ISSN: 2278-4632
Vol-11 Issue-01 2021

PREDICTION OF WATER QUALITY FOR AQUACULTURE USING DEEP LEARNING TECHNIQUES

SujithaNaredla[1], Nandinijallepalli [2], LallithaVedullapali[3], Snehaguntupalli[4].K.Chaitanya[5]
[1234] Student ,Department of Computer Science &Engineering, VNITSW,Guntur.
[5]Assistant Professor, Department of Computer Science&Engineering,VNITSW,Guntur.

ABSTRACT

Water is a fundamental for all parts of human and environment endurance and wellbeing. Along these lines, its quality is likewise significant. Water quality alludes to the piece of a water test. Assessments of water quality boundaries are important to improve the presentation of an evaluation activity and foster better water assets the executives and plan. Water Quality assumes a significant part in achieving a reasonable hydroponics framework, its combined impact can make the whole framework. Early location of fish illnesses and recognizing the fundamental causes are essential for ranchers to find important ways to moderate the likely flare-up. Normally, fish infections are brought about by infection and microscopic organisms; and this may influence the degree of pH, DO, BOD, COD, EC, PO43-, NO3-N, and NH3-N in water, bringing about the passing of fishes. Being roused by the new accomplishments of moving strategies ANN and CNN models has been embraced to distinguish and anticipate the corruption of water quality convenient and precisely, in this manner it helps making pre-emptive strides against potential fish infections. Looking at the aftereffects of the models showed that every one of them had arrived at assessment properties. In extra, Conventional Neural Network (CNN) catches the inserted spatial and precarious conduct in the researched issue utilizing its engineering and nonlinearity nature contrasted and the other old style displaying methods. The outcomes show that the proposed CNN forecast model has an extraordinary potential to recreate and foresee the all out disintegrated solids, electrical conductivity, and turbidity with outright mean blunder 10% for various water bodies.

Keywords: Water quality prediction, Water quality parameters, artificial neural network, Conventional neural network.

1. INTRODUCTION

Water quality straightforwardly influences practically all water employments. Fish endurance, variety and development; sporting exercises like swimming and sailing, city, mechanical, and private water supplies, rural uses, for example, water system and animals watering, garbage removal, and general feel all are influenced by the physical, compound, organic, and microbiological conditions that exist in conduits and in subsurface springs. Water quality disability is regularly a trigger for struggle in a watershed, basically in light of the fact that debased water quality implies that ideal uses are unrealistic or undependable (Heathcote, 1998). Malaysia is an agricultural nation that moves towards the vision 2020. Tragically the improvement that had been conveyed all through the nation additionally contributes terrible effect on the climate particularly water quality. This issue has gotten delicate, which influences human wellbeing, yet in addition the whole climate .The improvement influences the water quality, yet additionally the amphibian day to day routines that experience in it. Most adequate biological and social choices are hard to make without cautious displaying, forecast, and examination of waterway water quality for normal advancement situations. Water quality expectation empowers a director to pick a choice that fulfills huge number of recognized conditions. For example, water quality boundaries, like broke down solids, electrical conductivity and turbidity in water portray a mind boggling measure administered by an impressive number of hydrologic, hydrodynamic, and environmental controls that work at a wide scope of spatiotemporal scales. Wellsprings of the admixtures frequently can't be plainly distinguished, and the privately affected complex mass trade between the factors may not be known.

