PREDICTION OF IRRIGATION WATER QUALITY INDEX IN RAIGARH THROUGH ANN MODELLING

A DISSERTATION

In partial fulfilment of the requirements for the award of the degree of

Master of Technology

in

HYDRAULICS AND WATER RESOURCE ENGINEERING

Submitted by:

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JULY, 2021

CANDIDATE'S DECLARATION

I, SIDDHANT PANIGRAHI, Roll no. 2K19/HFE/02 student of M.Tech (Hydraulics and Water Resource Engineering), hereby declare that the project dissertation titled "PREDICTION OF IRRIGATION WATER QUALITY INDEX IN RAIGARH THROUGH ANN MODELLING" which is submitted by me to Department of Civil Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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I hereby certify that the project Dissertation titled "PREDICTION OF IRRIGATION WATER QUALITY INDEX IN RAIGARH THROUGH ANN MODELLING" which is submitted by SIDDHANT PANIGRAHI, Roll no. 2K19/HFE/02, Hydraulics and Water Resource Engineering, Department of Civil Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

M. Kumar.

Place: Delhi PROF. MUNENDRA KUMAR

Date: 3/08/2021 (SUPERVISOR)

ACKNOWLEDGEMENT

With immense pleasure I, Mr ….SIDDHANT PANIGRAHI…………….

Presenting **"PREDICTION OF IRRIGATION WATER QUALITY INDEX IN RAIGARH THROUGH ANN MODELLING."**

Major project Report as part of the Curriculum of 'Master of Technology'. I wish to thank

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ABSTRACT

Keywords:- Neural network, Backpropagation algorithm, Irrigation Water quality index, Raigarh District, Neural designer

The application of conventional methods in evaluation of irrigation water quality indexes is quite cumbersome and tedious. However the application of AI models is a great substitute in such scenarios which can forecast as well as evaluate IWQI using physiochemical analysis. This project deals with the prediction of kelo river suitability for irrigation around the areas of Raigarh and Janjgir-Champa districts. The aim is to forecast the Sodium adsorption ratio(**S.A.R**), Kelly ratio(**K.R.)** and Sodium percentage**(%Na)** in the kelo river irrigation project, Raigarh. A total 1500 water samples are to be analysed for different physiochemical parameters as such $_{P}$H, Electrical conductivity, Total dissolved solid, Calcium ions, Magnesium ions, Potassium ions, Chlorine ions and Sodium ions. These parameters are to be used as input variable in ANN. The ANN model will be developed through Neural designer and compared with MS- excel software. The best backpropagation algorithm and neuron numbers are to be determined for optimization of model architecture. The Relative mean square error, Coefficient of determination and Mean absolute percentage inaccuracy amid tentative data and prototypical output will be considered for its accuracy. The developed model will have its use in prediction of IWQI and will also be of great assistance for decision makers as well as farmers in management of irrigation water.

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ABRREVIATION USED

ET	Evapotranspiration
FAO	Food agricultural organization
TDS	Total dissolved solid
SAR	Sodium adsorption ratio
MAR	Magnesium adsorption ratio
KR	Kelly ratio
SSP	Soluble sodium percentage
EPA	Environmental protection act
MLR	Multiple linear regression
ARIMA	Auto regression integrated moving average
ANN	Artificial neural network
LMA	Levenberg marquardt algorithm
BPA	Backpropagation algorithm
NM	Newton method
QNM	Quasi newton method
MLP	Multilayer perceptron
RBFNN	Radial basis function neural network
GRNN	General regression neural network
ELM	Extreme learning machine
RNN	Recurrent neural network
LSTM	Long short term memory
CNN	Convolution neural network
WNN	Wavelet neural network
ANFIS	Adaptive neural fuzzy inference system
NARX	Non-linear autoregressive with exogenous input

CHAPTER-1

INTRODUCTION

1. IRRIGATION SYSTEMS

For over 5000 years now the most prominent feature of agriculture has been irrigation. It has been the basis for economies and societies across the world. Irrigation assists in growth of cultivable crops, manage landscapes, and revegetate disrupted soils in dry regions and during periods of scanty rainfall. Different employments of water system are in crop creation, including ice preservation, limiting weed development in grain fields and turning away soil union.

Water system frameworks has its application in cooling animals, dust concealment, removal of sewage, and in mining activities. Water system is every now and again considered close by seepage, which is the discharge of surface and sub-surface water from a given stretch. The shifting water system water sources are underground water (from springs and wells), surface water (from waterways, lakes and repositories) and the non-customary sources like treated wastewater, desalinated water, seepage water and so on .”Indian irrigation system has a network of major and minor canals on Indian rivers, groundwater based systems, tanks, and modern rainwater harvesting projects to satisfy the agricultural requirements. Among these groundwater system is the biggest. In 2013-14, only about 36.7% of total arable land in India was certainly irrigated, and remaining 2/3rd cultivated land in the country is relying upon monsoons. Presently about 51% of the arable area cultivating food grains is roofed by irrigation”[8]. It is estimated that greater than 60% of all water absconds revert back to the water cycle via return flows to rivers and groundwater, while the remaining is consumptive water use along evapotranspiration (ET). Globally, cumulative water absconds are only 9% of internal renewable water resources, although there are large discrepancies in water absconds in other regions. Surface water systems are naturally refilled by precipitation within their watersheds and naturally lost through discharge into the oceans, evaporation, ET and groundwater recharge. “It is computed that 505 000 km3, or a layer 1.4 m deep, evaporates from the oceans annually. Another 72 000 km3 evaporates from the land surface”[8]. The possibility of surface water in any system at any given time depends on oodles factors, that are depository capacity of lakes, wetlands and artificial reservoirs, soil type and local surface and soil evaporation rates. Human activities can have a large and sometimes staggering impact on these aspects, such as increasing depository capacity by constructing reservoirs and decreasing it by draining wetlands. The construction of roads and vegetation asserting can surge run-off quantities and velocities of stream flow. Human activities may also pollute a surface water resource by augmenting it with polluted water, thereby making it unusable for household and agricultural purposes. Surface water utilized for irrigation is extricated from rivers, lakes and aquifers. Recent estimates suggest that about 188 million ha (62% of the irrigated area) is supplied from surface water and about 113 Mha (38%) from groundwater (FAO, 2011). The varying application of water is based upon its unique physical & chemical properties. The utilizable water resource in India is insufficient in irrigating the arable area. In this manner endeavour’s are needed to amplify the odds of water for watering in agribusiness. “The water quality is an aftermath of the natural, physical and chemical state of water as well as any variance that might have occurred over time as a repercussion of anthropogenic activity. However factors as such industrial discharge, agricultural & domestic discharge, land use practices and rainfall forms affect the surface water quality”[3].

WATER QUALITY

The water quality is a repercussion of the regular, physical and compound condition of water just as any transformation that may have happened as a repercussion of anthropogenic action. However aspects as such discharge of industrial, agricultural & domestic water, land use practices and rainfall motifs affect the surface water quality. The inferior quality water used for irrigation may slash the crop yield and also hamper soil quality. “The aspects swaying the stream water composition, thus evoking disparity in stream water quality criterion includes pH measures, salinity, conductivity, turbidity, total dissolved solids (TDS), dissolved oxygen (DO), total suspended solid (TSS), forms of phosphorus and nitrogen, contaminants as faecal coliform and herbicide atrazine with their structure from place to place”[3]. The rain, volcanic activity, dissolution of rocks, pollution, chemical and biological interaction are persuading parameters of water quality (Allan and Castillo 2007).

The riverine biota and stream water quality parameters are influenced by specific environmental conditions that are present in longitudinal (Upstream and Downstream), lateral (aquatic and terrestrial), vertical (surface and groundwater) and temporal gradients characterizing ecosystems (Hauer and Lambetti 2007). The fundamentals of stream flow, fluvial ecosystem, fluvial geomorphology, stream water chemistry, biotic and abiotic process are all explained in (Allan and Castillo 2007).

“The suitability of surface water for irrigation is considerably based on the concentration of cations and anions present in the River water. The sodium adsorption ratio (SAR), residual sodium carbonate (RSC), magnesium adsorption ratio (MAR), Kelly’s ratio (KR) and %Na plays a vital role to determine the suitability of river water for irrigation purpose. The investigation of water suitability for irrigation should focus on salt concentration, which increases soil salinity and affects soil fertility and crop productivity”[6]. Water quality evaluation depends on its specific use. Most ordinarily dissolved ions in water are sodium (Na^+), magnesium (Mg^{2+}), calcium (Ca^{2+}), sulphate (SO_4^{2-}), nitrate (NO_3^{2-}), chloride (Cl^-), carbonate (CO_3^{2-}) and bicarbonate (HCO_3^{2-}).

The fixation and extent of the broke up particles in addition to other things deciding reasonableness of water for water system. The sum and attributes of the broke down salts rely upon the source and compound organization. Regularly nature of water system water is evaluated dependent on salt and salt initiating substance, the presence and wealth of full scale and miniature supplements, alkalinity, sharpness, hardness and measure of suspended solids.

“Water quality standards for surface waters vary significantly due to varying environmental condition, ecosystem, and intended human use. Toxic substance and high populations of certain microorganisms can present a health hazard for purposes as such irrigation, swimming, fishing, rafting, boating, and industrial uses. These conditions also affect wildlife, which use the water for drinking or as a habitat. According to the Environment Protection Act (EPA), water quality laws generally specify protection of fisheries and recreational use and require, as a minimum, retention of current quality standards”[16].

There exists some craving midst people in general to return water bodies to pre-modern state of affairs. Utmost momentum natural laws meet on the assignment of specific employments of a water body. In certain nations these assignments take into consideration some water pollution as long as the particular sort of defilement isn't unfavourable to the planned employments.

2. PREDICTING WATER QUALITY

Predicting water quality is one of the purpose of model development and its use. It thus achieves appropriate management over period of time. Water quality prediction essentially forecasts variation trend of water quality at a certain time in future. Precisely foreseeing water quality may assume significant part in ecological checking, environment supportability and human wellbeing. Also foreseeing future changes in water quality is essential for early control of insight hydroponics and water system later on. Subsequently water quality expectation has incredible common-sense importance. Also water quality has been threatened by various pollutant in recent decades thus making the modelling and prediction of water quality crucial in controlling pollution and enhancing the suitability for its intended use.

There are many traditional water quality prediction methods as such multiple linear regressions (MLR), visual modelling, statistical approaches, autoregressive integrated moving average (ARIMA) etc. MLR because of its linear inheritance do not detect a non-linear relationship between the water quality parameters. However "ARIMA pre-assumes the model to be linear, thus time series data must be checked to see if they are stationary or non-stationary, as its critical in creating ARIMA model. Traditional methods were unable to capture non-linearity and non-stationarity of water quality due to its complex and sophisticated nature"[14].

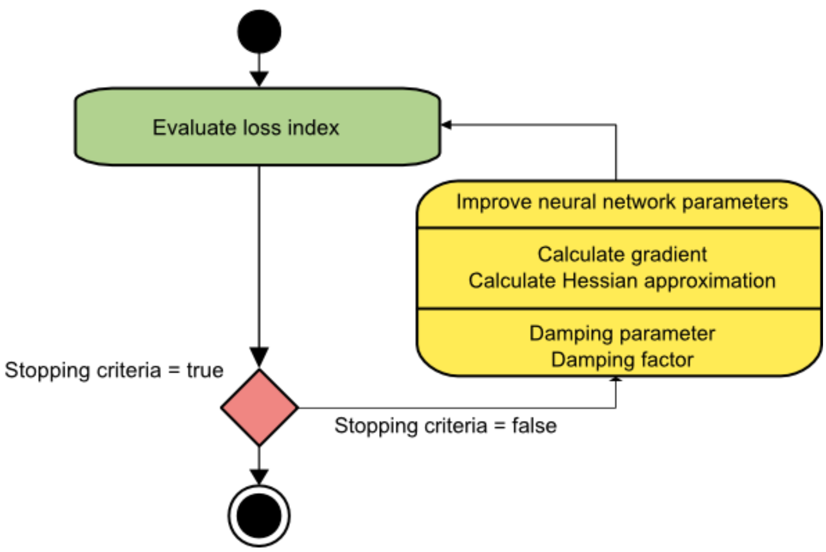
However considering the temporal dimensions for forecasting the water quality patterns ensures monitoring of seasonal change of the water quality. The use of separate variation of model together yields better results than using a single model for predicting water quality. For deciding connection and connections among various water quality boundaries normally multivariate factual methods are utilized. The geostatistical approaches are utilized for momentary likelihood, multivariate addition and relapse investigation.

