# Analyzing Remote Sensing Images Based on Climate Prediction Model for Water Resources Using Deep Learning

Asst. Prof. Dr. Reem Jafar Ismail[1], Asst. Lect. Soma Aziz M[1], Asst. Prof. Dr. Roojwan Sc. Hawezi[2], Asst. Lect. Adil Hussein Mohammed[3], Asst. Lect. Alyaa Assad Mahdi[1], Nwa Khalid Karim[1], Masrur Kamaran Darwesh Bag[1], Mustafa Sherwan Othman[1]

[1]Department of Computer Science, Cihan University-Erbil, Erbil, Kurdistan Region, Iraq.
[2]Department of Information Systems Engineering, Erbil Technical Engineering College, Erbil Polytechnic University, Erbil, Kurdistan Region, Iraq.
[3]Department of Communication and Computer Engineering, Cihan University-Erbil, Erbil, Kurdistan Region, Iraq.

***Abstract*— In recent years, satellite imagery can provide key information about the properties of land, water, and natural resources. Climate change threaten the environment and the satellite image processing has shown its potential to support future prediction of natural resources. The aim of this research is to proposed a model to analyze the extracted information from the environmental image for water area and follow the changes that may happen over time. The proposed model is (Image Time Series Tracking with LSTM Deep Learning Method) that has two stages: the first stage is analysis remote sensing images of water area and track its change over years and second stage is to predicate the future change by using LSTM deep learning method. In first stage a data set is collected for Aral Sea from 2003-2018 and in the second stage Long Short-Term Memory (LSTM) deep learning method is implemented to detect the future change in environment. The results show a promising prediction especially when the input that we used is real data set for Aral Sea sensing images for water area over long years in LSTM deep learning methods.**

***Index Terms*—Remote sensing images, water level, climate change, LSTM prediction model, Aral Sea.**

## I. INTRODUCTION

Remote Sensing (RS) refers to acquiring of information of earth surface features from a distance via remote sensors on satellites and aircraft [1]. The satellite image will help to collect data on areas which is unreachable [2] All the world are affected by climate changes in temperature and impacting on water resources. In [3] explain that the temperature is increased overall by approximately 0.8 °C for the last hundred years. Climate change can be caused by both natural and human factors. The Intergovernmental Panel on Climate Change (IPCC) states that human activities such as burning fossil fuels, deforestation, and agriculture are responsible for global warming [4, 5]. In general, of remote sensing images applications of the Earth include:

-Land cover change detection is necessary for updating land cover maps and the management of natural resources. The change is usually detected by comparison between two multi-date images, or sometimes between an old map and an updated remote sensing image, [6].

-Global Vegetation Map are very useful for producing a global vegetation map which cover the whole world, [7].

-Water Quality Monitoring
Water pollution has become a very serious problem in big cities and in offshore areas along industrial zones. Water quality monitoring is one of the typical applications of remote sensing, [8].

-Water Level Detection
The water level also known as stage is defined as the elevation or height of the free surface of water, such as water level of sea, river or lake. The water level of lakes is affected by the seasonal characteristics especially the temperature [9].

The contribution of this work:

- Beware of climate changes, regarding to water resources on earth that are very important to life.
- Explain the deep learning methods when it is used to track remote sensing images for water resources on earth such as sea, lakes and rivers on earth.
- Predicate the future change of water resources by using deep learning method.
- Proposed a model for prediction of remote sensing images.

The rest of the paper is organized as follows. The next section explains the deep learning and machine learning algorithms relate to remote sensing images applications. In the related works section, we highlight research issues for different remote sensing images that relate to water resources such as rivers and oceans. Next, data collection and a proposed method for predication future change over time for remote sensing images of water resources are explained. Finally, the results and

DOI:http://doi.org/10.24086/cocos2024/paper.1299

research conclusion give a summarized to the importance of the paper.

### A. Deep Learning and Machine Learning Methods

Machine learning has the ability to process input data and learn the system to find the output automatically according to the patterns. Deep learning is most suitable for real applications because the amount of data set is huge that increase the performance of the algorithm, as shown in figure (1), [10].