Hydroponics is the controlled cycle of developing amphibian life forms, particularly for human utilization. It's a comparable idea to agribusiness, yet with fish rather than plants or domesticated animals. Hydroponics is likewise alluded to as fish cultivating. Hydroponics is reproducing, raising, and reaping fish, shellfish, and amphibian plants. Hydroponics is an ecologically mindful wellspring of food and business items, assists with making better territories, and is utilized to remake loads of undermined or jeopardized species. Fishes represent around 15% of the creature protein admission of the human populace universally

In nations like Bangladesh, fishes give as high as 60% of the creature protein to the general population, likewise in monetary valuation fishes adds to roughly 3.6% to the public GDP which weighs almost 25% of the whole farming GDP. Besides, this segment utilizes about 11% of the all out populace in Bangladesh in full-time and low maintenance premise.In spite of being the extremely energetic monetary area for the country, one significant danger to the fish ranchers are the fish infections which in the long run puts an enormous limitation on the financial advancement, and seriously strains the development of the hydroponics and fish cultivating.Fish culture faces extreme danger from waterborne microbes, like microorganisms and infection, capable primarily for mass mortality and chronic weakness. It is, subsequently, basic to screen the immaculateness of the water territory to recognize fish illnesses opportune and precisely.

Fish performs all their physical activities under water; fish dependents on water for breathing, feeding, reproducing and growth. When the water quality of the habitat deteriorates it becomes unfavorable for fish to live in. Water quality depends on certain parameters, and when the parameters change the quality deteriorates. As a result, thehealth of fishes is threatened by the compromise of their immune system critically leading them to be vulnerable to harmful pathogens.

Oxygen plays a pivotal role in maintaining life under water. When oxygen level goes below to the preferable range, thephysiological and physical growth of fish species are hampered. Decreasing oxygen level under water results in increasing carbon dioxide level causing acidosis and nephron calcinos is that obstructs the development of granulomas in many internal organs of fish[5, 6].Moreover, recirculated water contains high pH which turns up ammonia level in water.High level of ammonia causes harm to the gills and liver of fishes. Depending on the levelof saturation and the time of exposure, Gas supersaturation of the water can result in thegas bubble disease. The main cause to the disease is the development of bubbles in theeyes, skin and gills. Degraded water quality causes pollution that creates serious problem to fish; necroticalteration, papilloma, degenerative, and finerosion is the result of water pollution. As a result, the fish body gets abnormal growth, and farmers do not getoptimum production. Problems such as these can easily be resolved if the farmers couldidentify them early. Artificial intelligent algorithms in recent years have been used extensively and very successfully in classification and decision-making problems. Smart algorithms can learn from parameter space ofsystem the correct desired classification based on real dataset, and infer very accuratelyany deviation from the desired sets of configuration, which may be exploited for decision-making. A hierarchical architecture to the algorithm ensures higher performance fromlearning. Inspiredbythesuccesses of such technique in variety of complex problems, we have employed thetechniquein this study to predict water quality by solving classification problems from real dataset composed of desired parameters of water purity. The decision-making process may be summarized in the following sequential steps:

- Step1: Taking sample of water to identify the water quality.
- Step 2: Making prediction of the water quality using deep learning algorithm. We have already collected and prepared dataset and trained our algorithm using it, so that machine can make prediction on probable fish diseases based on the water quality parameters.
- Step 3: Analyzing the disease and identifying.
- Step 4: Making smart decision to minimize harm to fish farm and ensuring healthy habitat.

The paper is arranged as following: the review of the related literature is conducted inthe second section followed by an in-depth look into the proposed machine learningalgorithm and parameters of the model in the section three. The dataset is discussed in thesection four along with the preparation, processing, and implementation in the model. The experimental results are discussed in the following sections by concluding remarks.

2. LITERATURE SURVEY

Recently, applications of ANNs in the areas of water engineering, ecological sciences, and environmental sciences have been reported since the beginning of the 1990s. In recent years, ANNs have been used intensively for prediction and forecasting in a number of water-related areas, including water resource study (Liong et al., 1999, 2001; Muttil and Chau, 2006; El-Shafie et al., 2008), oceanography (Makarynskyy, 2004), and environmental science (Grubert, 2003). J. A. Bowers (2000) developed model to predict suspended solids conceder local precipitation, stream flow rates and turbidity as input. Hatim (2007) employed an ANN approach using six variables for the initial prediction of suspended solids in the stream at Mamasin dam. Most of them employed almost all possible environmental parameters as input variables without considering the optimal choice amongst them. The present study attempted to model Johor River Basin water quality parameters using ANN modeling for the first time.