“With the advancement of computing power data driven models and artificial neural network (ANN) models have been developed. These models can easily capture the functional relationships among water quality data. ANN models still work when underlying relationships of obtained data are difficult to describe. Moreover these models require fewer prior assumptions and still achieve higher accuracy compared with traditional approaches. These models prove to be beneficial for solving the non-linear and uncertain problems due to its similar characteristics with the brain functioning of human body”[19]. Accordingly at present specialists for the most part accentuate on upgrading the appropriateness and dependability of water quality expectation demonstrating by utilizing advancements as such fluffy rationale, stochastic, ANN and profound learning.

3. ARTIFICIAL NEURAL NETWORK

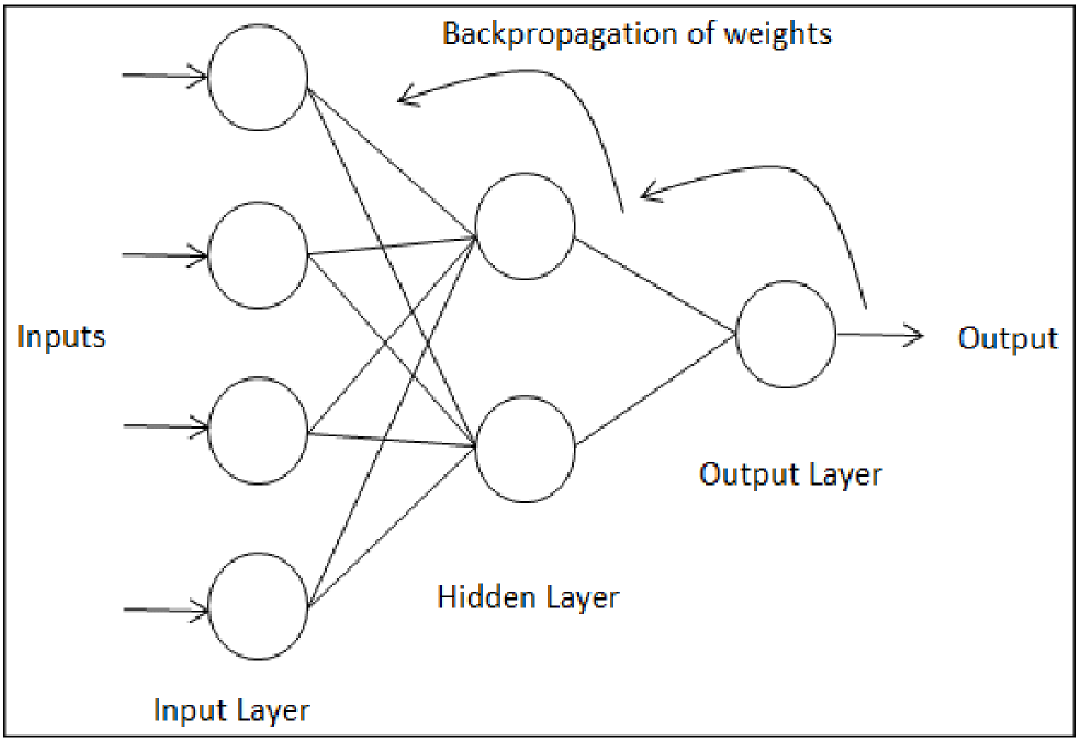
Counterfeit neural organization (ANN) is a piece of measuring framework conceived to reproduce the manner in which the human cerebrum asks and measures data. It is the establishment of man-made brainpower (AI) and translates issues that would demonstrate pointless by human or measurable guidelines. ANNs make them learn capability in this way empowering them to outturn fitter outcomes as more information opens up. “The artificial neural network is a totality of processing elements called neurons, which are linked to each other by a set of weights. It takes number of inputs weight them, sums them up, adds a bias and uses a results as the squabble for singular valued function, the transfer function, which emanates in the neurons output. In the ANN model three layers are utilized first one is input variables, then hidden neurons and the last one being output. The input variables are processed with some weight and the forecasted output is delivered. Neural networks have pliable non-linear function mapping potentiality that can approximate any continuous quantifiable function with arbitrarily coveted precision, whereas most of the commonly used factual models do not have this property. Second, being non parametric and data-driven, neural networks inflict lesser prior hypothesis on the underlying process from which data are generated. Also, high computation rate, learning potentiality through pattern presentation, foretelling of unknown patterns, and adaptability affronts for noisy patterns are other specifics of using ANNs. The neurons receive information from different inputs and obtain non-linearity through activation functions. The ANN models bet massively on bulk of data”[10]. For that reason it is not praised for reasonably small records and dinkier inputs modelling. As usually some pragmatic information is obscured in petite term records which might prime to pitiable forecasting outcomes. In accumulation data apportioning is imperative to modelling process.

Selection of training algorithm to calibrate the model parameters is a vital step for network in approximation of complicated non-linear input-output relation. Most commonly used algorithm are Levenberg-Marquardt algorithm, Backpropagation algorithm, Newton method and Quasi newton method etc. Levenberg-Marquardt calculation is intended to work with misfortune capacities, which appear as amount of squared blunders. This makes it to be quick when preparing neural organizations estimated on that sort of blunders.



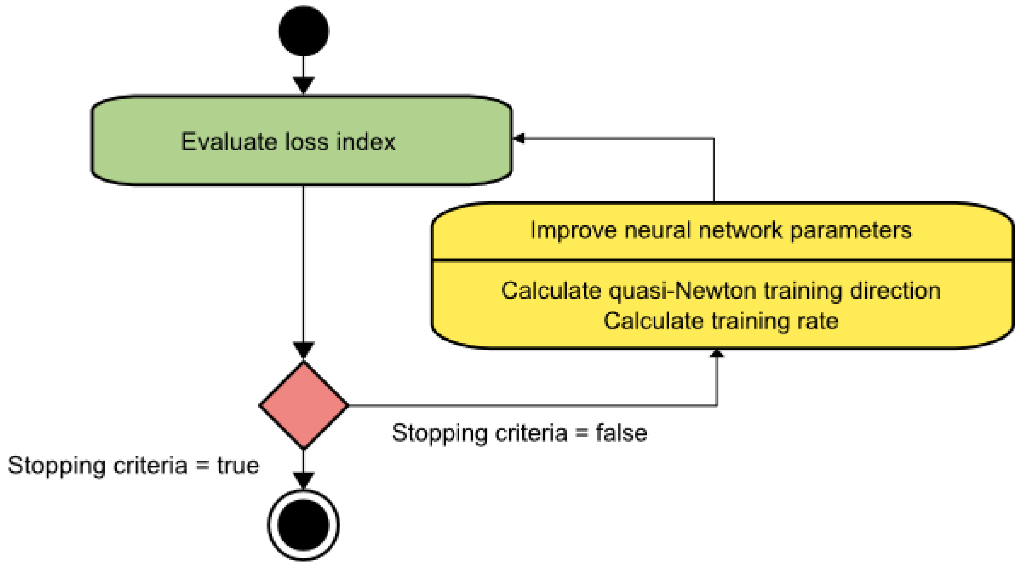
1.State diagram for Levenberg Marquardt algorithm

ANN uses a set of learning decree called backpropagation to aces their output results. It originally goes through training phase where it learns to perceive data patterns. During the supervised phase network confronts actual output produced with the coveted output. The difference between actual output and coveted output is rectified using backpropagation. Thus the network works backward from output unit to input unit adapting weight of its connection between units until lowest possible error of difference is produced.



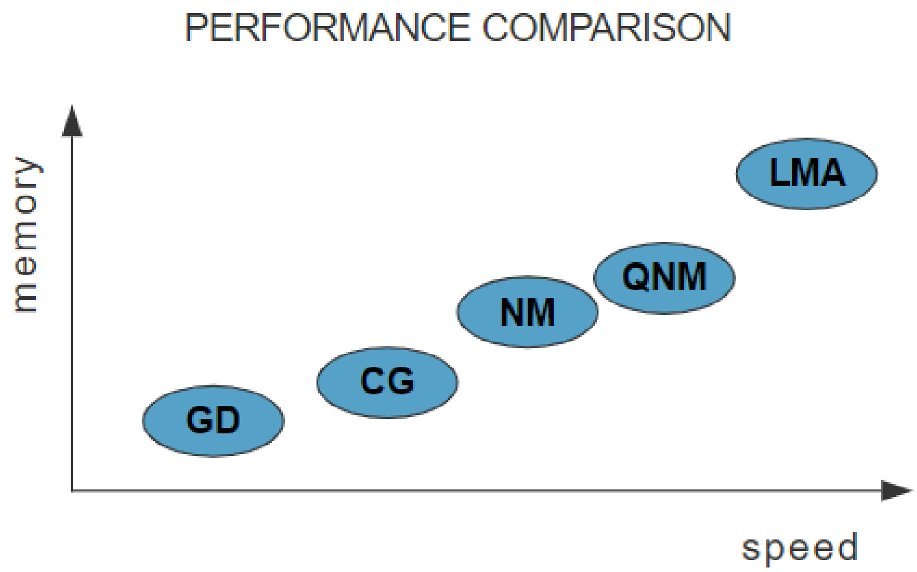
2. State for Backpropagation algorithm

Be that as it may the Quasi newton technique as opposed to computing the Hessian straightforwardly, and afterward assessing its reverse, develop an estimation to the opposite Hessian at every cycle of the calculation. This estimate is processed utilizing just data on the principal subsidiaries of the misfortune work. Improvement of the boundaries is performed by first acquiring the semi Newton preparing bearing and afterward tracking down a good preparing rate. It's the default strategy much of the time.



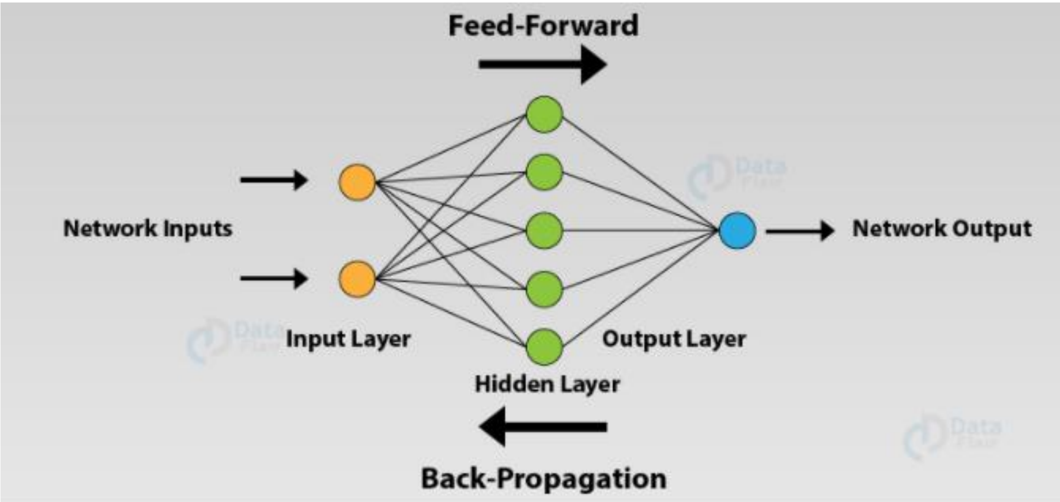
3. State for Quasi newton algorithm

“The slowest training algorithm is usually gradient descent, but it is the one requiring less memory. On the contrary, the fastest one might be the Levenberg-Marquardt algorithm, but it normally requires much memory. A good accord might be the quasi-Newton strategy”[14]. The chart below portrays the computational speed and memory requirements of training algorithm.