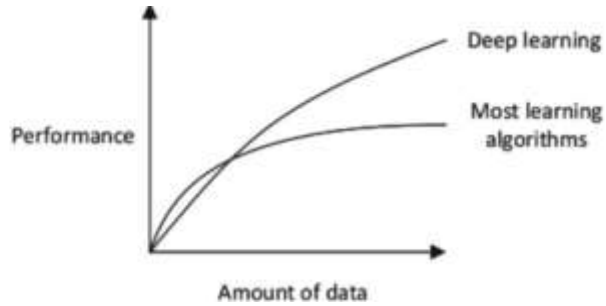


***Figure (1): Performance comparison between deep learning* and *other machine learning algorithms***

According to Bokonda et. al. [11], the learning methods can be categorized to: decision tree, super vector machine (SVM), k-nearest neighbor, regression and artificial neural networks [12, 13, 14, 15, 16]. Machine learning can be classified to supervised an unsupervised learning. Decision tree is a classification method belong to supervised learning. This method is like tree, where it has a root and different nodes such as: root node, leaves nodes and decision nodes. SVM algorithm is used when the data set has a clear division to be classified to classes, [17]. K-nearest neighbor (KNN) algorithm used Euclidean distance metrics between two points to locate the nearest neighbor. KNN needs training sets and it is used when the data set is large. KNN is robust to noisy training data, [18]. Regression in machine learning use mathematical model is to build an equation that defines y (the outcome variable) as a function of one or multiple predictor variables (x). Next, this equation can be used to predict the outcome (y) based on new values of the predictor variables (x), [19]. Regression has a wide range of real-life applications. It is essential for any machine learning problem that involves continuous numbers – this includes, but is not limited to, a host of examples, including, such as: weather forecasting, time series analysis and water level predication, [20, 21].Deep Learning is a part of machine learning that deals with algorithms inspired by the structure and function of the human brain. It uses artificial neural networks to build intelligent models and solve complex problems. Artificial neural networks can learn from real input data and predicate the unknown data, [22].

## II. Background and Related Works

For the literature review of deep learning in remote sensing applications, the study in [23], shows the statistics till 2019 for a number of published articles relate to deep learning in different types of study areas (e.g., "urban areas", "vegetated areas", and "water areas"). In this study, the most of the studies was relate to urban areas. As shown in Figure (2), [23].

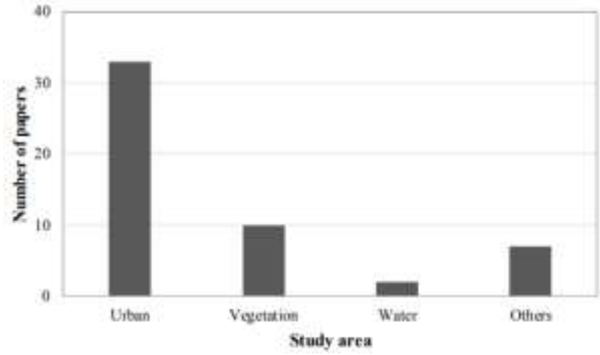


***Figure (2): Distribution of application area***

Taiguo Li et al., [24], enhanced the method of land information extraction from remote sensing images by fusing multi-scale feature map information. The proposed method uses HRNet (High-level Resolution Network) to improve accuracy of the information extraction of land. Xiaofeng Li et al., [25], this article enhanced the ocean remote sensing imagery processing by suggesting a cooperation of domain-knowledge-based with specific task-driven. Ocean remote sensing time series image differ from remote sensing images since the video stream is captured using computer vision. Zhao Shun et. al., [26], applied a method of deep learning to remote sensing for block of image after segmentation, where asymmetric convolution-CBAM (AC-CBAM) module based on the convolutional block attention module is proposed. In this proposal an optimization module and sliding window prediction method are used to enhance the segmentation accuracy. Ali N. et. al., [27], used many methods for the river level predication and found that Gaussian Process Regression (GPR) method was accurate in daily prediction related to other methods and the limitation was addressed by finding a complete data set. Finally, the data set that is captured and analyzed was for one year for Durian Tunggal River in Malaysia. B. Kalantar et. al., [28], Analyze the parameters that effect riverbank changes and related land changes over time for Zab River. Satellite remote sensing for Zab River in Iraq is integrated with Geographic Information Systems to track the change that concluded in the eastern section close to Kirkuk for the data set over years 1989, 1999, 2015 and 2019. Kusudo T. et. al., [29], used deep learning models and for water-level predictions the methodology used the level of water as input. The model gives good predication and water resource management to used it for irrigation especially when heavy rainfall season threaten the area because of flooding.