Limited water quality data and the high cost of water quality monitoring often pose serious problems for process-based modeling approaches. ANNs provide a particularly good option, because they are computationally very fast and require many fewer input parameters and input conditions than deterministic models. ANNs do, however, require a large pool of representative data for training. ANNs are, however, still not widely used tools in the fields of water quality prediction and forecasting. ANNs are able to approximate accurately complicated non-linear input– output relationships. Like their physics-based numerical model counterparts, ANNs require training or calibration. After training, each application of the trained ANN is an estimation of a simple algebraic expression with known coefficients and is executed practically instantaneously. The ANN technique is flexible enough to accommodate additional constraints that may arise in the application. Moreover, The ANN model can reveal hidden relationships in the historical data, thus facilitating the prediction and forecasting of water quality. This paper demonstrates the application of ANNs to model the values of selected river water quality parameters, having the dynamic and complex processes hidden in the monitored data itself. In addition, objective of this study is to investigate whether it is possible to predict the values of water quality parameters measured by a water quality monitoring program; this task is quite important for enabling selective monitoring of water quality parameter.

Limited water quality data and the high cost of water quality monitoring often pose serious problems for process-based modeling approaches. ANNs provide a particularly good option, because they are computationally very fast and require many fewer input parameters and input conditions than deterministic models. ANNs do, however, require a large pool of representative data for training. ANNs are, however, still not widely used tools in the fields of water quality prediction and forecasting. ANNs are able to approximate accurately complicated non-linear input– output relationships. Like their physics-based numerical model counterparts, ANNs require training or calibration. After training, each application of the trained ANN is an estimation of a simple algebraic expression with known coefficients and is executed practically instantaneously. The ANN technique is flexible enough to accommodate additional constraints that may arise in the application. Moreover, The ANN model can reveal hidden relationships in the historical data, thus facilitating the prediction and forecasting of water quality. This paper demonstrates the application of ANNs to model the values of selected river water quality parameters, having the dynamic and complex processes hidden in the monitored.

3. PROPOSED MODEL

3.1 Convolutional Neural Network:

CNN is a feed-forward neural network. Input, convolution, pooling, full connection, and output layers are the basic elements of the traditional CNN. In recent years, CNN has been used as an emerging method in water quality prediction. The operation of convolution can be implemented more than one time to reveal the relationship between the parameters hidden in the input matrix.series of multiple convolution layers perform progressively more refined feature extraction at every layer moving from input to output layers. Fully connected layers that perform classification follow the convolution layers.

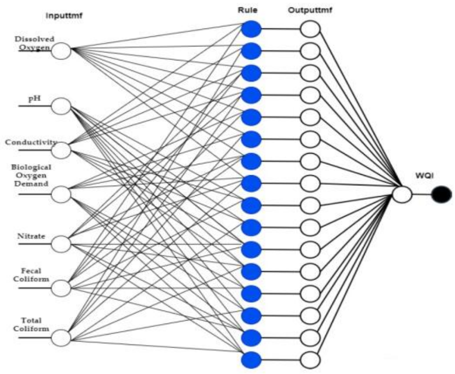


Figure: Framework to predict water quality

Unlike other neural networks, neurons in each feature extraction layers of CNN are not connected to all neurons in the adjacent layers. Instead, they are only connected to the spatially mapped fixed sized and partially overlapping neurons in the previous layer's input layer or feature map. This region in the input is called local receptive field. The lowered number of connections reduces training time and chances of over fitting. All neurons in a filter are connected to the same number of neurons in the previous input layer (or feature map) and are constrained to have the same sequence of weights and biases. These factors speed up the learning and reduce the memory requirements for the network.