4. Performance of different algorithm

Artificial neural network models persuades the number of connection weights and the flow of intelligence through the network. Multilayer perceptron is an extensively used architecture with three layers in many types of feedforward ANNs. Some of the conventional feedforward ANNs are as such Radial basis function neural network (RBFNN), General regression neural networks (GRNN) and Extreme learning machines (ELM) etc. An enhancement of recurrent neural network (RNN) which intents to address the vanishing gradient problem is Long short term memory (LSTM) neural network. Convolutional neural network is an looming framework extensively utilized in the field of image.



5. ANN Structure

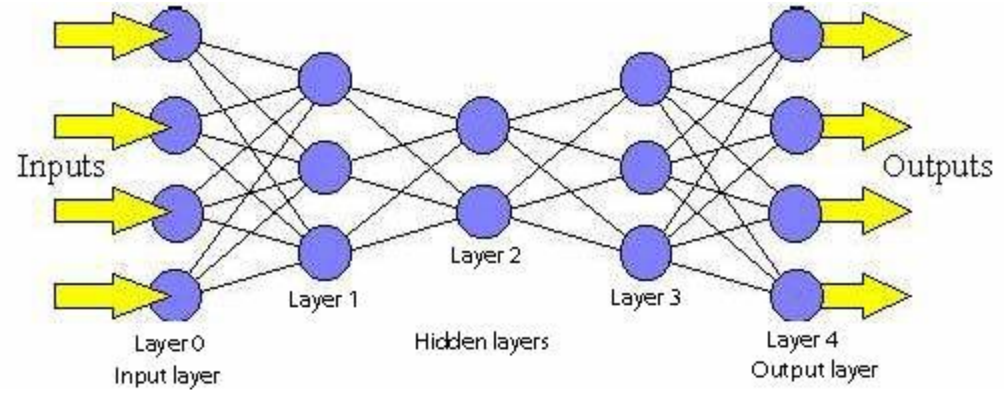
ANN platforms are disrupting the accustomed way of doing things. These networks stand flagging the way for life altering solicitations to be evolved for use in all sections of society. These are accepted in all areas of operation. ANNs can be tellingly employed to ascertain and delete spam from user’s inbox, to foretell the direction of company’s stock, to reveal the credit scoring methods, to personalize approbation to audience, to foretell prospect of an event and the roster verves on through manifold sectors and industries. The pragmatic application of ANN are distant and broad surrounding industry, education, personal communication, e-commerce, finance and so on.

4. MODEL STRUCTURES IN WATER QUALITY PREDICTION

Model engineering alludes to the general design stream of data starting with one layer then onto the next. The basic model structure include feedforward architectures, intermittent networks and hybrid prototypes.

➢ Feedforward architectures

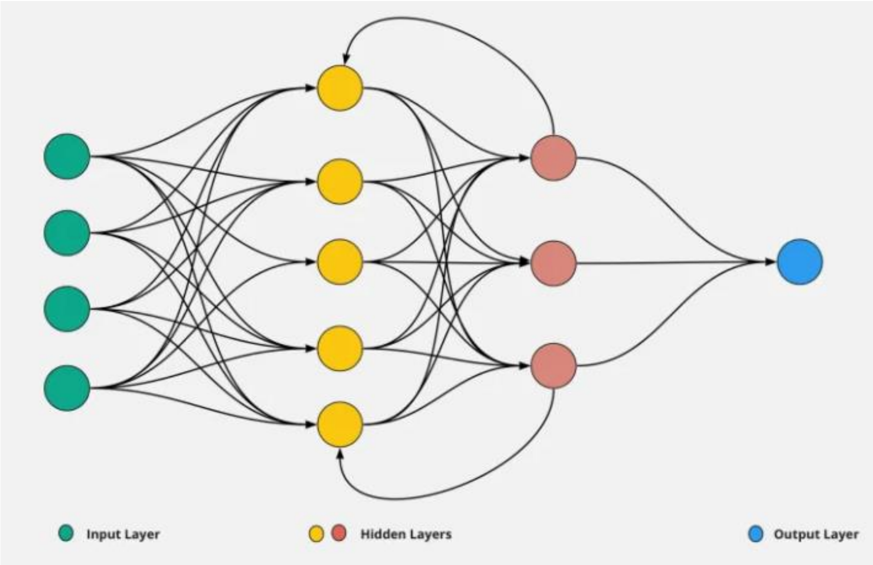
It's anything but a neuron association just subsists from a neuron in the info layer to different neurons in the secret layer or from a neuron in the secret layer to the neuron in yield layer. The neurons exclusive of layer are disengaged however.



6. Multilayer feedforward network

➢ Recurrent architectures

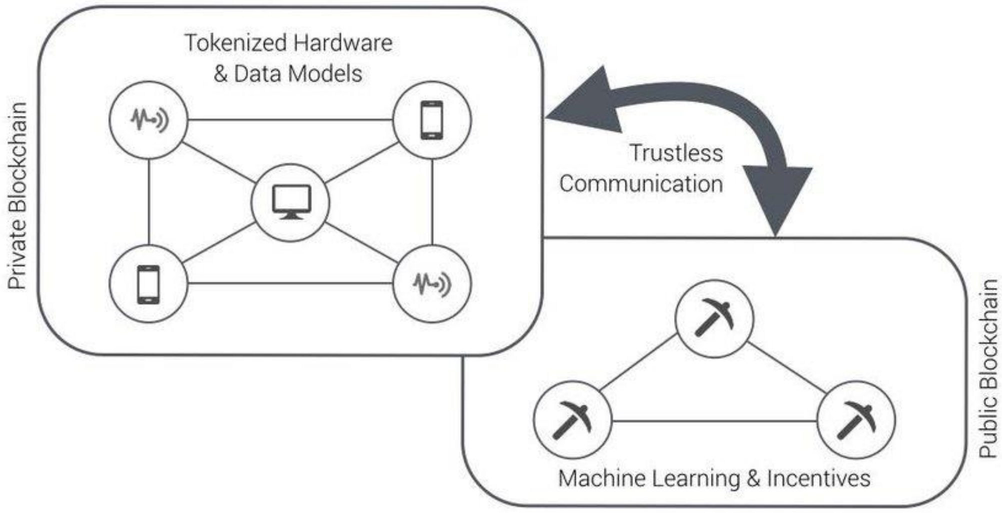
These diverge from feedforward such hat neurons inside a layer are interconnected and permit feedback. These are developed so that neural networks have superior memory ability. The dominant idea behind recurrent architectures is to process sequential data adroitly. These diverge from traditional neural network only due to its notion of internal memory. RNN is the basic and most dynamic neural network. The enhancement over RNN is LSTM..



7. Recurrent architecture

➢ Hybrid architectures

The hybrid architectures play a gigantic role in modelling because of their potentiality to integrate with other traditional and more progressive modelling . Techniques to create pliable and efficient models. These prototypes are arranged into three classes in particular model serious, method concentrated and information escalated. Model concentrated methodologies model sub segment of entire actual framework and total the general reaction of each model. Technique Intensive strategies flourish a modelling framework taking dominance of different technologies. Data intensive approaches combine various technologies to pre-process the data.



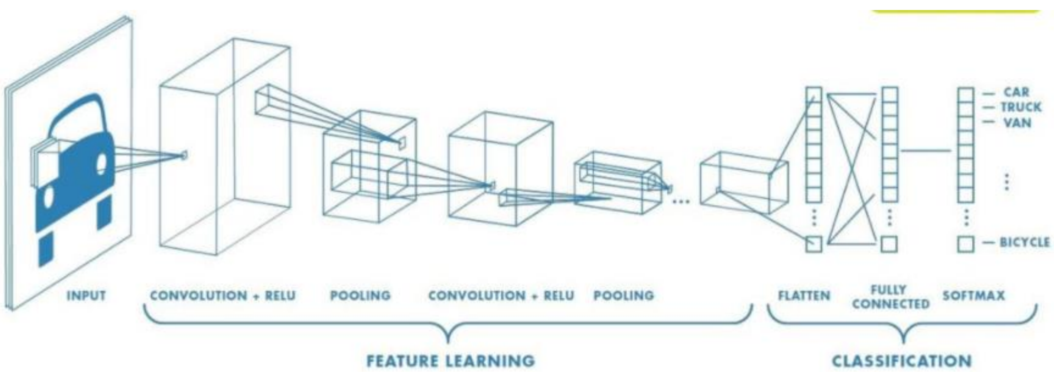
8. Hybrid architectures

Feedforward	• MLP, RBFNN, GRNN • Time delay neural network
Recurrent	• RNN, LSTM • NARX, Time lag recurrent network
Hybrid	• ARIMA-ANN, LSTM-RNN • Principal component analysis with backpropagation network

9. Example of model architectures

- **Emerging methods**

The feedforward neural network as such CNN are essentially utilized in the image field. The basic element of CNN are input, convolution, pooling, full connection and output layer. Convolution can be actualized multiple times to affirm relationship between the parameters hidden in input. Deep learning neural network is akin to feedforward architecture and is now being widely utilized. Aspects of network execution such as running time and prediction accuracy are improved.



10. CNN architecture

The table below summarizes the foundation and advantages of development model structure.

CATEGORIES	STRUCTURES	ADVANTAGES
Multilayer perceptron (MLP)	Based on an understanding of biological nervous system.	Solving non-linear problems.
Radial basis function neural network (RBFNN)	Similar to MLP but the activation function is in hidden layer.	Overcomes the local minimum problems.
General regression neural network (GRNN)	Here exists an example and totalization layer among info and yield layers.	Unravelling lesser trial problems.
Wavelet neural network (WNN)	Replaces the linear sigmoid activation function of MLP.	Solving the non-stationary problems.
Recurrent neural network (RNN)	Developed with development of deep learning.	Solving the problems of long term dependence.
Long short term memory (LSTM)	Memory cell state is added to hidden layer.	Solving vanishing gradient problems.
Non-linear autoregressive with exogenous input (NARX)	Recurrent connections are from output.	Solving the problem of long term dependence.
Hybrid methods	Internal integration of ANN methods.	Exploring advantages of each method.

Convolution neural network (CNN)	Input, convolution, pooling, connection and output layers.	Emerging method to solve dissolve oxygen problems.
Echo state network (ESN)	Three strata are input, pool and information layer.	Conquers the issue of nearby minima and evaporating angle.

Table 1. Types of neural network and types

5. AIM OF PROJECT

ANN models were more perturbed about the water quantity e.g., (flow and rainfall-runoff prediction) and less cynosure was given to water quality forecasting. Also model development was carried out scorning the output strategies between input(s) and output(s) in a prediction task. The project focuses on use of ANNs method for water quality forecasting with more water quality variables. The intent of the current investigation is to evolve the advanced ANN prototypical to arbitrate the river water fitness for watering. The estimate of SAR, KR and %Na were computed from the physiochemical examination of river water. The ANN resilient backpropagation algorithm is to be embraced to foretell the values of the same. This paper assesses the river water quality and its suitability for irrigation through the irrigation indices. The Neural designer and Microsoft office-Excel software are to be engaged for figuring distinct insights and ANN examination of the information. At last, we will go to an assessment of the suggested model with the planned neural organization to foresee the waterway water appropriateness dependent on insightful outcomes.