DOI:http://doi.org/10.24086/cocos2024/paper.1299

**Deep Learning Algorithms: LSTM (Long Short-Term Memory)**

Long Short-Term Memory Network is a type of Recurrent Neural Networks that aims at utilizing long-term dependencies of time-series data in prediction problems. LSTM can handle the vanishing gradient problem in RNNs. LSTM was designed by Hochreiter and Schmidhuber that improves traditional RNNs and machine learning algorithms by resolving the problem they faced. Keras library in Python can be used to implement LSTM Model [30]. LSTM (Long Short-Term Memory) lies in their ability to effectively handle long-range dependencies in sequential data. The vanishing gradient problem is a common limitation of RNNs, which is addressed by LSTM by using a gating mechanism that controls information flow through the network. This gating mechanism enables LSTMs to learn and keep past information, which makes them effective in many tasks [30, 31]. The main architecture of LSTM is interpreted as a memory cell $\boldsymbol{c_t}$, that keeps its state over time, and three gates; the input gate $\boldsymbol{i_t}$, the output gate $\boldsymbol{o_t}$ and the forget gate $\boldsymbol{f_t}$ that all are changed over time [32]. The structure of LSTM is described as

$$i_t = \sigma(W_{ih}h_{t-1} + W_{ix}x_t + b_i) \quad (1)$$
$$o_t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o) \quad (2)$$
$$f_t = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f) \quad (3)$$
$$\tilde{c}_t = tanh(W_{ch}h_{t-1} + W_{cx}x_t + b_c) \quad (4)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (5)$$
$$h_t = o_t \odot \tanh(c_t) \quad (6)$$

where weights $\boldsymbol{W}$ and biases $\boldsymbol{b}$ are parameters related to each gate to be learned. ***tanh*** is the hyperbolic tangent function, $\boldsymbol{\sigma}$ is the sigmoid function that its output is a value between 0 and 1, $\boldsymbol{x_t}$ is input value and $\boldsymbol{h_t}$ is hidden state. These three gates have elements that their values are between 0 and 1. When their value is 0, means no information should be passed, while value 1 indicates full information flow. Later, the candidate update to the memory cell is generated, $\boldsymbol{\tilde{c}_t}$, according to equation (4). Afterwards, as seen in equation (5), according to the forget gate and input gate, the candidate update $\boldsymbol{\tilde{c}_t}$ is combined with the elements of the previous cell $\boldsymbol{c_{t-1}}$. In the end, the new hidden state $\boldsymbol{h_t}$ is generated after using ***tanh*** activation function on the memory cell and weighting elements based on output gate [32]. The information which are added or deleted from the memory cell is regulated by gates. One of the well-known applications of LSTM is Time Series Forecasting, which leverages characteristics of LSTM in performing forecasting tasks on time series data. Time series forecasting tasks can learn some patterns in time series data and use them in making predictions on events in future [31].

## III. Proposed Model for Deep Learning Algorithms for Remote Sensing Images and Methodology

**I. Data Collection:**

Image sensing data are collected from Nasa Earth Observatory of Aral Sea. The Aral Sea is located between Kazakhstan and Uzbekistan, the water level of the sea started to decrease in 1960 and approximately dried up now. A total of 16 years of image sensing of Aral Sea has been collected from 2003-2018 [33]. Figure (3) shows samples of study area for remote sensing of Aral Sea, changing water level over years [33]. The data used in this study are converted into jpg files.