3.2 Back propagation:

Backpropagation is used solely for training all parameters (weights and biases) in CNN. Here is a brief description of the algorithm. The cost function with respect to individual training example (x, y) in hidden layers can be defined as:

$$I\,(W, \theta; n, m) = \frac{1}{2} \| gw, \theta(n) - m \|^2$$

The equation for error term δ for layer L is given by:

$$\delta^{(L)} = \left((W^{(L)})^T \delta^{(L+1)} \right) .h'\,(z^{(l)})$$

Where δ (L+1) is the error for (L + 1) th layer of a network whose cost function is I (W, θ; n,m). h' $(z^{(l)})$ represents the derivate of the activation function.

$$\nabla w^{(L)} I(W, \theta; n, m) = \delta^{(L+1)} (i^{(L+1)})^T$$

$\nabla\theta^{(L)} I\,(W, \theta; n, m) = \delta^{(L+1)}$ where i is the input, such that $i^{(1)}$ is the input for 1st layer (i.e., the actual input) and $i^{(L)}$ is the input for L − th layer.

Error for sub-sampling layer is calculated as:

$$\Delta_q^{(L)} = \text{upsample}\left((W_q^{(L)})^T \delta_k^{(L+1)} \right) \cdot h'\,(z_q^{(L)})$$

Where q represent the filter number in the layer. In the subsampling layer, the error has to be cascaded in the opposite direction, e.g., where mean pooling is used, upsample evenly distributes the error to the previous input unit. And finally, here is the gradient w.r.t. feature maps:

$$\nabla w_k^{(L)} I(W, \theta; n, m) = \Sigma_{t-1}(i_t^{(L)}) * \text{rot90}(\delta_k^{(L+1)}, 2)$$

$$\nabla\theta_k^{(L)} I\,(W, \theta; n, m) = \Sigma_{i,j} (\delta_q^{(L+1)})_{i,j}.$$

Algorithm

Input:

Output:

ISSN: 2278-4632
Vol-11 Issue-01 2021

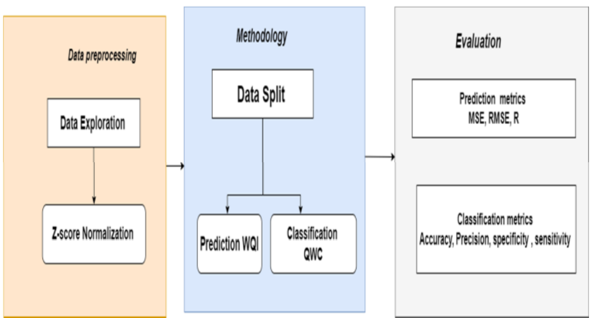
Backpropagation Algorithm in CNN

1. Initialization weights to randomly generated value(small)
2. Set learning rate to a small value (positive)
3. Iteration x = 1; Begin
4. for x< max iteration OR Cost function criteria met, do
5. for input n_1 to n_i , do
   - Forward propagate through convolution, pooling and then fully conflected layers
   - Derive Cost Function value for the input
   - Calculate error term $\delta^{(L)}$ with respect to weights for each type of layers.
6. Note that the error gets propagated from layer to layer in the following sequence
   - Fully connected layer
   - Pooling layer
   - Convolution layer
7. Calculate gradient $\nabla w_q^{(L)}$ and $\nabla\theta_q^{(L)}$ for weights $\nabla w_q^{(L)}$ and bias respectively for each layer
8. Gradient calculated in the following sequence
   - Convolution layer
   - Pooling layer
   - Fully connected layer
9. Update weights
   $w_{ji}^{(L)} \leftarrow w_{ji}^{(L)} + \nabla w_{ji}^{(L)}$
10. f.Update bias
   $\theta_j^{(L)} \leftarrow \theta_j^{(L)} + \nabla \theta_j^{(L)}$

3.3 Datasets for Experiment:

Figuredisplays the framework of the methodology used.