CHAPTER-2

LITERATURE REVIEW

1. **Ayers and Westcott (1994**), deduced that inferior quality water utilized for irrigation minimizes the crop yield and damages the soil quality. They rooted that crop productivity bets on water being used for irrigation.
2. **Kinda (1997),** investigated water suitability for irrigation with spotlights on salt concentration and its effects on soil fertility and crop productivity.
3. **Gorelick & Zheng (2015),** studied the interplay between heterogeneous users of ground as well as surface water and the hydrologic response to evolve hydroeconomic models for water resource allocation and management..
4. **Nikolao D. Katopodes, Albert J. clemmens (2010),** outlined a mathematical model for assimilation of surface irrigation parameters based on quasi newton approximations.
5. **Mc Neil and Cox (2000),** diagnosed easy measurement of water quality through Total dissolved ions as such Na^{+}, Mg^{2+}, Ca^{2+}, K^{+}, Cl^{-}, HCO^{-}_{3} & CO_3^{2-} etc. in both surface water as well as groundwater.
6. **Huang & Foo (2018),** applied Artificial Neural Network for evaluation of variation of water salinity in Apalachicola river in Florida.
7. **Misaghi and Mohammadi (2013),** studied water quality in Zayandeh Rud River using General Regression neural network (GRNN).
8. **Gholamreza Asadollahfardi and Aidin Taklify (2016),** advanced a Multilayer perceptron (MLP) model to foretell Total Dissolved Solid as water quality indicator for water quality management, applied to Talkheh Rud River.

9. **Manuel A. Andrade, Christopher Y. Choi and Kevin Lansey (2016**) looked into to upgrade the exhibition of ANN's applied to ideal plan of Water appropriation framework by considering their results based on ANN engineering and information utilized for ANN preparing, two factors that sway their speed and exactness.
10. **Dandy, Broad (2012),** utilized ANN and the differential evolution optimization method to curtail the capital cost of water distribution system subject to hydraulic and water quality restraints..
11. **Rahim Barzegar, Jan adamowski (2020**), forecasted DO and chlorophyll in small prespa lake in Greece testing deep learning coupled CNN-LSTM Model. By blending LSTM and CNN prototypes the fusion model seized both the stumpy and elevated levels of the river eminence variables.
12. **Liu, Yangzhou and Chen (2019),** projected a multivariate deep belief network exemplary by particle flock optimization to foretell NH_3-nitrogen concentration over ponds. Chlorine deliberation has been surmised using DL models..
13. **Lu Huang, Jie Liang, Jiayu Liu and Shuang Nie (2017),** surmised future groundwater vulnerabilities under an ensemble of climate change scenarios in Hunan Province, China. The DRASTIC model was utilized to generate map of groundwater vulnerability.
14. **W.Wu, G.C. dandy and H.R. Maier (2014),** evolved an ANN-GA based model pertinent for advisory control of disinfectant dosing for water distribution system. They exhibited that evolved MPC formulation can potentially be used to cater additional information to water quality operators on dosing rate control.
15. **Jagadeesh Anmala, Ovida w. Meier and Scott Grubbs (2014**), "a statistical GIS and a Neural Network based water quality model is evolved to investigate stream water quality parameter structure in

geographic framework in USA comprising of stream network, watershed and variety of different land use practices”[20].

16. **Amiri and Nakane (2009),** stream water Total Nitrogen was surmised from landcover and human population density for 21 river basin testing ANN and Multiple Linear Regression. They also analyzed the linkage between land use and buffer zone with water quality.
17. **Ali el bilali, Youssef Brouziyne and Abdeslam Taleb (2020),** evaluated whether the Machine learning prototypes are treasured tool to foretell IWQI factors exhausting somatic factors as sorts and to examine their understanding to input factors. This improved Groundwater quality monitoring for irrigation purposes in real time at low cost.
18. **H. Orouji, M.A. Marino and E.Fallah Mehdipour (2013),** investigated the capability of Adaptive Neural Fuzzy Inference System (ANFIS) and Genetic Programming as two data driven models to foretell and simulate water quality parameters at Aitan station in Sefidrood river IRAN. ANFIS & GP models illustrated flexibility of GP in time series modelling relative to ANFIS.
19. **Tadesse A. Sinshaw, Cristiane Q. Surbeck, Hakan Yasarer (2019**), utilized an ANN approach a powerful computational tool for non-linear relationships to evolve a model that computes summer concentration of Total Nitrogen and Total Phosphorus in US lakes.
20. **Yingyi Chen, Lihua Sang, Yeqi Liu and Ling Yang (2020),** “conducted extensive investigation and analysis on ANN based water quality prediction from three aspect namely feedforward, recurrent and hybrid architectures and deduced that ANN models are capable of dealing with different modelling problems in rivers, lakes, reservoirs, ponds, groundwater and waste water treatment plants”[19].
21. **Min Goo Kang, Seung Jin Maeng (2015),** presented two gray models to foretell groundwater levels at two study sites, one on an island area and

the other on an inland area. They made use of moving average of daily infiltration depth, historical GW level and water demand from irrigated paddy field district as variables. The precision of model were found to be higher than the base model.

22. **Di wu, Hao wang and Razak Seidu (2019),** bestowed a new high order tensor model for quality prediction in industrial DWS Systems. They built a three order tensor model seeing water quality parameter, location and time domains. The result exhibits method is flexible and fulfills requirement from domains.
23. **Xuejiao li, Zhiwei chang, Yun bai (2017),** deliberated a Multi Support Vector Regression (MSVR) approach combining the Ensemble empirical mode decomposition (EEMD) and the least square support vector regression is advised to foretell the dissolved oxygen concentration. The advised MSVR method is practiced to the data of water quality parameter from a monitoring station in Chongqing.
24. **Mahyar Aboutalebi, Omid Bozarg-Haddad and Hugo A. Loaiciga (2016),** evolved and analyzed a multi objective optimization strategy for water quality monitoring network in river reservoir system deployed to test sudden release of methyl tert butyl ether or other pollution. They utilized SVR to improve the accuracy of pollution prediction.
25. **Peyman yousefi, Gholamreza naser and Hadi mohammadi (2018),** studied multilayer perceptron ANN and invoked to foretell TDS in Sufi chai river, Iran. They analyzed the impacts of chemical composition in source water, climatic variables and hydrometric variables on the predictions. Correlation method was exercised and results were accustomed with garson method
26. **Omid Bozorg- Haddad, Shima soleimani and Hugo A. loaiciga (2017**), employed two data driven methods for modeling water quality parameter. The results imply the superiority of Genetic algorithm – Least

square support vector regression algorithm over the genetic programming in a way that the use of GA-LSSVR led to bettering in R-square, RMSE and statistics of water quality parameter.

27. **Lohani AK AND Krishan G. (2015),** examined the most efficient and stable neural network configuration for predicting groundwater level in Amritsar and Gurdaspur districts Punjab. They endowed that precise predictions can be attained with standard feed-forward neural network practiced with Levenberg-marquardt algorithm.
28. **W.Thoe and Joseph H.W.Lee (2014),** evolved a daily forecast system of marine beach water quality (WATERMAN) for Hongkong. The projection scheme was evolved over facts integration with utmost latest water quality facts and backed by field examinations. An inclusive veracity of 78-100% in projecting passivity or accidence of water eminence objective can be attained by right positives of around 30-70%.
29. **Lindell ormsbee, Ben Albritton, Ellie White and Kyle Peterson (2017),** "examined the expediency of exhausting an substitute method in which descried streamflow time sequences are disaggregated into base flow, point source and nonpoint source time series which are then utilized to as forcing functions to generate point and nonpoint source pollution load prediction"[4].
30. **Mohammed Karamouz, S. Ali Mojahedi and Azadeh Ahmadi (2010), "**deliberated execution of water transfer project environmentally and frugally. The feasibility of two interbasin water transfer project from karoon river in western part of Iran to central part of country is investigated. An optimization model with an economic objective function to augment net benefit of interbasin water transfer project is advanced. ANN model is educated stationed on simulation results of river water quality model to be cohabited with optimization model"[14].
31. **Herman Bouwer (2007),** exercised the time it takes for deep percolation

water from irrigated fields to ambit underlying groundwater increases with decreasing particle size of the vadose zone material and increasing depth to groundwater. He emphasized that additional exploration is obligatory on downhill crusade of water and compounds in vadose region.

32. **Thiruvenkatachari viraraghavan and Geeyerpuram N. Mathavan (1998),** inspected on the low temperature effects on the consummation of aeration, sedimentation, filtration, disinfection and eviction of chlorine byproducts as trihalomethanes, ozonation, gas transfer and adsorption in water treatment.
33. **Jian ping suen and J. Wayland Eheart (2003),** exercised ANN to gauge nitrate concentrations in Illinois. Backpropagation neural networks and Radial basis function neural networks are distinguished as to their effectiveness in water quality modelling. The RBFNN attained best results of all models on terms of overall accuracy.
34. **D. Sivakumar, K. Vasuki, B. Lavanya and S. Lavanya Pavithra (2015),** evaluated the quality of irrigation water to dodge or at least to belittle impacts on agriculture and human health. He examined the suitability of groundwater for irrigation around places of perungalathur lake, Chennai, Tamilnadu, India.
35. **Patrick M. Reed and Barbara S. Minsker (2004), "**evinced the use of high order pareto optimization on a long term monitoring application. Their investigation shows that high order pareto optimization holds compelling potential as a tool that can be utilized in balanced design of water resource systems"[12].
36. **Mahyar Aboutalebi, Omid Bozorg- Haddad and Hugo A. Loaiciga (2017),** evolved and approved a method for multiobjective optimization of water quality monitoring networks in river reservoir systems. They enforced NSGAII-SVR method i.e., non-dominated sorting genetic

algorithm-2 support vector regression and evinced this one's capability to project water eminence observing networks that see numerous intents in river-reservoir system.

37. **Lewis A. Rossman, Paul F. Boulos (2006)** made a comparison between formulation and computational performance of four numerical method (2-eulerian and 2-lagrangian based) for modelling and transient behavior of water quality in water distribution systems. Result showed that lagrangian methods are more efficient for simulating chemical transport.
38. **Emanuel Idelovitch, Herman Bouwer (1997),** studied irrigation as an excellent use for sewage effluent as it is mostly water with nutrients. Agronomic aspects related to crops and soils were taken into account. The chemical and biological composition of effluent are compared with known quality standard for irrigation.
39. **Yoo Hu and Steave Beattie (2019),** "developed an agent based model using two stage optimization strategy with the goal of optimizing decision making of heterogeneous farmers on crop choice and groundwater irrigation. Performance of optimization strategy is evaluated under the influence of four behavioral factors"[7].
40. **A. Jafar Ahmed, S. Ananthakrishnan, K. Loganathan and K. Manikandan (2013),** assessed suitability of groundwater for irrigation uses in Alathur block in parembalur district of Tamilnadu. Chemical aptness of under groundwater was visualised through diagrammatic elucidations. They concluded that groundwater of most stations require a special type of irrigation method.
41. **Vasant Madhav Wagh, Deepak Baburao Panaskar, Shrikant Vitthal and Yogesh Popatrao Lolage (2016),** bestowed an ANN model forecasting SAR, RSC, KR,MAR and % Na values in ground water of Nanded tehsil of Maharashtra. They examined 50 groundwater samples for various physiochemical parameters. Geographical distribution maps

of computed and surmised values of irrigation indices were groomed using arc-GIS Software.