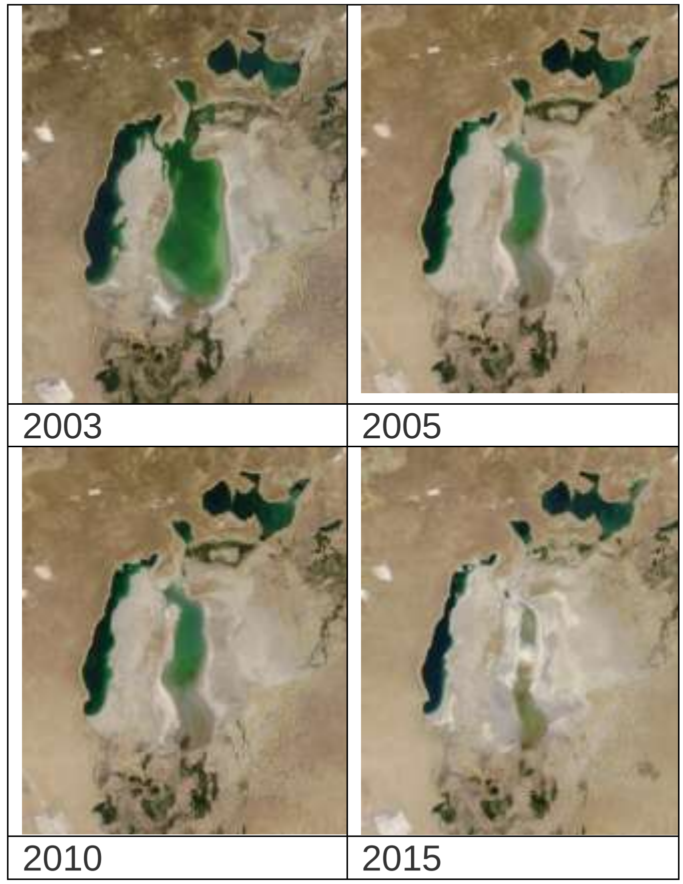


***Figure (3): Samples of Study Area for Remote Sensing of Aral Sea, Changing Water Level over Years [33]***

**Proposed Model for Prediction:**

Remote sensing images often need pre-processing because of the color variations, poor contrast, and noise. Remote sensing image preprocessing will enhance the image and eliminate the error in image that comes from satellite sensor itself, [34]. Figure (4), shows a block diagram of the proposed methodology. Algorithm (1) (Proposed Image Time Series Tracking) is a proposed algorithm for tracking the change that happed over time for the amount of water. In this algorithm each two images are taken and enhanced to find the amount of blue/ green color in the images and find the percentage of change between them, equation (7). This model is important to speed the processing time in LSTM deep learning method since the input to the model is integer numbers instead of all image. Table (1), compare between the related works and the proposed model.
In Algorithm (1), we use the equation of percent change, [35]:

$$Percentage\ Change = \frac{(\text{Final Value} - \text{Initial Value})}{(\text{Initial Value})} \times 100 \quad \dots (7)$$

DOI:http://doi.org/10.24086/cocos2024/paper.1299

LSTM Prediction of Water Level Reduction Method is implemented as a deep learning algorithm and the input to the system was the output from Algorithm (1).

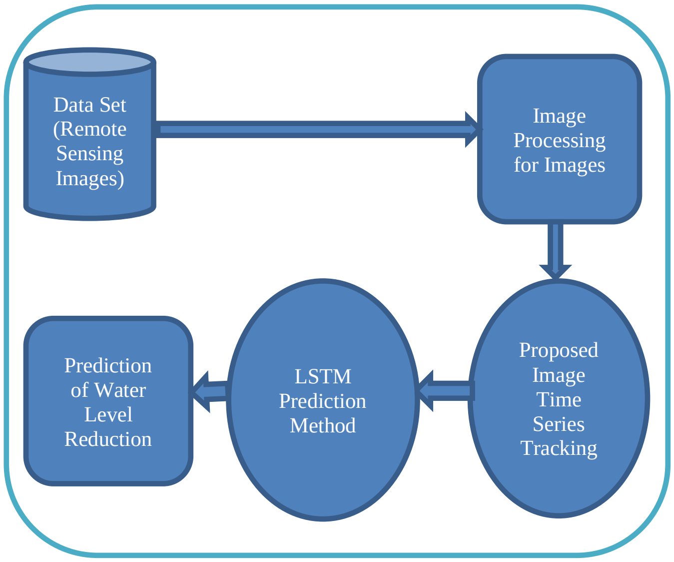


*Figure (4): Block Diagram of the Proposed Methodology*

**Algorithm 1. Proposed Image Time Series Tracking**

**Input:** Number of remote sensing images for Aral Sea (16)
**Output:** Change percentage over years, vector (a).
**Begin**
1: Collect remote sensing images of sea
2: For each Image do image processing for noise removal and color enhancement
3: For each Image adject the size and diminutions
4: For i (1 to n-1)
Read image i and Read image i+1
Mask water_area_1 form image i
Mask water_area_2 form image i+1
Percentage change = (water_area_1 - water_area_2) / water_area_2 * 100
a(i)= Percentage change
End
5: Call LSTM Prediction of Water Level Reduction Method
**End**