Figure: Framework of the proposed methodology were acquire from different



locations in India and contained 1679 simples from 666 different sources of rivers and lakes in the country. The data was collected between 2005 and 2014. The link to the datasets is attached. The datasets include eight important parameters: DO, pH, conductivity, biological oxygen demand, nitrate, fecal coliform, temp, and total coliform. However, seven parameters were considered to show significant values, and the developed models were evaluated based on some statistical parameters. All the experiments consisted of temp parameters. The Indian government collected these data to ensure the quality of the drinking water supplied. This dataset was obtained from Kaggle

3.4 Data Pre-processing:

The processing phase is very important in data analysis to improve data quality. In this phase, WQI was calculated from the most important parameters of the dataset. Then, water samples were classified on the basis of WQI values. The z-score method was used as a data normalization technique for superior accuracy.

3.5 Water Quality Index (WQI) Calculation:

The WQI, which is calculated using several parameters that affect WQ [32], was used to measure water quality. The performance of the proposed system was evaluated on the published dataset, with seven important water quality parameters. The WQI was calculated using the following formula:

$$WQI = \frac{\sum_{i=1}^{N} q_i \times w_i}{\sum_{i=1}^{N} w_i} \quad (1)$$

where N denotes the total number of parameters included in the WQI formula, qi denotes the quality estimate scale for each parameter i calculated by Formula (2), and wi denotes the unit weight of each parameter in Formula (3).

$$q_i = 100 \times \left(\frac{V_i - V_{Ideal}}{S_i - V_{Ideal}}\right) \quad (2)$$

Where Vi is a measured value that refers to the water samples tested, VIdeal is an ideal value and indicates pure water (0 for all parameters except OD = 14.6 mg/L and pH = 7.0), and Si is a standard value recommended for parameter i.

$$w_i = \frac{K}{S_i} \quad (3)$$

where K denotes the constant of proportionality, which is calculated using the following formula:

$$K = \frac{1}{\sum_{i=1}^{N} S_i}$$

WQI can be used to calculate more parameters, including our selecting parameters. The WQI depends on the variable data. The proposed system can test any parameters with any water quality data.

S.No	Water Quality Parameters	Range
1	Dissolved Oxygen (DO)	(4-10) ppm
2	Ammonia	(0-0.1) ppm
3	pH	(7.5-8.5) ppm
4	Temperature	21^0C-33^0C
5	Salt	(0-2)ppt
6	Carbonates (CO_3^{2-})	(20-40)ppm
7	Bicarbonates(HCO_3^-)	(150-500)ppm
8	Nitrates(NO_2)	(0-0.3)ppm
9	Sour gas (H_2S)	(0-0.4)ppm

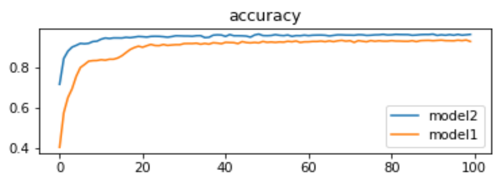
Table.1 water quality parameters with threshold range

Z-Score Normalization Method:

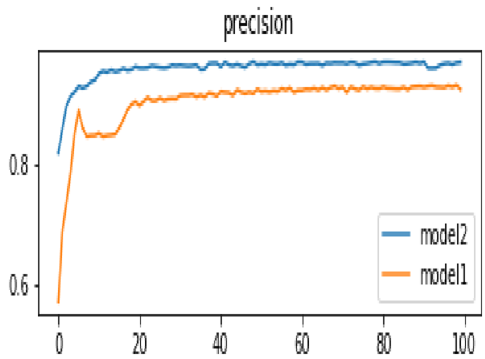
Z-score a is used to normalize data by computing both the mean (μ) and standard deviation. The Z-score was applied to scale parameter values between 0 and 2. It is calculated using the following formula:

