (ADS-Net) are implemented using Java language. In order to predict the cyclone, Diabetes 130-US hospitals for years 1999-2008 Dataset is taken from the UCI Machine Learning Repository. The URL of mentioned dataset is given as https://www.kaggle.com/kmader/satellite-images-of-hurricane-damage. The data are satellite images from Texas after Hurricane Harvey partitioned into two groups (damage and no_damage). The objective is to automatically identify when given region is likely to include flooding damage. In the dataset, 5000 images of every class validation another. Among the features, relevant features are selected to perform the cyclone prediction. Result analysis of existing techniques are estimated with parameters are,

- Cyclone Prediction Accuracy,
- Cyclone Prediction Time and
- Error Rate

Analysis on cyclone prediction accuracy

Cyclone prediction accuracy is computed as the ratio of number of data points that are correctly predicts the cyclone through to the total number of patient data taken. The cyclone prediction accuracy '$CyclonePrediction_{Acc}$' is determined as,

$$CyclonePrediction_{Acc} = \left(\frac{Numberofdatapointsthatarecorrectlypredicted}{Numberofdatapoints}\right) * 100 \quad (1)$$

From (1), the cyclone prediction accuracy is computed. The cyclone prediction accuracy is determined in terms of percentage (%).

Table 1
Tabulation for Cyclone Prediction Accuracy

Number of data points (Number)	Cyclone Prediction Accuracy (%)		
	Two-step scheme	Scene classification network architecture	ADS-Net
50	85	81	78
100	88	83	80
150	90	85	83
200	87	82	81
250	85	80	79
300	82	78	75
350	84	80	78
400	86	82	80

450	89	84	82
500	92	87	84

Table 1 explains the cyclone prediction accuracy with respect to number of data points ranging from 50 to 500. Cyclone prediction accuracy comparison takes place on the existing two-step scheme, scene classification network architecture frameworkand attention mechanism-based deep supervision network (ADS-Net). The graph of cyclone prediction accuracy is described in figure 1.

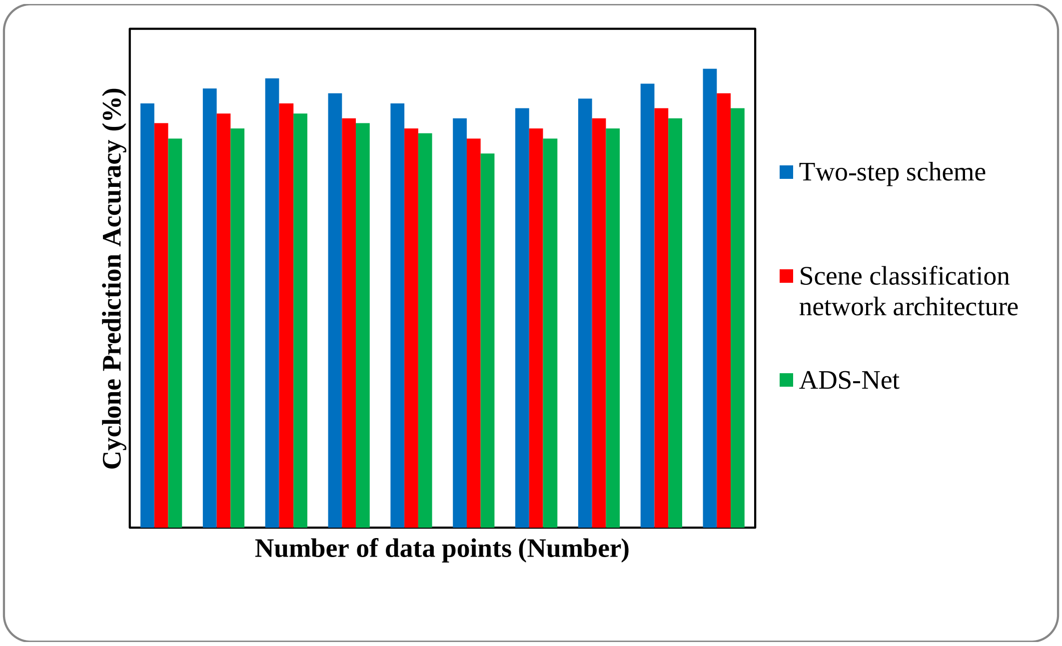

Figure 2. Measurement of Cyclone Prediction Accuracy

From the above figure 1, cyclone prediction accuracy depending on different number of data points is explained. The blue colour bar in figure denotes the cyclone prediction accuracy of two-step scheme. The red colour bar and green colour bar denotes the cyclone prediction accuracy of scene classification network architecture frameworkand attention mechanism-based deep supervision network (ADS-Net) correspondingly. It is clear that the cyclone prediction accuracy using two-step scheme is higher when compared to scene classification network architecture frameworkand attention mechanism-based deep supervision network (ADS-Net). This is due to because of applying the TC centre location framework depending on convolutional network and IP algorithms to handle multiple cyclone scenarios. Multiscale fusion features on varied scales were built by deep convolutional network to process multiple clouds. Therefore, cyclone prediction accuracy of two-step scheme is increased by 6% when compared to the scene classification network architecture framework and 8% when compared to the attention mechanism-based deep supervision network (ADS-Net).