42. **S. Mohan and K.S.Jinesh Babu (2009),** “a new algorithm for design of water distribution network namely “Heuristic based algorithm ” which completely utilizes implicit information associated with water distribution network to be designed has been proposed and validated with two water distribution network. They found that proposed algorithm performs well for least cost design of water distribution networks”[3].
43. **Emery Coppola Jr., Ferenc Szidarovszky, Mary Poulton and Emmanuel Charles (2003),** studied viability of teaching ANN for precisely foretelling temporary water altitudes in an intricate multi-layered groundwater scheme in flexible state, pumping plus weather situations is demonstrated. The ANN more closely reproduced the dynamic water level responses to pumping and climate conditions.
44. **H. Hidayat , A.J.F. Hoitink, M.G. Sassi and P.J.J.F.Torfs (2014),** explored the possibility to predict discharge from water level information starting gauge locations by marine and river is discovered. Hindcast exemplary is recognized for tide conquered low land site by means of an ANN exemplary.
45. **Mohammed Zaman, Lee Heng and Shabbir A. Shahid (2018),** “studied the importance of determining the irrigation water quality. The concentration and composition of soluble salts in water determines its quality for irrigation. The procedure for water salinity reduction through blending of different water and management of water sodicity using gypsum are described with examples”[13].
46. **Bhange H.N., Gavit B.K., P.M. Ingle and P.K.Singh (2019),** developed ANN model with MLFBP Sigmoid transfer function for prediction of KR, %Na, PI, SAR, and SSP using neurosolutions. Model performance was assessed by RMSE, MBE and Statistical method as such R.

47. **R.C. Purohit, H.N. Bhange and P.M. Ingle (2018),** studied specific significance of groundwater utilized for consumption households and farming. Water of 15 well from dapoli region was selected to study chemical characteristics. The analyzed data was used to conclude forecast results that is appraisal of appropriateness of groundwater for irrigation purpose.
48. **Chun chieh Yang, Shiv O. Prasher and Rene Lacroix (2013),** reported on the development of ANN model for design and evaluation of sub-irrigation systems. The DRAINMOD model was used to simulate sub-irrigation in clay loam soil with 26 years of weather data. Compared to DRAINMOD the ANN model was executed lot faster and required little data to run.
49. **Sahaya Vasanthi and Adish Kumar (2018),** studied ANN model followed for determining water quality index parameters. Seven water quality parameter of Parakai lake were chosen at Four monitoring stations. Water quality index predicted ANN model bring better output when compared with multiple regression model.
50. **C. Ashwini, Uday pratap singh, Ekta Pawar (2019),** proposed a system to check water quality and warn when it gets contaminated. The different parameters that can contaminate the water are used for predicting when to clean the water. The system uses Internet of things and Machine learning. The neural network algorithm is used for predicting result.
51. **Mohammed Al-Yaari, Hasan Alkahtani and Theyazn H. Aldhyani (2020),** developed advanced Artificial Intelligence algorithm to predict water quality index and water quality classification. For Water quality Index prediction non-linear autoregressive neural network (NARNET) and long-short term memory (LSTM) deep learning algorithm were advanced. For Water Quality Classification forecasting support vector machine (SVM) and K nearest neighbor (K-NN) has been used.

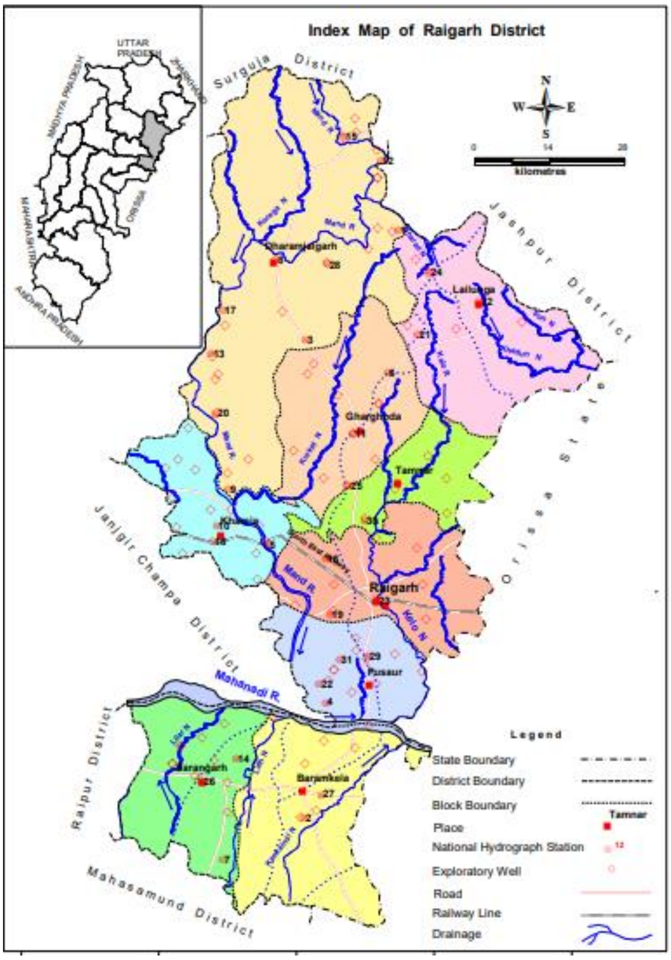
52. **S. Angel vergina, Dr. S. Kayalvizhi and Kalpana Devi (2020),** studied intelligent process of monitoring the water quality through Internet of Things by processing sensors data and instantly provide notification to water analyst when quality is abnormal. This proposed model can safeguard standard quality water to rural people using low prices embedded devices like Raspberry pi.
53. **Ali El Bilai, Abdeslam Taleb (2020),** developed 8 machine learning models namely Artificial neural network, Multiple linear regression, Decision tree, Adaptive boosting, Stochastic gradient descent, K- nearest neighbor, Random forest and Support vector regression besides foretelling 10 IWQI for instance Sodium absorption ratio, Adjusted SAR, Exchangeable sodium percentage, % sodium, Residual sodium carbonate, Kelly ratio, Magnesium absorption ratio, Permeability index, Chloride Cl^- and Total dissolved solid in water surface. The results reveal except SVR and K-NN all other models are highly accurate. It demonstrates that machine learning models are efficient tools for predicting quality of irrigation water in short time.

CHAPTER-3

MATERIALS AND METHODS

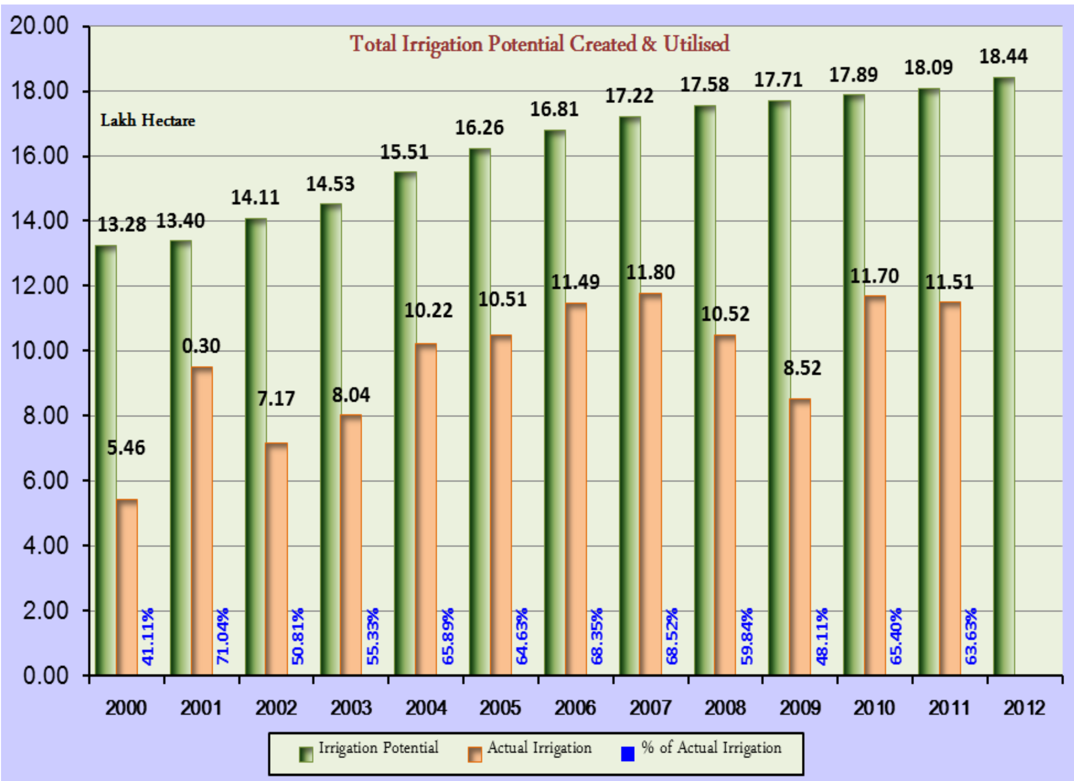
1) INVESTIGATION AREA

The present survey area is located in Raigarh district of Chhattisgarh which lies between latitude of $21^{0}20^{'}32^{"}$ to $22^{0}47^{'}26^{"}$ and longitude of $82^{0}55^{"}35^{"}$ to $83^{0}48^{"}14^{"}$ with total geographical area of 6275km^{2}. The area receives an average rainfall of 1240mm and has a population of 14,93,627 (2011 census). The kelo river is one of the major river in the region which falls into Mahanadi basin. The river originates from dongbra forest reserve near hirapur village in Raigarh and travels through the district over a length of 113km and then confluences with Mahanadi river. The river is perennial in nature with catchment area of 920.20km^{2}. The kelo river project irrigates an area of 22,800hec in Raigarh and Janjgir-champa district with an intensity of irrigation of 117.54%. The Dam site is located at 8Km North of Raigarh town near danote village. The dam is of earthern type with length of 1270m and height of 24.22m.



11.Raigarh map

“The cumulative length of main canal and branch canal is 28.31 km with head discharge sufficiency of 24.58 m³/sec and the length of distributaries and minors is 165 km & 215 km respectively mutually housing CCA of 24,396 ha. Primary crops currently matured in the command area are paddy, Kodo, kutki, sugarcane, wheat, pulses, oil seeds, vegetables and miscellaneous crops. The Kelo irrigation project covers Kharsia, Pussore and Raigarh blocks of Raigarh district and Dabhara block of Janjgir-Champa district. Raigarh is one of the drought prone district in Chhattisgarh and thus kelo irrigation project is the heart and soul of the district. Raigarh receives an Annual rainfall of 1240mm with a slight increase from south to north. An overall stage of ground water development within the district is around 43.16%. The contribution of groundwater comes to nearly 50% in the district. The maximum utilization of groundwater is in non-command area. Large aerial variation is observed in the soil of the district”[9]. The red coloured residual soil is the dominant soil in the region locally known as ‘bhata’.



12. Irrigation potential of Chattisgarh

"Irrigation amplitude was 1.328 Million hectares at the time of induction of the state which was 23% of the gross sown area. However the irrigation amplitude has now been hoisted to 1.844 Million hectares which is 33.15% of gross sown area (i.e., 5.56 Million Hectare). It has been computed that 75% of gross sown area of the state can be irrigated with the prudent use and management of water resources"[1]. For overall augmentation of the state irrigation is the elite need and thus augmentation of irrigation amplitude is the top priority of state government. The district amplitude created and utilized in Raigarh district is portrayed below

SR.NO.	**DISTRICT**	**Irrigation potential created (hec)**			**Irrigation potential utilised (hec)**		
1	Raigarh	Kharif	Rabi	total	Kharif	Rabi	Total
		52290	15796	68086	30374	900	31274

Table 2. Irrigation potential of Raigarh district

The immense gap between amplitude conceived and actual irrigation in the district is mainly due to deficient beneficiary participation in design and maintenance of irrigation projects, deficient double cropping, infrastructure deterioration due to low appropriation in maintenance and absence of water courses from outlets of irrigation canals to fields.

DISTRICT	**Cultivable area (lakh hect)**	**Potential created (lakh hect)**	**Area irrigated (lakh hect)**	**Fractional cultivable area**	**Index of creation**
Raigarh	2.84	0.37	0.3	0.05	0.53

Table 3. Raigarh agricultural statistics

Importance of water as a catalyst for the development of a region cannot be understated. Beside irrigation key uses of kelo river includes domestic purpose, industry and powerplants.