$$Z - \text{score} = \frac{(x - \mu)}{\sigma} \quad (5)$$

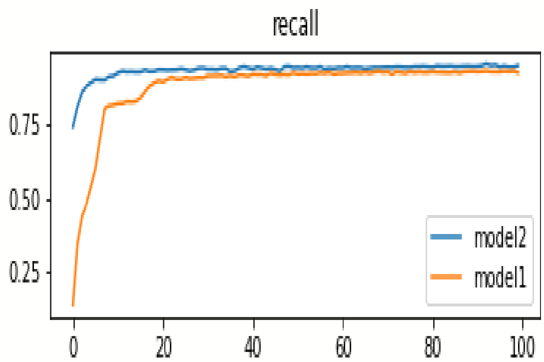
Where x represents the tested sample in the dataset to be evaluated.



Plot precision of the both model1 and model2

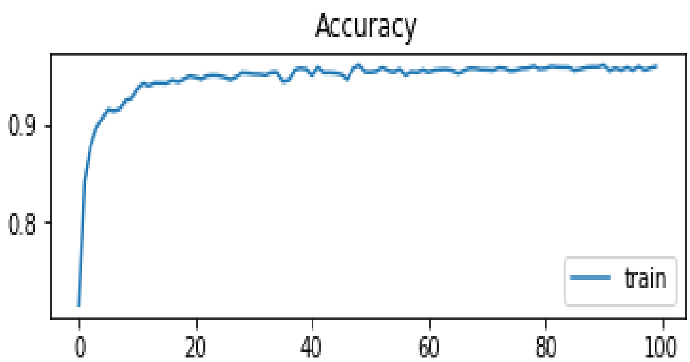


Plot precision of the both model1 and model2

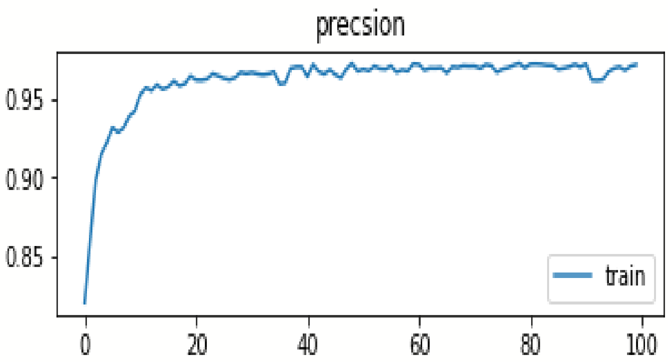


Plot recall of the both model1 and model2

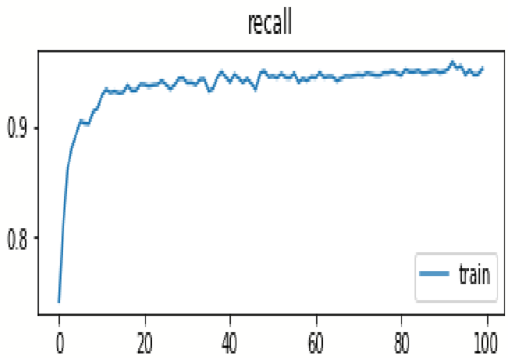
4. EXPERIMENTAL RESULTS:



Plot accuracy during training



plot Precision during training



plot Recall during training

4.1 Performance Measurement:

Performance measurement approaches, such as MSE, were applied to evaluate the ability of the proposed model to predict the WQI. Furthermore, the accuracy, specificity, sensitivity, precision, recall, and F-score performance measurements were determined to evaluate the FFNN and KNN where R is Pearson's correlation coefficient, x is the observation input data in the first set of the training data, y is the observation input data of the second set of the training data, and n is the total number of input variables.