*Table (1): Overview of the literature works compared to proposed method*

| Authors/ Year | Data Set for Prediction | Prediction Method |
|---|---|---|
| Taiguo Li et al., [24], 2021 | Images of land | High-level Resolution Network |
| Xiaofeng Li et al., [25], 2022 | Images for ocean remote sensing imagery taken from video streaming | Domain-knowledge-based with specific task-driven |
| Zhao Shun et. al., [26], 2022 | Images for lakes in China over one year | Asymmetric convolution- CBAM (AC-CBAM) |
| Ali N. et. al., [27], 2022 | Images for River level predication for Durian Tunggal River in Malaysia over one year | Gaussian Process Regression (GPR) method |
| B. Kalantar et. al., [28], 2020 | Images for Zab River bank in Iraq over 4 years | Using Sinuosity Index for the bank of the river to check meandering of the Zab River in Iraq. |
| Kusudo T. et. al., [29], 2022 | Level of water for Takayama Reservoir in Japan over 3 years | LSTM SO- Single Output and LSTM ED- Encoder-Decoder |
| Reem J. Ismail et. al. proposed method, 2024 | Percentage change of water level as integer numbers for remote sensing images of Aral Sea between Kazakhstan and Uzbekistan over 16 years | Time series tracking percentage with LSTM deep learning |

## IV. Experimental Results and Discussion

In this section, we present the implementation of the proposed Image Time Series Tracking with LSTM deep learning method then evaluate it, where we use Spyder IDE 5.5.1, Python 3.11.7 and Jupyter Notebook with Keras libraries. Table (2) and table (3) shows the output when algorithm (1) is implemented when detecting change of Aral Sea for each year, and each two years.

*Table (2): Percentage change of water for each year for Aral Sea sensing images*

| Years | Water Area Change Percentage % |
|---|---|
| 2003-2004 | 9.26 |
| 2004-2005 | 38.10 |
| 2005-2006 | 22.09 |
| 2006-2007 | 5.69 |
| 2007-2008 | 11.83 |
| 2008-2009 | 25.45 |
| 2009-2010 | 23.84 |
| 2010-2011 | 9.73 |
| 2011-2012 | 0.57 |
| 2012-2013 | 2.44 |
| 2013-2014 | 6.67 |
| 2014-2015 | 3.56 |
| 2015-2016 | 17.13 |
| 2016-2017 | 7.55 |
| 2017-2018 | 11.86 |

DOI:http://doi.org/10.24086/cocos2024/paper.1299

*Table (3): Percentage change of water for each two years for Aral Sea sensing images*

| Years | Water Area Change Percentage % |
|---|---|
| 2003-2005 | 50.91 |
| 2005-2007 | 17.65 |
| 2007-2009 | 10.60 |
| 2009-2011 | 16.43 |
| 2011-2013 | 1.86 |
| 2013-2015 | 2.87 |

In each remote sensing image of the sea, we plot the amount of water, where the water part is separate from the land part in the image. Figure (5), shows the amount of water in the image over time for 2003 and 2005 years when we implement Algorithm (1).

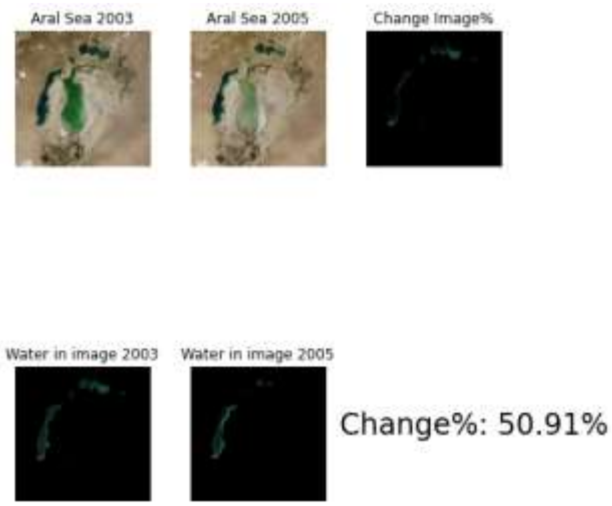


***Figure (5) The amount of water in the image over time of years (2003 and 2005)***

In order to minimize the processing time of predication, the input image had been segmented and only part of it is used and masked which is the water section of the image (the blue/ green color shades). One of the most difficulties that face the implementation of the research is to represent the time series of image for predication. The dataset is created form the Aral Sea remote sensing images as an input to the system by finding the percentage of water reduction when it is changed over years hence percentage numbers is used instead of images to increase the speed of processing and predication when implementing the proposed Image Time Series Tracking algorithm (1) and LSTM method.