2) DATA COLLECTION AND ANALYSIS

The water samples were collected form the kelo river at varying location from different monitoring stations along the river route. The samples were collected in sterilized bottles and immediately stored in a refrigerator to avoid contaminations. The samples were analysed for various physiochemical parameters like pH with the use of pH meter, electrical conductivity with the help of electrical conductivity meter, anions like calcium (Ca), magnesium (Mg), sodium (Na), potassium (K) and cations like sulphate (SO4), nitrate (NO3), chloride (Cl) and fluoride (F) as per the standard procedures recommended. Measuring of ions were altered from (mg/L) to (meq/L) to amount the diverse irrigation aptness ratios. Values obtained from these parameters are used to determine the stability of river water for the purpose of irrigation. The various indices like Sodium Adsorption Ratio (SAR), Kelly Ratio (K.R.) and Sodium Percentage are used to identify the suitability of river water samples for irrigation purpose. The testing of the sample is usually carried out in water treatment plant located in chandmaari, Raigarh. The sample taken from various locations around Raigarh area were analysed and the results exhibit variations from sample to sample. The analyses were carried out around the temperature of 30 ºC. River water quality shows variation within samples for the parameters EC, pH, Ca, Mg, Na, K, Cl, TDS. The data of the tested water sample is sent to Irrigation department as well as to Municipal Corporation. These departments use the BIS standard values to identify the suitability of water sample for concerned use of irrigation and domestic water supply. I have collected the weekly data of last 28 years of the kelo river from the irrigation department. These data were utilised to carry out the regression analysis and neural network modelling. The descriptive statistics of the collected samples is given below.

Parameters	*ph*	*EC(ųs/cm)*	*Ca2+*	*Mg2+*	*Na+*	*K+*	*Cl-*	*TDS(mg/L)*
Mean	7.3098	1937.5	384.16	262.35	328.44	40.587	535.12	1356.383
Standard Error	0.0248	62.1273	23.543	5.2005	6.7446	0.6610	20.494	43.48858
Median	7.3	1170	234	218.98	265.18	35	62.5	819
Mode	7.38	1010	453	643	675	53	0	707
Standard Deviation	0.9618	2406.18	911.82	201.42	261.22	25.601	793.76	1684.306
Sample Variance	0.9251	5789709	831417	40569	68235	655.45	630055	2836885
Kurtosis	32.638	14.70222	78.941	0.7678	0.5693	-0.906	7.1391	14.70415
Skewness	-4.715	3.537453	8.5943	1.0672	1.0866	0.4460	2.3079	3.537641
Range	9.07	16204	9028.2	936.23	1125.8	104	4700	11343.2
Minimum	0.01	394	20.78	53.761	32	6	0	275.8
Maximum	9.08	16598	9049	990	1157.8	110	4700	11619
Sum	10964	2906250	576246	393526	492655	60880	802684	2034575
Count	1500	1500	1500	1500	1500	1500	1500	1500

Table 4. Data statistics

The collected dataset provides an overview of stream water quality with particular focus on permissible levels of various Irrigation water quality indices. The dataset can prove to be beneficial for local administrator, decision makers, researchers and urban planners concerned with the sectorial development. It can be used to improve upon the agricultural productivity by revealing potential areas suitable for short term and long term irrigation.

The various physiochemical parameters such as pH, EC, Calcium ion, Magnesium ion, Sodium ion, Potassium ion, Chlorine ion and TDS are utilised to calculate the irrigation water quality indices such as Sodium Adsorption ratio, Kelly ratio and soluble sodium percentage. The methodology adopted to determine these physiochemical parameters has been depicted below.

Parameter	Methodology and formula adopted
pH	Multi-parameter pcs tester (35)
EC	Electrometric method
TDS	Ꜫ cation and anion
Ca	Titration method
Mg	Titration method
Co_3	Titration method
HCO_3	Titration method
TH	Titration method
Na	Flame photometer method
K	Flame photometric method
Cl	Titration method
S.A.R	$\sum \frac{Na}{\sqrt{\frac{Ca+Mg}{2}}}$
K.R.	$\frac{Na}{Ca+Mg}$
%Na	$\frac{Na+K}{Ca+Mg+Na+K} * 100$

Table 5. Parameters and their testing methodology

Sodium Adsorption Ratio

The propriety of water for irrigation is dogged by estimating S.A.R The extent of sodium held by soil is given by S.A.R i.e. the measure of sodicity of the soil. If S.A.R. in irrigation water is high, sodium can replace calcium and magnesium ions in soil thus diminishing the soils competency. This in turn perturbs availability of water to crop. S.A.R. can be computed as:-

$$\sum \frac{Na}{\sqrt{\frac{Ca+Mg}{2}}}$$

All ions are expressed in meq/L.

Sodium Hazard class	S.A.R (meq/L)	Quality of Irrigation water
S1	<10	Excellent
S2	10-18	Good
S3	18-26	Doubtful
S4	>26	Unsuitable

Table 6. SAR Hazard class

Soluble Sodium Percentage

It is an essential aspect for analyzing sodium hazard. It critics the quality of water for agricultural purpose. Sodium is the most hazardous element of irrigation water, the excess of it characterizes water as alkaline. This in turn harshly impacts plant growth as well as soil permeability. Though it's not an essential nutrient but is taken freely by many plants. The SSP can be computed as:-

$$\frac{Na + K}{Ca + Mg + Na + K} * 100$$

All ions are expressed in meq/L.

Soluble sodium hazard class	SSP (meq/L)	Quality of Irrigation water
SP1	<20	Excellent
SP2	20-40	Good
SP3	40-80	Doubtful
SP4	>80	Unsuitable

Table 7. SSP Hazard class

Kelly Ratio

It gauges the quality and classification of water for irrigation purpose based upon the concentrations of sodium against calcium and magnesium. It indicates the degree of promising effect of sodium on water quality for irrigation. It can be computed as:-

$$\frac{Na}{Ca + Mg}$$

All ions are expressed in meq/L.

KR≤1 (Recommended for Irrigation)

KR>1 (Not Recommended for Irrigation)

TOTAL DISSOLVED SOLID (TDS)

TDS in stream water contains mineral, nutrients and also includes major ions such as calcium, magnesium sodium, potassium, chlorine, carbonate, bicarbonate and sulphate. Salt accumulation at root zone creates obstacle in sucking of water resulting in moisture stress.

Salinity Hazard class	TDS (mg/L)	Remark
T1	<1000	Freshwater
T2	1000-10000	Brackish water
T3	10000-100000	Saline water
T4	>100000	Brine

Table 8. TDS Hazard class

Electrical Conductivity

It portions water's dexterity to conduct electric current. Most of the dissolved salts in water are in ionic form and are culpable to conduct electric current. However excessive presence of salt concentration is major concern with the water being utilized for irrigation as it degrades the land and may also pollute groundwater. Its dimension is µmhos/cm.

Hazard Class	EC (µmhos/cm)	Remark
C1	100-250	Excellent
C2	250-750	Good
C3	750-2250	Doubtful
C4	>2250	Unsuitable

Table 9. EC Hazard class

3) REGRESSION ANALYSIS

Regression analysis is a set of analytical methods used for the assessment of relations between dependent and one or more independent variables. Most prevailing being simple linear and multiple linear regression analysis. Non-linear regression analysis is utilized for complex data sets. Regression predictions are valid only for range of data used to estimate the model. Relation between independent and dependent variable will change out of that range. While evolving a model certain insights such as cause and effect relationship among the variables, range of data, degree of determination are quite necessary. In this project multiple regression analysis was carried out. These are similar to linear models with the exception of multiple independent variables used in the model. The mathematical expression of multiple linear regressions is:-

$$Y = a + bX_1 + cX_2 + dX_3 + \in$$

Where; Y = Dependent variable a = Intercept

X_1, X_2, X_3 = Independent variable b, c, d = Slopes

$\in = Residual\ error$

Here the independent variables should show a minimum of correlation with each other because if they are highly related it becomes difficult to assess the true relationship among dependent and independent variables.

Dependent variable = S.A.R., Kelly Ratio, Sodium %

Independent variable = $_p$h, Electrical conductivity, Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, Cl^{-}, Total dissolved solid

The maximum correlation coefficient among independent variable was found to be 0.99. The detailed correlation statistics have been shown below:-

	ph	*EC*	*Ca*	*Mg*	*Na*	*K*	*Cl*	*TDS*
ph	1							
EC	-0.03578	1						
Ca	0.001032	0.108306	1					
Mg	0.030105	0.702122	0.15256	1				
Na	0.003802	0.434248	0.206637	0.592746	1			
K	-0.01791	0.602728	0.262964	0.693772	0.610291	1		
Cl	0.006819	0.791785	0.12759	0.711967	0.488657	0.675977	1	
TDS	-0.03578	0.999999	0.108309	0.702076	0.434408	0.602817	0.791715	1

Table 10. Correlation statistics

The Regression equation obtained from the regression analysis done on Microsoft office-EXCEL has been shown below. This equation is being utilized to obtain the predicted values.

Sodium Adsorption Ratio = $\mathbf{23.06 + (-1.16 * pH) + (-0.083 * EC) + (-0.004 * Ca) + (-0.035 * Mg) + (0.074 * Na) + (-0.016 * K) + (-0.0009 * Cl) + (0.120 * TDS)}$

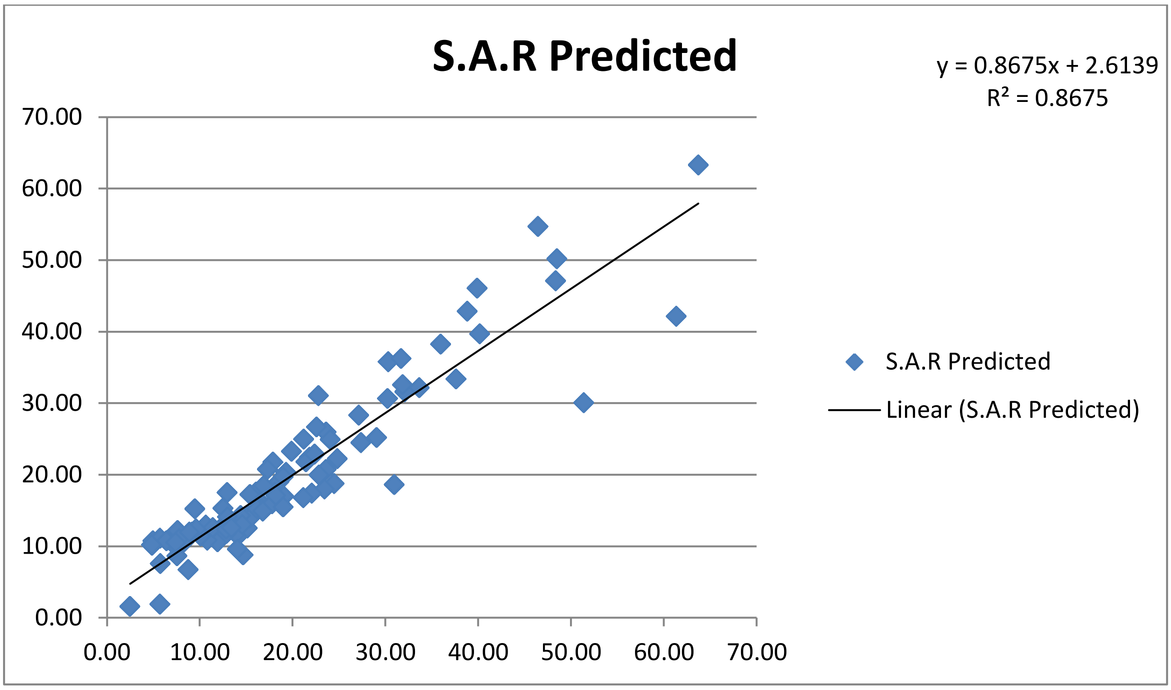
$$\textbf{Sodium \%} = \mathbf{1.525} + (-\mathbf{0.088} * \boldsymbol{pH}) + (-\mathbf{0.00016} * \boldsymbol{EC}) + (-\mathbf{0.00013} * \boldsymbol{Ca}) + (-\mathbf{0.0018} * \boldsymbol{Mg}) + (\mathbf{0.0015} * \boldsymbol{Na}) + (-\mathbf{0.0043} * \boldsymbol{K}) + (\mathbf{0.00005} * \boldsymbol{Cl}) + (\mathbf{0.00028} * \boldsymbol{TDS})$$