- Accuracy

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100\%$$

- Specificity

$$Specificity = \frac{TN}{TN + FP} \times 100\%$$

- Sensitivity

$$Sensitivity = \frac{TP}{TP + FN} \times 100\%$$

- Precision

$$Precision = \frac{TP}{TP + FP} \times 100\%$$

5. CONCLUSION

In this study, deep learning models (CNN) to simulate the water level and the water quality parameterspH, DO, BOD, COD, EC, PO43-, NO3-N, and NH3-N. Among the deep learning models, the CNN model was adopted to simulate the water level. We found the following in this study:

- The water level from the CNN model produced the NSE value of 0.933 that can be regarded as acceptable model performance. The water levels increased in the rainy season, while those were low in the dry season.
- For all of the pollutants, the NSE values of the CNN model for the training and validation periods were above 0.75 which is within the “very good” performance range. The CNN model in this study well represented the different temporal variations of each pollutant type.

This study suggests that the approach of the two deep learning techniques proposed in this study has promise as a tool in accurately simulating the water level and water quality and that this approach can contribute to developing effective strategies for better water sustainability and management. Although our model showed the acceptable model performance, only the three different pollutants were investigated in this study. However, most process-based models can simulate a lot more water quality including the three pollutants (e.g., chlorophyll, algae, dissolved oxygen, and fecal bacteria). A further study is recommended to develop deep learning models so that more pollutants including chlorophyll, algae, dissolved oxygen, and fecal bacteria can be simulated. In addition, further study on the deep learning model with “visual explanations” is required, such as Gradient-weighted-Class Activation Mapping (Grad-CAM) and CAM, because the deep learning model is a black-box model that has general difficulty in identifying physical features. In addition, the approach outlined in this study should be replicated with other datasets.

REFERENCES

1. Han, H.G.; Qiao, J.F.; Chen, Q.L. Model predictive control of dissolved oxygen concentration based on a self-organizing RBF neural network. Control Eng. act. 2012, 20, 465–476. [Google Scholar] [CrossRef]
2. Liu, S.; Yan, M.; Tai, H.; Xu, L.; Li, D. Prediction of dissolved oxygen content inquaculture of hyriopsiscumingii using elman neural network. IFIP Adv. Inf. Commun.Technol. 2012, 370 AICT, 508–518. [Google Scholar] [CrossRef]
3. Chen, S.; Fang, G.; Huang, X.; Zhang, Y. Water quality prediction model of a water diversion project based on the improved artificial bee colony-backpropagation neural network. Water 2018, 10, 806. [Google Scholar] [CrossRef]
4. Fijani, E.; Barzegar, R.; Deo, R.; Tziritis, E.; Konstantinos, S. Design andimplementation of a hybrid model based on two-layer decomposition method coupledth extreme learning machines to support real-time environmental monitoring of waterquality parameters. Sci. Total Environ. 2019, 648, 839–853. [Google Scholar][CrossRef] [PubMed]
5. Wang, Y.; Zhou, J.; Chen, K.; Wang, Y.; Liu, L. Water quality prediction method basedon LSTM neural network. In Proceedings of the 2017 12th International Conference onIntelligent Systems and Knowledge Engineering, ISKE 2017, Nanjing, China, 24–26November 2017. [Google Scholar] [CrossRef]
6. Nourani, V.; Alami, M.T.; Vousoughi, F.D. Self-organizing map clustering technique forANN-basedspatiotemporal modeling of groundwater quality parameters. J.Hydroinformatics 2016, 18, 288–309. [Google Scholar] [CrossRef]
7. Chang, F.J.; Chen, P.A.; Chang, L.C.; Tsai, Y.H. Estimating spatio-temporal dynamics ofstream total phosphate concentration by soft
8. Kanumalli, S.S., Chinta, A.,ChandraMurty, P.S.R. (2019). Isolation of wormhole attackers in IOV using WPWP packet. Revue d'IntelligenceArtificielle, Vol. 33, No. 1, pp. 9-13. https://doi.org/10.18280/ria.330102
9. Narayana, Vejendla Lakshman, et al. "Secure Data Uploading and Accessing Sensitive Data Using Time Level Locked Encryption to Provide an Efficient Cloud Framework." Ingénierie des Systèmesd'Information 25.4 (2020).

