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Neuron Efficiency in Fluid Dynamics and Prediction of Groundwater Reservoirs" Properties Using Pattern Recognition

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Abstract**—**The application of neural network using pattern recognition to study the fluid dynamics and predict the groundwater reservoirs properties has been used in this research. The essential of geophysical survey using the manual methods has failed in basement environment, hence the need for an intelligent computing such as predicted from neural network is inevitable. A non-linear neural network with an XOR (exclusive OR) output of 8-bits configuration has been used in this research to predict the nature of groundwater reservoirs and fluid dynamics of a typical basement crystalline rock. The control variables are the apparent resistivity of weathered layer (p_1), fractured layer (p_2), and the depth (h), while the dependent variable is the flow parameter (F= λ). The algorithm that was used in training the neural network is the back-propagation coded in C++ language with 300 epoch runs. The neural network was very intelligent to map out the flow channels and detect how they behave to form viable storage within the strata. The neural network model showed that an important variable g_r (gravitational resistance) can be deduced from the elevation and apparent resistivity p_a. The model results from SPSS showed that the coefficients, a, b and c are statistically significant with reduced standard error at 5%.

Keywords—Neural network, gravitational resistance, pattern recognition, non-linear.

I. Introduction

THE annual rainfall of the study area is high every year, yet there is limited supply of portable water in the study area, hence need to study the fluid dynamics in the area. Liker et al. used the neural network approach to study the monthly rainfall estimate and fluid dynamics of an area [2], and got an appreciable result, but in this research, monthly rainfall is not part of the variables employed to predict the flow dynamics of the study area. The parameters that were examined are the flow rate, apparent resistivity, depth of fractures.

The problem of finding groundwater in basement crystalline rocks is that they only exist within the existence of fractured or weathered layers; great computational efforts are needed to get the regions with these geological features [1].

The modeling approach applied in this research is the multiple regressions analysis using the SPSS software, and the results is compared with that of the non-linear neural network model for proper estimation of some parameters. This modeling approach was examined in the work of Sagantani et al. [4]. They examined that equations of fluid dynamics are simply the equations of local conservation of the corresponding charge currents, supplemented by constitutive relations that express these currents as functions of fluid mechanical variables. The thermodynamics coordinates and fluid dynamics are related as a complex function, and the coefficients can be determined from computational algorithm [4]. The problem involves several non-linear and deformation, and accurate choice of these parameters is very difficult. However, a trial and error method can be employed using the efficacy of neural network analysis through several standard procedures because of its ability to adapt without priority knowledge of the input.

In the work of Holmes et al., a three-dimensional smooth particle hydrodynamics (SPH) simulator for modeling grain scale fluid flow in porous media is presented. The versatility of the SPH method has driven its use in increasingly complex areas of flow analysis, including the characterization of flow through permeable rock for both groundwater and petroleum reservoir research [5]. This approach will be employed in this research for the purpose of analysis and evaluation.

II. Model Conception

If the flow parameter F is represented as the property of fluid dynamics in the study area, and that it relates to the existence of fractured zone, rock types, flow properties (such as porosity, permeability of the subsurface). The neural network is expected to map out and use pattern recognition to detect how the channels behave in respect of how the groundwater reservoirs are formed throughout the entire study area, by predicting these parameters (Fig. 1). The flow is related to the variables used as neurons in the input segment of neural architecture and are used purposely for the prediction. The change in hydrostatic pressures can be obtained from; $\Delta p = p_2 - p_1 = h_2\rho_2 g_r - h_1\rho_1 g_r$, it is assumed that the flow parameter is well behaved and differentiable, and we expect the flow F to be a function of some reservoir properties of the form $F(\rho_{1,}\rho_{2,}h) = a\rho_1 + b\rho_2 + ch + e_i$.

The function is expected to be linearly dependent on the three variables, where a, b and c are constants to be determined from iterations from the SPSS software.

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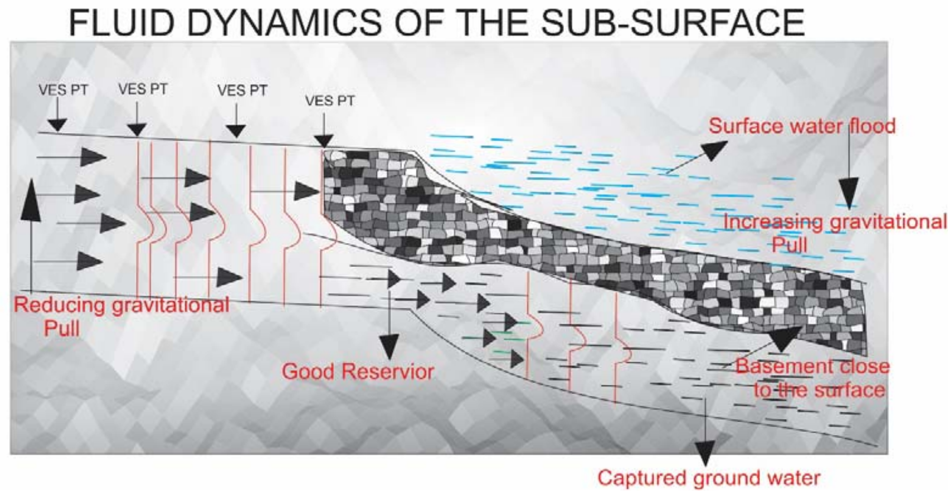