The Regression statistics is being shown below:-

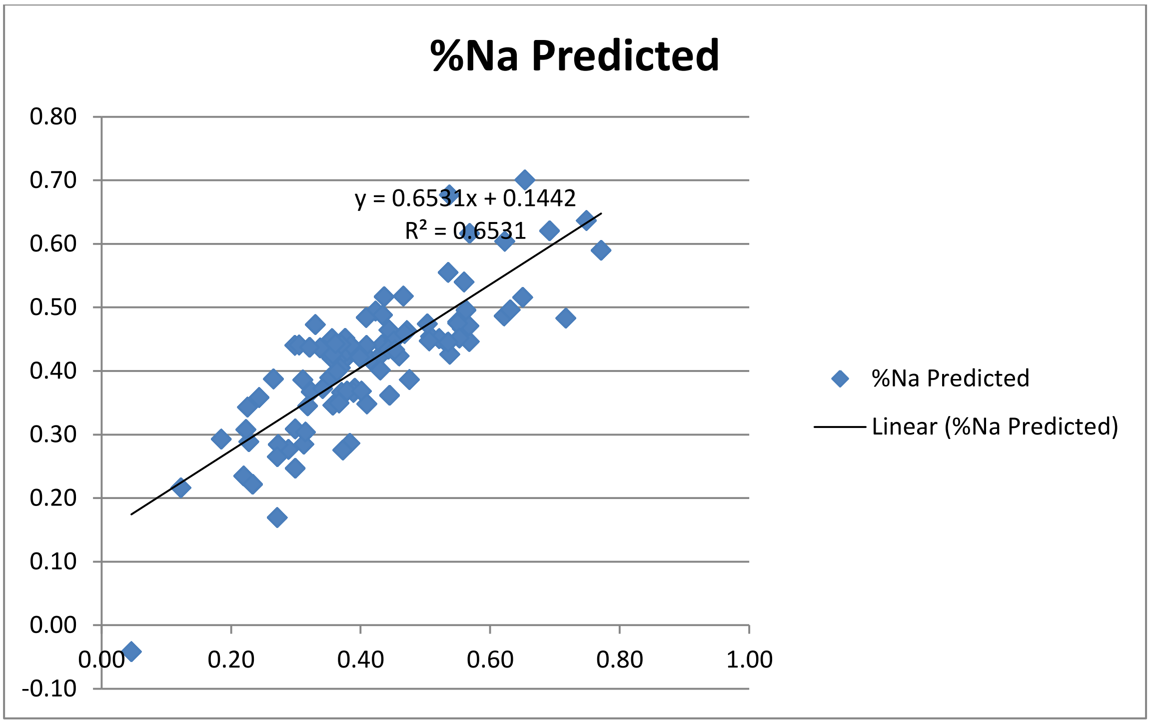
Regression Statistics	
Multiple R	0.931372
R Square	0.867454
Adjusted R Square	0.866743
Standard Error	4.421672
Observations	1500

Table 11. Multi regression statistics

The graphical observations of the regression analysis have been portrayed below:-



13. SAR REGRESSION LINE GRAPH



14. SSP Regression line

These graphical and regression statistics were utilised to calculate the following parameters:-

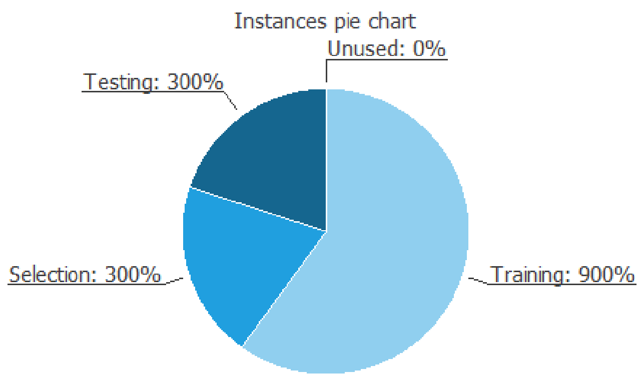
Mean Absolute Percentage Error (MAPE) $=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y\ estimated - Y\ actual}{Y\ actual}\right| * 100 =$ 6.67%

$R^2 = 1 - \frac{\sum_i (Y\ predicted - Y\ actual)^2}{\sum_i (Y\ predicted - (\frac{1}{n})\sum_i Y\ predicted)^2} = 0.87$

Higher R^2 represents more precise value. It assesses the scatter of data points around fitted value. Cause and effect relationship among the variables is to be checked before estimating R^2. Mean absolute percentage error (MAPE), Root mean square error (RMSE) and correlation coefficient R are used to reflect performance of model from different perspective of model evaluation. The prediction results are intuitively realized in vision and through estimate of standard error. These regression prediction are valid only for range of data used to make model. Relation between variable will change out of that range. The detail steps of the same have been shown in excel file attached below :-(data Rgh (1).xlsx - Google Drive).

4) ANN MODELLING

ANNs advances bountiful inputs or dataset to influence the next data or future data. Datasets have a pattern or characteristics and Training use these patterns to produce weight in each neurons network. The whole mechanism of ANN is a cross training or research process that utilizes perceptron, backpropagation and deep learning with each one using analogous training system. Selection of neuron at input and output is of great gravity and thus causal variable is to be known to get efficient output. These neurons may possibly have a threshold such that signal is guided only if cumulative signal marks threshold. These neurons have weights that adjust as learning progresses and these weights increases/decreases the strength of signal at connection. If the process is complex connection weight will be more and vice versa. Signal travel from first layer to last layer i.e., from input to output after traversing through layers multiple times. More the data more is the degree of determination and the system can't perform more than degree of determination. Model performance should not be the function of data range and should be independent of it. ANN model is developed using Neural designer software as it's a code free platform for data science and machine learning and is convenient to avail. The available data is separated into model improvement and assessment data and then it's normalized to train the network.



15. Instances pie chart

The aggregate number of inspecting is 1500. The quantity of preparing examining is 900 (60%), the quantity of choice inspecting is 300 (20%), the quantity of testing inspecting is 300 (20%), and the quantity of unused inspecting is 0 (0%). There are no lost qualities in the dataset. Preparing inspecting are utilized to shape model, determination samplings are utilized for choosing ideal request, testing examining are utilized to approve working of the model and unused examining are not utilized by any means.

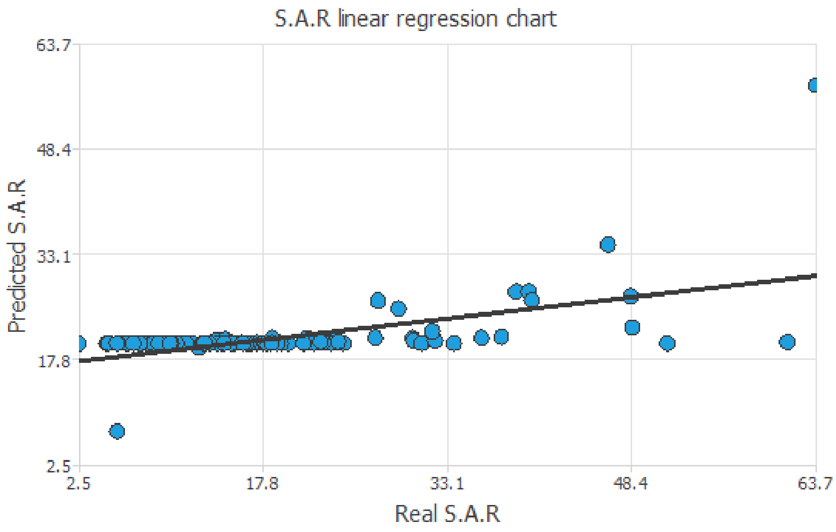
The numbers of inputs, targets and unused variables here are 8, 3, and 1, respectively.

S. NO.	Parameter	Use
1	pH	Input
2	EC	Input
3	Ca^{2+}	Input
4	Mg^{2+}	Input
5	Na^{+}	Input
6	K^{+}	Input
7	Cl^{-}	Input
8	TDS	Input
9	S.A.R	Target
10	Kelly Ratio	Target
11	% Na	Target

Table 12. Input and Target selection

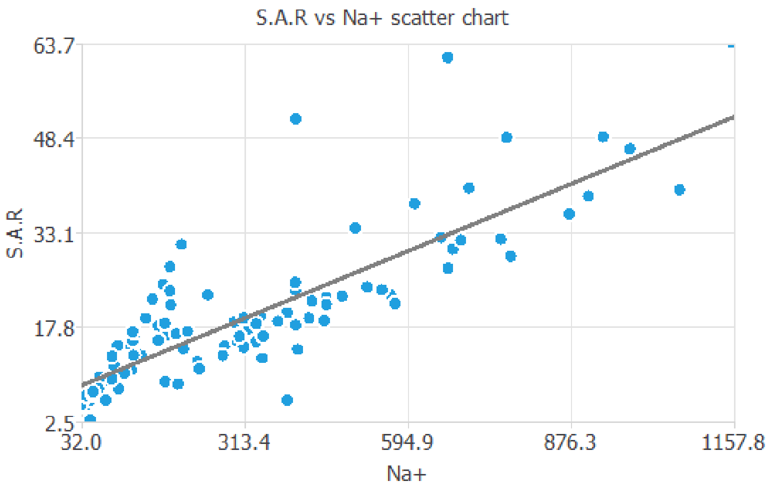
The data sources will be the autonomous factors; the objectives will be the reliant factors; the unused factors will nor be utilized as data sources nor as targets. Fundamental measurements are entirely significant data when planning a model, since they may make aware of the presence of deceptive information. It is an unquestionable requirement to check for the rightness of proportions.

An usual strategy to check the departure of an exemplary is to play out a straight relapse examination amongst the scaled neural organization yields and the relating focuses for a free testing subset. The subsequent illustration represents the straight relapse for the scaled yield S.A.R. The anticipated qualities are intrigued versus the genuine ones as circles. Dim line demonstrates the best direct fit.



16. SAR Regression chart

The minimum correlation is -0.0357844 between the variables pH and EC (µmhos/cm). The maximum correlation is 0.999999 between the variables EC (µmhos/cm) and TDS(mg/L). Scatter chart is plotted to see the dependencies of the targets with input.