Analysis on cyclone prediction time

Cyclone prediction time is described as amount of time used for predicting the cyclone. It is the product of number of data points and amount of time consumed for predicting the one patient data. Consequently, the cyclone prediction time '$cycloneprediction_{Time}$' is computed as,

$$Cycloneprediction_{Time} = Numberofdatapoints * timeconsumedforpredictingonedata \quad (2)$$

From (2), the cyclone prediction time is determined. The cyclone prediction time is determined in terms of milliseconds (ms).

Table 2
Tabulation for Cyclone Prediction Time

Number of data points (Number)	Cyclone Prediction Time (ms)		
	Two-step scheme	Scene classification network architecture	ADS-Net
50	33	25	38
100	36	28	40
150	39	30	43
200	42	32	46
250	44	35	48
300	46	37	50
350	49	40	53
400	52	42	56
450	54	44	58
500	56	47	60

Table 2 describes the cyclone prediction time with respect to number of data points ranging from 50 to 500. Cyclone prediction time comparison takes place on the existing two-step scheme, scene classification network architecture frameworkand attention mechanism-based deep supervision network (ADS-Net). The graph representation of cyclone prediction time is portrayed in figure 2.

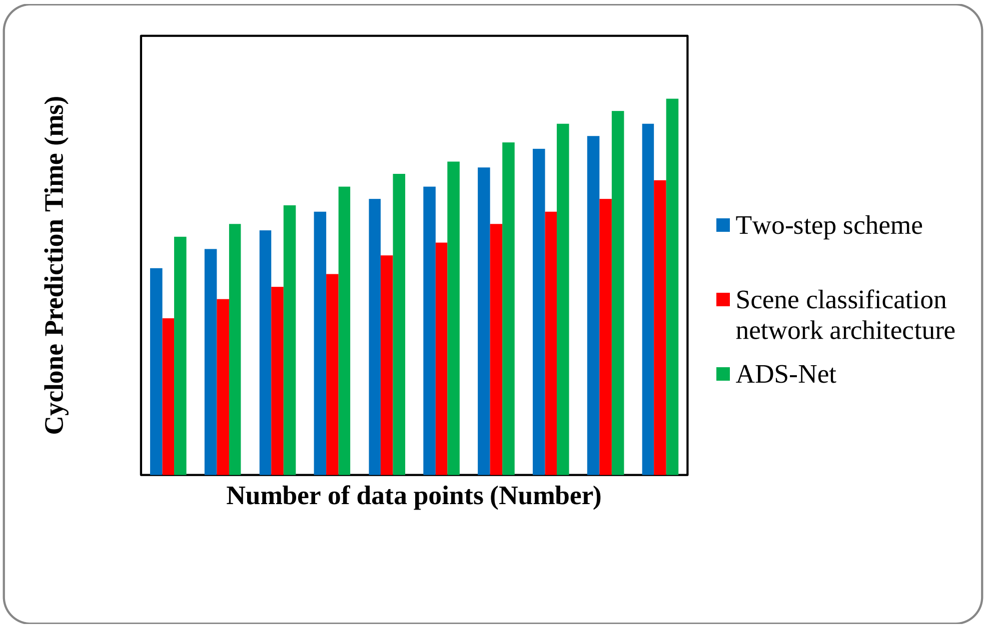

Figure 3. Measurement of Cyclone Prediction Time

From the above figure 2, cyclone prediction time depending on different number of data points is illustrated. The blue colour bar in figure represents the cyclone prediction time of two-step scheme. The red colour bar and green colour bar denotes the cyclone prediction time of scene classification network architecture frameworkand attention mechanism-based deep supervision network (ADS-Net) correspondingly. It is observed that the cyclone prediction time using scene classification network architecture framework is lesser when compared to two-step scheme and attention mechanism-based deep supervision network (ADS-Net). This is because of applying the network architecture coding and searching by evolutionary algorithm to implement flexible hierarchical extraction of image scene information. A search space definition was determined to present the flexible test of connection modes between convolution layers. Consequently, cyclone prediction accuracy of scene classification network architecture framework is reduced by 21% when compared to the two-step scheme and 27% when compared to the attention mechanism-based deep supervision network (ADS-Net).

Analysis on Error rate

Error rate is defined as the ratio of number of data points that are incorrectly predicted to the total number of data points taken. Consequently, the error rate 'Err_{Rate}' is determined as,

$$E_{Rate} = \left(\frac{Number of datapoints that are incorrectly predicted the cyclone}{Number of datapoints}\right) * 100 \qquad (3)$$

From (3), the error rate is computed. The error rate is measured in terms of percentage (%).