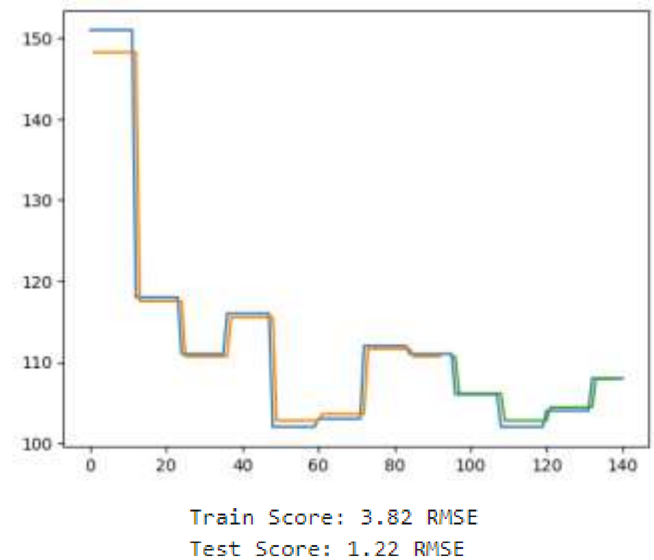


***Figure (6): Output of LSTM***

Figure (6), shows the output of LSTM deep learning where the prediction is for input from table (2) and table (3). The x-axis is the data set over time, and y-axis is the amount of water reduction over the year. Where the blue line is data set, the orange line is the training set and the green line is the prediction set.

The training size was 67% from the data set. Root means square error (RMSE) is used in the proposed predication model. The RMSE is compared with Euclidean distance to measure the prediction output, to have more accurate output we need to have less RMSE values. In figure (6), the output of RMSE is 3.82 for training sets and 1.22 for testing set. The limitation of this study is in data set collection. Long Short-Term Memory (LSTM) deep learning method needs large amount of data for predication, in this study the data that are collected was by year, the performance of the predication will be more accurate when the remote sensing images is collected for each month in each year, over many years. In this study in order to implement the prediction with the limited data set over years the data set is extended with a proposed values for 12 months per year approximately for the average of percentage per year, as shown in figure (6), (squared shapes instead of curves). Also, the remote sensing image quality and resolution is important in analysis. This work could be more enhanced if more parameters are considered in predication such as: the wind and the temperature of the area.

## V. Conclusion and Future Works

This research proposed a model for remote sensing images using deep learning and the case study is based on climate prediction model for water resources. In this study the remote sensing images for water resources are collected and deep learning methods are implemented to track the changes that happen over time relate to water level of the lakes or rivers because of climate change. Image processing methods has been

DOI:http://doi.org/10.24086/cocos2024/paper.1299

applied for the remote sensing images in order to enhance the input. The collected remote sensing images are real images processed by implementing the Proposed Image Time Series Tracking. In this work, a deep learning method predicate the water reduction by implementing LSTM model for processed satellite imagery and geospatial datasets. The results shows that the prediction in figure (6) with the 9.80 % is related to the percentage from table (2) for each year which is approximately 11.86 % in 2017 and 2018 years. In order to speed up the computational processing a segmentation for remote sensing GEE images is applied for water area only and an integer number for percentage change of water area is input to LSTM learning instead of images. The research will give a predication model about the future of water resources on earth and be aware about the climate change that threaten the life. The limitation and difficulties of this research is related to finding enough data set as an input to the proposed model per month for each year.

For future work, the proposed model could be applied for prediction of the lakes and rivers in Iraq if the data set is available to detect the future changes of water resources when the climate start to be changed in the last years. Also, this model could be used to detect change for the remote sensing image for agricultural areas and natural resources. Moreover, real-time forecasting will improve the model when sensors are used.

## Acknowledgment

The authors would like to acknowledge Cihan University-Erbil, for their support and sponsorship of this project. Also, special thanks for the students of computer science department at Cihan University-Erbil, Shahin Hasib, Mohammed Khoshnaw Wahid, and Basoz Niyaz.

## References

[1] Ranganath R. Navalgund, V. Jayaraman and P. S. Roy. Remote sensing applications: An overview. Special section: Indian space program, Vol. 93, no. 12, 25 December 2007.

[2] Nelly Aurora, Oscar Efraín, Helga Kelly and Michael N. Satellite Image Classification for Environmental Change Prediction Using Image Processing and Machine Learning Techniques. Neuro Quantology. August 2022, Volume 20, Issue 9, Page 1253-1263. doi: 10.14704/nq.2022.20.9.NQ44142.