Fig. 1 Neural prediction for fluid dynamics

III. The Design Techniques

To design the groundwater potential model of Alagbaka GRA South Western Akure, Nigeria, a four-input XOR neural network with 8-bits pattern is assumed. Each input has a three-continuous weight as a control rate for the neural network. The input variables; $X_{1,}X_{2,}X_{3,}X_4$ are attached with control weights $w_{11,}w_{12,},...,w_{43.}$ at the input stage, which were constructed into a 4x3 input matrix. The adjusted weights are automatically sorted by the algorithm, to reflect the weights and the bias at each level. There are two separate hidden layers comprising of three and four neurons, respectively. The control weights in the first three hidden layer are $w'_{11}, w'_{12},..., w'_{43}$, and those of the second Hidden layers comprising of four neurons are, $w''_{11}, w''_{12}, w''_{13}..., w''_{44}$.

These two hidden layers formed the processing units before the required XOR output patterns recognition for the fluid dynamics and the groundwater potential model of the regions under consideration. The various outputs are summed into sigmoid functions to obtain the values to be compared to the threshold values before assigning the correct pattern of the area.

The variable X_1 ($Rateofsoilconsolidation$), which is segmented the nature of the flow rate(λ); as $\lambda < 1$, when the soil sample is highly consolidated, accompanying the pressure increases due to fluid forcing through the earth subsurface, while the value of $\lambda > 1$ depicts the soil sample being unconsolidated and the pressure of fluid is reduced because of the resistant force through the rock particles. The particles of the fluid and that of the soil sample are in phase, and it allows the fluid to settle in the groundwater reservoir. When the value of $\lambda = 1$, the soil sample is expected to be stable. For the purpose of this research, the fluid motion is resisted when the soil sample is highly consolidated and dominated with clayey/sandy formation of the subsurface. The neural is assumed to guess intelligently those regions as been highly pressurized to guide the water management authority not to site promising boreholes in those regions. Therefore, the controlled weights that were assigned to the highly consolidated subsurface neurons are $w_{11} = 0.85$, $w_{12} = 0.10$ and $w_{13} = 0.05$. The variable X_2 (if the soil sample is clayey/sandy dominance), for a clayey/sandy formation, the apparent resistivity ρ_i is chosen in the range $99\Omega m \le \rho_i \le 290\Omega m.$ The three continuous apparent resistivity values; $\rho_1 = 290\Omega m,$ $w_{21} = 0.90$, $\rho_2 = 160\Omega m,$ $w_{22} = 0.05$ and $\rho_3 = 99\Omega m$, $w_{23} = 0.05$. Since the clayey dominance of the area is classified high as 290 Ωm, a higher control rate which is attached to this value is 0.90 for the neural to detect it as the unwanted parameter, to be avoided in the pattern recognitions.

The variable X_3 (the condition of the basement rocks being very close to the surface) makes the regions to be highly pressurized and makes the fluid move upward to resist the pressure, and the water stays on the surface and cannot percolate through the hard rock with very thin thickness of soil sample layer covering it. For the purpose of this study, the basement apparent resistivity has been found in the range $\rho_i \ge 4500\Omega m$. These Vertical Electrode Sounding (VES) locations have been assigned values of apparent resistivity, as $\rho_1 \ge 50000\Omega m$, $w_{31} = 0.90$, $\rho_2 = 5000\Omega m$, $w_{32} = 0.05$, and $\rho_3 = 4500\Omega m$, $w_{33} = 0.05$. These are the common values obtained from computer iterations and interpretations and are used for the analysis of basement in this location.

The next input variable is X_4 (determination of fractured zone with clayey dominance), the range of the apparent resistivity is as: $\rho_1 = 2000\Omega m$, $w_{41} = 0.95$, $\rho_2 = 1000\Omega m$, with weights $w_{42} = 0.06$ and $\rho_3 = 159\Omega m$, with control rate $w_{43} = 0.04$. The fractured zones with clayey dominance can lead to increasing pressure; therefore, a higher control rate has

been assigned in the neural network. The clayey fracture holds water and does not release it, therefore forming a flood in the regions dominated with clayey soil sample. The neural is expected to guess and avoid such layers having these attributes. These variables have been modeled as: $X_1 = f(\lambda_1, \lambda_2, \lambda_3) = f(x_{11}, x_{12}, x_{13})$
$X_3 = f(\rho_1, \rho_2, \rho_3) = f(x_{31}, x_{32}, x_{33})$ and $X_4 = f(x_{41}, x_{42}, x_{43})$.

The inputs are coded as an XOR pattern to assist in the non-linear classification of the regions into whether being or not suitable for groundwater prospect, since the separation cannot be divided into a hyper plane of model $Y(x) = f(x)$.