Table 3
Tabulation for Error rate

Number of data points (Number)	Error rate (%)		
	Two-step scheme	Scene classification network architecture	ADS-Net
50	21	18	12
100	23	20	15
150	20	17	13
200	18	15	10
250	16	13	8
300	19	16	9
350	21	18	11
400	23	20	13
450	25	22	15
500	28	24	16

Table 3 explains the error rate with respect to number of data points ranging from 50 to 500. Error rate comparison takes place on existing two-step scheme, scene classification network architecture frameworkand attention mechanism-based deep supervision network (ADS-Net). The graphical representation of error rate is illustrated in figure 4.

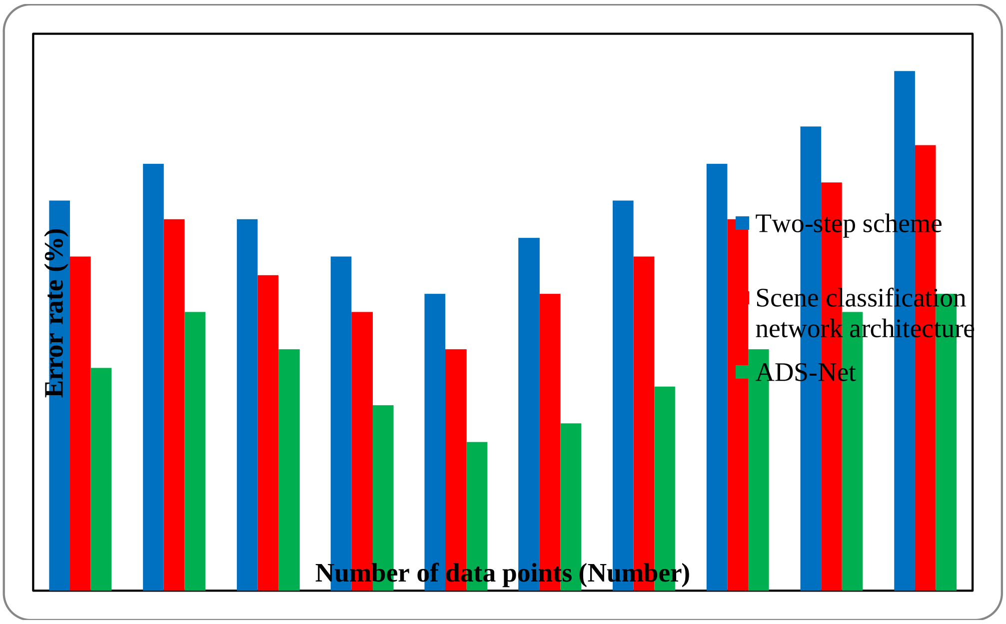

Figure 4. Measurement of Error Rate

From the above figure 3, error rate depending on different number of data points is explained. The blue colour bar in figure denotes the error rate of two-step scheme. The red colour bar and green colour bar denotes the error rate of scene classification network architecture frameworkand attention mechanism-based deep supervision network (ADS-Net) respectively. It is clear that the error rate using ADS-Net is lesser when compared to two-step scheme and scene classification network architecture framework. This is because of applying an adaptive attention mechanism to highlight the change characteristics through joining spatial and channel features. As a result, error rate of attention mechanism-based deep supervision network (ADS-Net) is reduced by 43% when compared to the two-step scheme and 34% when compared to the scene classification network architecture framework.

Discussion and limitation on existing cyclone prediction methods

A new scene classification network architecture framework (SceneNet) was introduced for search deepnd on multi-objective neural evolution. The network architecture coding and searching were attained by evolutionary algorithm. But, the SceneNet handled additional flexible hierarchical extraction of remote sensing image scene information. However, the computational complexity was not decreased by the scene classification network architecture framework.

A two-step scheme identified the tropical cyclone centre with the object detection for TCs centre. The global and local features were extorted through network to form fusion feature map through upsampling and concatenation. A high detection rate and low false alarm rate were attained with object detection to give initial position for TC centre. But, the error rate was not reduced by two-step scheme. An attention mechanism-based deep supervision network (ADS-Net) was employed for change detection with the remote sensing images. ADS-Net method attained enhanced robustness than other change detection methods. The pre-processing task was not performed in efficient manner.

Future Direction

The future direction of work can be carried out using deep learning techniques for increasing the cyclone prediction performance with improved accuracy and lesser time consumption.

Conclusion

A comparison of different existing cyclone prediction methods was illustrated. From the study, it is examined that the pre-processing task was not performed in efficient manner. The survival review shows that the error rate was not reduced by two-step scheme. In addition, the computational complexity was not minimized by the scene classification network architecture framework. The wide range of experiments on many existing cyclone prediction method determines the performance with its problems. Finally, the research work can be carried out using deep learning methods for increasing the cyclone prediction performance.

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