[3] Ahmed T, Zounemat-Kermani M, Scholz M. Climate Change, Water Quality and Water-Related Challenges: A Review with Focus on Pakistan. Int J Environ Res Public Health. 2020 Nov 17;17(22):8518. doi: 10.3390/ijerph17228518. PMID: 33212957; PMCID: PMC7698392.

[4] W. Verweij, J. van der Wiele, I. van Moorselaar and E. van der Grinten. Impact of climate change on water quality in the Netherlands. National Institute for Public Health and the Environment. © RIVM 2010. Report 607800007/2010

[5] Intergovernmental Panel on Climate Change 2007. Climate change 2007: Synthesis report. Janse J 1997. A model of nutrient dynamics in shallow lakes in relation to multiple stable states. Hydrobiologia 342/343, p:1-8.

[6] Liu B, Song W, Meng Z, Liu X. "Review of Land Use Change Detection—A Method Combining Machine Learning and Bibliometric Analysis". Land Journal. 2023; 12(5):1050. https://www.mdpi.com/2073-445X/12/5/1050

[7] S. Vijayalakshmi, S. Magesh Kumar." Novel Vegetation Mapping Through Remote Sensing Images Using Deep Meta Fusion Model". Intelligent Automation & Soft Computing 2023, 36(3), 2915-2931. https://doi.org/10.32604/iasc.2023.034165

[8] Gehad hassan, mohamed e. Goher, masoud e. Shaheen, and shereen a. Taie. "Hybrid Predictive Model for Water Quality Monitoring Based on Sentinel-2A L1C Data". IEEE Access, 2021.

[9] Xu, W.; Duan, L.; Wen, X.; Li, H.; Li, D.; Zhang, Y.; Zhang, H. Effects of Seasonal Variation on Water Quality Parameters and Eutrophication in Lake Yangzong. *Water* 2022, *14*, 2732. https://doi.org/10.3390/w14172732.

[10] Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. SN COMPUT. SCI. 2, 160, 2021. https://doi.org/10.1007/s42979-021-00592-x

[11] P. L. Bokonda, K. Ouazzani-Touhami and N. Souissi. Predictive analysis using machine learning: Review of trends and methods. 2020 International Symposium on Advanced Electrical and Communication Technologies (ISAECT), Marrakech, Morocco, 2020, pp. 1-6, doi: 10.1109/ISAECT50560.2020.9523703.

[12] B. E, L. R. Flaih, D. Yuvaraj, S. K, A. Jayanthiladevi and T. S. Kumar, "Use Case of Artificial Intelligence in Machine Learning Manufacturing 4.0," *2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, Dubai, United Arab Emirates, 2019, pp. 656-659, doi: 10.1109/ICCIKE47802.2019.9004327.

[13]Arsalan Mahmoodzadeh , Hossein Ghafourian , Adil Hussein Mohammed , Nafiseh Rezaei , Hawkar Hashim Ibrahim , Shima Rashidi. "Predicting tunnel water inflow using a machine learning-based solution to improve tunnel construction safety". Transportation Geotechnics. Volume 40, May 2023.

[14] Alkhazraji, Afaneen A., and Sammar J. Ismail. "Restoring the Iraqi transmission network using k-shortest path algorithms." Advances in Natural and Applied Sciences, vol. 11, no. 4, Apr., 2017.

[15] H. H. Thannoon, W. H. Ali and I. A. Hashim, "Detection of Deception Using Facial Expressions Based on Different Classification Algorithms," 2018 *Third Scientific Conference of Electrical Engineering (SCEE)*, Baghdad, Iraq, 2018, pp. 51-56, doi: 10.1109/SCEE.2018.8684170.

[16] Srwa Hasan Abdulla, Ali Makki Sagheer, Hadi Veisi. Breast Cancer Classification Using Machine Learning Techniques: A Review. Turkish Journal of Computer and Mathematics Education. Vol.12 No.14, 2021.

[17] Malti Bansal, Apoorva Goyal and Apoorva Choudhary. "A comparative analysis of K-Nearest Neighbor, Genetic, Support Vector Machine, Decision Tree, and Long Short-Term Memory algorithms in machine learning ". Decision Analytics Journal. Volume 3, June 2022, doi.org/10.1016/j.dajour.2022.100071.

[18] Ernest Yeboah Boateng, Joseph Otoo and Daniel A. Abaye. "Basic Tenets of Classification Algorithms K-Nearest-Neighbor, Support Vector Machine, Random Forest and Neural Network: A Review". Journal of Data Analysis and Information Processing . Vol. 8 No.4, November 2020. DOI: 10.4236/jdaip.2020.84020.