10. Kotamraju, Siva Kumar, et al. "Implementation patterns of secured internet of things environment using advanced blockchain technologies." Materials Today: Proceedings (2021).
11. Krishna, Komanduri Venkata Sesha Sai Rama, et al. "Classification of Glaucoma Optical Coherence Tomography (OCT) Images Based on Blood Vessel Identification Using CNN and Firefly Optimization." Traitement du Signal 38.1 (2021).
12. Satya Sandeep Kanumalli, Anuradha Ch and Patanala Sri Rama Chandra Murty, "Secure V2V Communication in IOV using IBE and PKI based Hybrid Approach" International Journal of Advanced Computer Science and Applications(IJACSA), 11(1), 2020. http://dx.doi.org/10.14569/IJACSA.2020.0110157
13. CHALLA, RAMAIAH, et al. "Advanced Patient's Medication Monitoring System with Ardunio UNO and NODEMCU." 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA). IEEE, 2020.
14. Kanumalli, Satya Sandeep, Anuradha Ch, and Patanala Sri Rama Chandra Murty. "Advances in Modelling and Analysis B." Journal homepage: http://iieta. org/Journals/AMA/AMA_B 61.1 (2018): 5-8.
15. Venkatramulu, S., et al. "Implementation of Grafana as open source visualization and query processing platform for data scientists and researchers." Materials Today: Proceedings (2021).
16. Sandeep, Kanumalli Satya, Anuradha Chinta, and PatanalaMurty. "Isolation of Wormhole Attackers in IOV Using WPWP Packet." Rev. d'IntelligenceArtif. 33.1 (2019): 9-13.
17. Gopi, ArepalliPeda, et al. "Classification of tweets data based on polarity using improved RBF kernel of SVM." International Journal of Information Technology (2020): 1-16.
18. Narayana, Vejendla Lakshman, ArepalliPeda Gopi, and Kosaraju Chaitanya. "Avoiding Interoperability and Delay in Healthcare Monitoring System Using Block Chain Technology." Rev. d'IntelligenceArtif. 33.1 (2019): 45-48.
19. Arepalli, Peda Gopi, et al. "Certified Node Frequency in Social Network Using Parallel Diffusion Methods." Ingénierie des Systèmesd'Information 24.1 (2019).
20. Narayana, Vejendla Lakshman, ArepalliPeda Gopi, and R. S. M. Patibandla. "An Efficient Methodology for Avoiding Threats in Smart Homes with Low Power Consumption in IoT Environment Using Blockchain Technology." Blockchain Applications in IoT Ecosystem. Springer, Cham, 2021. 239-256.
21. Kotamraju, Siva Kumar, et al. "Implementation patterns of secured internet of things environment using advanced blockchain technologies." Materials Today: Proceedings (2021).
22. Bharathi, C. R., et al. "A Node Authentication Model in Wireless Sensor Networks With Locked Cluster Generation." Design Methodologies and Tools for 5G Network Development and Application. IGI Global, 2021. 236-250.
23. Vejendla, Lakshman Narayana, Alapati Naresh, and Peda Gopi Arepalli. "Traffic Analysis Using IoT for Improving Secured Communication." Innovations in the Industrial Internet of Things (IIoT) and Smart Factory. IGI Global, 2021. 106-116.
24. Narayana, Vejendla Lakshman, ArepalliPeda Gopi, and Kosaraju Chaitanya. "Avoiding Interoperability and Delay in Healthcare Monitoring System Using Block Chain Technology Avoiding Interoperability and Delay in Healthcare Monitoring System Using Block Chain Technology."
25. Yamparala, Rajesh, and Balamurugan Perumal. "EFFICIENT MALICIOUS NODE IDENTIFICATION METHOD FOR IMPROVING PACKET DELIVERY RATE IN MOBILE AD HOC NETWORKS WITH SECURED ROUTE." Journal of Critical Reviews 7.7 (2020): 1011-1017.