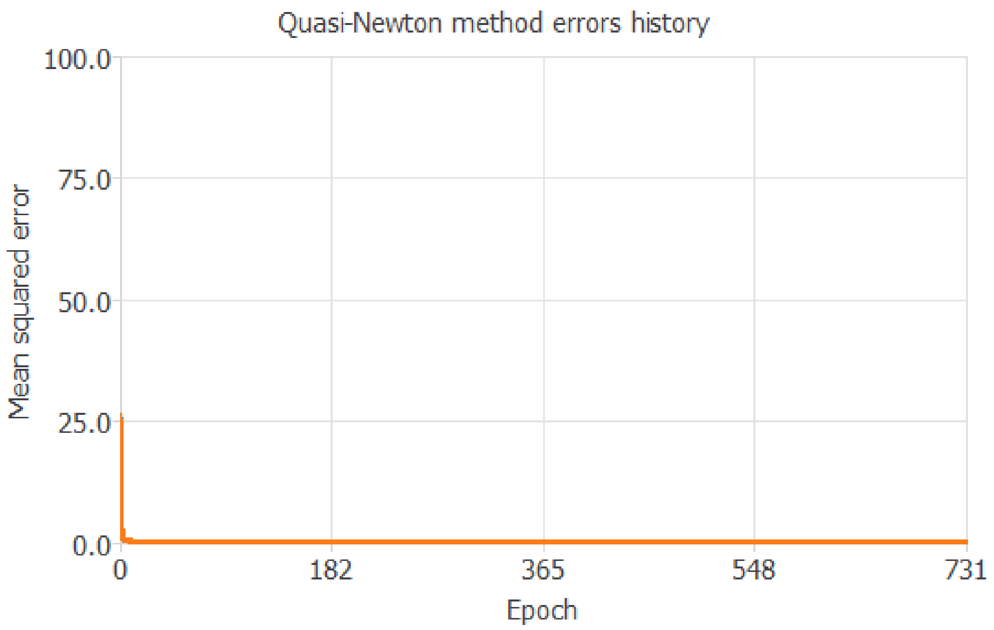


17. SAR vs SSP Scatter Graph

The maximum correlation (0.836341) is yield between the input variable Na+ and the target variable S.A.R. This chart indicates the dependency of the target S.A.R with input values.

TRAINING STRATEGY

The direct used to do the investigating interaction is called preparing approach. The preparation approach is upheld to the neural organization to achieve the most ideal misfortune. The semi Newton strategy is utilized here as enhancement calculation. It depends on Newton's technique, yet doesn't need calculation of second subordinates. All things considered, the semi Newton technique processes a guess of the reverse Hessian at every redundancy of the calculation, by just utilizing inclination data. The accompanying plot clusters the preparation and choice blunders in every reiteration. The orange line depicts the choice blunder. The underlying worth of the preparation mistake is 26.3422, and the last worth after 731 epoch is 0.00187024. The underlying worth of the choice mistake is 26.1165, and the last worth after 731 epoch is 0.00198505.



Ma

18. Quasi newton method error graph

ximum number of epochs to perform training = 1000

Maximum number of epoch at which selection error increases = 100

Maximum training time = 3600 sec

The table shows the training results by the quasi-Newton method. They include some final states from the neural network, the loss functional and the optimization algorithm.

DESCRIPTION	VALUE
Final training error	0.00187
Final selection error	0.00199
Final gradient norm	0.000898
Epochs number	731
Elapsed time	00:04
Stopping criterion	Gradient norm goal

Table 13. Quasi newton training statistics

Prototypical determination is implemented to track down a neural organization with a geography that propels the blunder on new information. Two particular kinds of calculations for model determination are: Order choice controls and information choice controls. Request choice controls are utilized to track down the ideal number of stowed away neurons in the organization. The request determination calculation fixed for this activity is gradual request. This calculation begins with the base request and adds a given number of perceptron's in every redundancy. Data sources determination calculations are blamable for tracking down the ideal subset of info factors. The information sources choice calculation fixed for this activity is developing information.

NEURAL NETWORK

The neural set-up implies the foretelling exemplary. Neural set-ups consent deep designs, which are a course of widespread similarity.

Total count of variable stands 11 with 8 input and 3 output. The extent of the scaling stratum is 8, being input counts. The adopted scaling method being Minimum plus Maximum. The extent of the unscaling stratum is 3, being output count. The adopted unscaling method is same as scaling one. Total count of perceptron strata in the neural set-up is 3. The subsequent table portrays the extent of individual stratum and its equivalent initiation function.

S. NO.	INPUT NUMBER	PERCEPTRON NUMBER	ACTIVATION FUNCTION
1	8	5	Hyperbolic Tangent
2	5	7	Hyperbolic Tangent
3	7	3	Linear

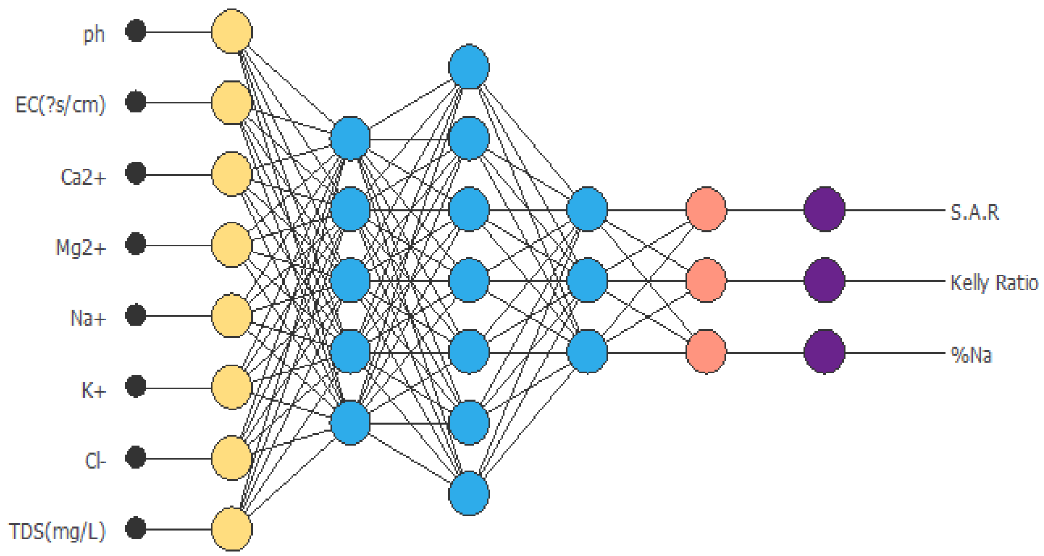
Table 14. Perceptron layer and their Activation function

The following table shows the values of the bounds for each output.

Parameters	Lower Bound	Upper Bound
S.A.R	2.49	63.7
Kelly Ratio	0.04	3.27
% Na	0.05	0.77

Table 15. Output Bound statistics

An elucidating depiction of the organization engineering is point by point straightaway. It's anything but a scaling stratum, a neural organization and an unscaling stratum. Count of input being 8, while the count of yields and bounding are 3. The intricacy, addressed by the quantities of covered up neurons, is 5:7.



19. Neural network structure

$$Total\ number\ of\ connection\ weight\ = 8 \times 5 + 5 \times 7 + 7 \times 3$$

$$= 45 + 35 + 21 = 96\ wt$$

Accuracy of the Model

$$Total\ number\ of\ instances = \frac{100}{100 - x} \times Total\ number\ of\ connection\ weight$$

$$1500 = \frac{100}{100 - x} \times 96$$

$$x = 93.6\%$$

A neural set-up delivers a set of yields for each set of inputs practices. The yields bet upon the values of the parameters. The adjacent table portrays the input values and their equivalent output values.

Parameters	Value
pH	7.3098
EC	1937.5
Ca^{2+}	384.16
Mg^{2+}	262.35
Na^{+}	328.43
K^{+}	40.58
Cl^{-}	535.12
TDS	1356.38
S.A.R	20.08
Kelly Ratio	0.69
% Na	0.42

Table 16. Forecasted values (ANN modelling)

The adjacent table arrays all the errors of the data for specific application of them. It hauls into account each worn sampling and computes the model for each application.

Type of Error	Training	Selection	Testing
Mean squared error	104.34	101.94	118.35
Root mean squared error	10.22	10.09	10.88

Table 17. Error statistics

CHAPTER-4

RESULT AND DISSCUSSIONS

A. REGRESSION MODELLING ANALYSIS

The Kelo river water is being tested for certain water quality parameters and these in turn are utilised for obtaining Irrigation water quality index. The data of these parameters was obtained from the irrigation department for past 28 years. Multiple regression analysis using MS-EXCEL was carried out to develop predicting water quality model. Regression modelling of the datasets revealed following regression statistics:-

Multiple R = 0.93

R^2 = 0.87

Adjusted R^2 = 0.867

Standard error = 4.42%

Mean Absolute Percentage Error = 6.67%

R^2 value of 0.87 indicates that input values represent precise value of output parameter. Mean absolute percentage error expresses accuracy as percentage of error. The results indicate that forecast is off by 6.67%.These regression prediction are valid only for range of data used to make model. Relation between variable changes out of that range. The prediction results are intuitively realized in vision and through estimate of standard error. This approach generates reliable and accurate prediction results owing to multiple regression analysis feature learning. It is suggested to use nonlinear regression analysis if the dataset is more complex.

B. ANN MODELLING ANALYSES

The parameters like pH, EC, Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, Cl^{-}, TDS of stream water were obtained, analysed and compared with BIS Standards. These were utilised to obtain Irrigation water quality indices as such S.A.R, K.R and SSP. The factors such as soil type, rain density, crop type, crop pattern etc. also play an important role for determining suitability of irrigation water.

PARAMETERS	UNDERGROUND WATER	FORECASTED STREAM WATER	CANAL WATER
pH	6.7	7.31	7.16
EC	2312	1937.5	984.44
Ca^{2+}	98	384.16	46.84
Mg^{2+}	68	262.35	56.94
Na^{+}	79	328.43	98.35
K^{+}	19	40.58	28.32
Cl^{-}	312	535.12	133.39
TDS	872	1356.38	518.67
S.A.R	8.67	20.08	13.65
K.R	0.48	0.69	0.95
SSP	37.12%	42%	54.96%

Table 18. Comparing IWQI of irrigation sources.

The pH value of underground water, canal water and forecasted stream water is more or less near 7. This indicates that these can be quite effectively utilised as irrigation water. The EC of underground water makes it unsuitable for irrigation while that of forecasted stream water and canal water depicts its use for irrigation with proper management practices. The TDS value of forecasted stream water is of brackish nature while that of underground water and canal water are of fresh nature. The SAR value of underground water is quite excellent with little or almost no hazard, forecasted stream water is doubtful being quite unsatisfactory for most of the crops and that of canal water is quite good making it effective as irrigation water. The KR of underground water, forecasted stream water and canal water is well within the range of 0 to 1 making it suitable for irrigation aspects. The SSP of underground water falls within good category for irrigation water while that of forecasted stream water and canal water falls within doubtful category i.e., proper management practices are required.

However considering all important aspects of irrigation water canal water is quite safe for virtually all situations and does not require special management practices. However the stream water is at risk of soil structure problems and has the potential to cause damage to irrigation system as well.

The ANN modelling is a powerful projecting substitute to conventional regression modelling technique and its quite evident from the results. However for modelling under limited data conditions node numbers in hidden layer can be utilized.

C. CONCLUSION

In this study Multiple regression analysis and ANN models have been recognized for calculation of SAR, KR and SSP using the water quality parameters such as pH, EC, Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, Cl^{-}, TDS. The data were obtained from the respective irrigation department for last 28 years and were utilised for modelling. Neural network model consisting of 8 input neuron, 5 and 7 hidden neuron and 3 output variable were utilized for computing river water suitability for irrigation in study area. These models have been trained, validated and tested for given datsets. After validation and testing of datasets good agreement was found between actual data and model output. Comparison between different irrigation water quality index computed through MS-EXCEL and ANN model indicates that it improves the accuracy to determine suitability of kelo river water for irrigation purposes. ANN model is an applied tool to predict SAR, KR and SSP concentration. It’s quite evident that ANN is an useful tool for predicting irrigation water quality index. It can also be utilized in various other fields to get better understanding of the system. Results of regression modelling and ANN modelling assure suitability of these models for predicting water quality indicator for irrigation purpose. These models can be considered by local development authority for effective management of irrigation water.

D. FUTURE SCOPE

The future scope of this project is to check the crop productivity of major crops in the region from canal water and compare it with underground water and stream water. This will be useful in enhancing the use of canal water as irrigation water and reduce the dependence upon the underground water.

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