[19] Shen Rong and Zhang Bao-wen. "The research of regression model in machine learning field". 6th International Forum on Industrial Design (IFID 2018). MATEC Web Conf. Volume 176, 2018. doi.org/10.1051/matecconf/201817601033.

[20]P. Chaudhary, S. D'Aronco, J.P. Leitão, K. Schindler, J.D. Wegner. Water level prediction from social media images with a multi-task ranking approach. ISPRS Journal of Photogrammetry and Remote Sensing. Volume 167, September 2020, Pages 252-262.

[21] Herath, M.; Jayathilaka, T.; Hoshino, Y.; Rathnayake, U. Deep Machine Learning-Based Water Level Prediction Model for Colombo Flood Detention Area. Applied Sciences 2023, 13, 2194.

[22] Shreyas D K, Srivatsa N Joshi, Vishwas H Kumar, Vishaka Venkataramanan, Kaliprasad C S. A Review on Neural Networks and its Applications. Journal of Computer Technology & Applications. 2023; 14(2): 59–70p.

[23] Lei M., Yu Liuc, Xueliang Zhanga, Yuanxin Yed, Gaofei Yind and Brian Alan Johnsonf. Deep learning in remote sensing applications: A meta-analysis and review. ISPRS Journal of Photogrammetry and Remote Sensing. Vol. 152, June 2019, Pages 166-177.

[24] T. Li, Q. Li, T. Zhang and L. Yang. Land use information extraction from remote sensing images based on deep learning. 2021 IEEE 5th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Xi'an, China, 2021, pp. 1570-1576, DOI: 10.1109/ITNEC52019.2021.9587292.

[25] Xiaofeng Li, Yuan Zhou, and Fan Wang. Advanced information mining from ocean remote sensing imagery with deep learning. Journal of Remote Sensing, 2022. Article ID: 9849645. DOI: 10.34133/2022/9849645.

[26] Shun Z, Li D, Jiang H, Li J, Peng R, Lin B, Liu Q, Gong X, Zheng X, Liu T. Research on remote sensing image extraction based on deep learning. PeerJ Comput Sci. 2022 Jan 20;8:e847. doi: 10.7717/peerj-cs.847.

[27] Ali Najah Ahmed, Ayman Yafouz, Ahmed H. Birima, Ozgur Kisi, Yuk Feng Huang, Mohsen Sherif, Ahmed Sefelnasr & Ahmed El-Shafie. Water level prediction using various machine learning algorithms: a case study of Durian Tunggal River, Malaysia, Engineering Applications of Computational Fluid Mechanics, 2022. 16:1, 422-440, DOI: 10.1080/19942060.2021.2019128

[28] B. Kalantar, M. H. Ameen, H. J. Jumaah, S. J. Jumaah, A. A. Halin. ZAB River (Iraq) Sinuosity and mean during analysis based on the remote sensing data. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2020.

[29] Kusudo, T.; Yamamoto, A.; Kimura, M.; Matsuno, Y. Development and Assessment of Water-Level Prediction Models for Small Reservoirs Using a Deep Learning Algorithm. *Water* 2022, *14*, 55. https://doi.org/10.3390/w14010055

[30] N. Tripathy, S. Hota, S. Prusty and S. K. Nayak, "Performance Analysis of Deep Learning Techniques for Time Series Forecasting," 2023 International Conference in Advances in Power, Signal, and Information Technology (APSIT), Bhubaneswar, India, 2023, pp. 639-644, doi: 10.1109/APSIT58554.2023.10201734.

[31] Zixu Zhao. Comprehensive Review of Machine Learning-Based Methods for Electricity Load Forecasting. E3S Web of Conferences 394, 01002, 2023.

[32] DiPietro, Robert, and Gregory D. Hager. "Deep learning: RNNs and LSTM." Handbook of medical image computing and computer assisted intervention. Academic Press, 2020. 503-519.

[33] https://en.wikipedia.org/wiki/Aral_Sea [Assess on 5 April 2024].

[34] Yang K, Li M, Liu Y, Cheng L, Huang Q, Chen Y. River Detection in Remotely Sensed Imagery Using Gabor Filtering and Path Opening. *Remote Sensing*. 2015; 7(7):8779-8802. https://doi.org/10.3390/rs70708779

[35] Sarah Bansila. "The application of the percentage change calculation in the context of inflation in mathematical literacy" Journal of the Association for Mathematics Education of South Africa, 2017.