The field data were classified into six caches: A, B, C, D, E and F to make the classifications by the neurons easier, with cache A containing the VES locations: 21, 22, 23, 24, 25, 27, 28, and 29, while B contains: 30, 31, 32, 33, 34, 3, 11, and 12, the cache C contains: 15, 16, 17, 26, 43, 45, 47, and 37, while cache D contains: 35, 36, 38, 39, 40, 41, 48, and 19, while cache E contains: 20, 7, 10, 5, 9, 8, 13, and 14, and cache F contains: 1, 2, 4, 6, 42, 44, 18, and 46. These are not ordered, they are picked arbitrarily as they were sampled during the data collection.

A. The Coding Procedures for the Algorithm

The areas that are characterized with high pressure and resistant to fluid motion are represented by digit 1 as being high, and those with low pressure, such containing fractures or highly weathered regions are with digit 0 as being low. The generalized truth values can be represented as: X_1= ($x_{11}, x_{12}, x_{13}) \equiv (100)$, $\lambda_1 < 1$ that is highly consolidated, and eventually, leads to high resistant area preventing the fluid to form in the groundwater container. In X_2, the resistivity ranges which are high give high pressure values and they should be avoided by the neurons in the computations. The values in X_3 have resistivity values that give high pressure conditions (100) to be avoided by the neurons. For the variable X_4, the first two resistivity range meets the fluid resistant conditions to be predicted by the neurons with both having high values of digits 1, as shown in the flow equations below.

$X_2 = (x_{21}, x_{22}, x_{23}) \equiv (110)$, $X_3 = (x_{31}, x_{32}, x_{33}) \equiv (100)$
$X_4 = (x_{41}, x_{42}, x_{43}) \equiv (110)$.

The three continuous parameters segmentations in the X_1 input neurons are (x_{11}, x_{12}, x_{13}) where the rates of flow constant values are chosen according to the prescribed weights for the neurons to guess intelligently using the following rules. The fluid resistance conditions for the neural pattern recognition are 101, i.e. $\lambda_1 < 1, \lambda_2 > 1, \lambda_3 = 1$, or 100 which means that only λ_1 met the fluid dynamics condition, while $\lambda_2 > 1$ and $\lambda_3 = 1$ do not meet the condition.

The neurons are expected to output digit 1 when the formation is either 011 or 010 and digit 0 when it is either 101 or 100; since the soil consolidation is higher with accompanying high subsurface pressure.

The conditions for susceptibility of not being a good reservoir should be either 101 or 100 and 000 or 111, while for good reservoir and less fluid resistance conditions are either 011 or 010. The expected XOR output patterns that classified and demarcated the susceptible areas to low resistant flow dynamics using neuron X_1 are either 011 or 010.

The suggested output digits for the neuron X_2 are either101 or 110 patterns, and they are regarded as high value (1), while 001 or 010 is being regarded as low value (0) for this neuron. The low values in this research are the expected regions to be predicted by the neural network, for an efficient fluid dynamic into reservoirs.

The above outcomes are from the three inputs neurons (x_{21}, x_{22}, x_{23}), which are the apparent resistivity values of the second input neurons. For the purpose of generalization and with a closer identification, X_1, X_3 have the same output patterns, while X_2, X_4 have the same patterns and are coded the same way.

The back-propagation algorithm ensures that the input data are repeatedly presented to the neural network in the training process. In each presentation to the input of the neural network, the expected value is compared to the threshold output while the error is computed. The computed error is feedback into the algorithm for further adjustments in a repeated iteration processes until the model gets closer to the desired threshold value as the neural output.

The coding procedures as they are fed into the algorithm can be selected according to the following rules, $\lambda_1^{x_1}, \rho_1^{x_2}, \rho_1^{x_3}, \rho_1^{x_4}$ in the sequence one and these selections can be viewed from the table below. It is worth noting that the last digit in all the cases is the bias, which is always digit 1. This is the way they have been supplied to the code in the C++ program written.

TABLE I
LOCATIONS AND CODING SHEET FOR THE RAW DATA

A		B		C		D		E		F	
21	00001	30	01001	15	00011	35	01001	20	01001	1	01001
22	00001	31	00011	16	00011	36	00101	7	00001	2	01001
23	00001	32	00001	17	10001	38	00001	10	01001	4	01001
24	00001	33	00011	26	01011	39	00001	5	01001	6	00001
25	01001	34	00011	43	01001	40	00011	9	01001	42	00101
27	00011	3	00001	45	00011	41	00001	8	00001	44	01011
28	00001	11	00001	47	00001	48	01001	13	01001	18	00001
29	00001	12	01001	37	01001	19	00001	14	11001	46	01001`

The neural network model using the XOR data is repeatedly presented to the neural network. At the presentation of input into the neural network, errors are calculated through the sigmoid function to the hidden layer and the output.

The computed values are then fed back to the neural network for proper adjustments. The neural network uses these errors to adjust its weights such that the error will be decreased [3]. These sequences of events were done repeated until an acceptable error has been reached, when the network no longer appears to be learning, and the final output computed as can be seen in Fig. 3.

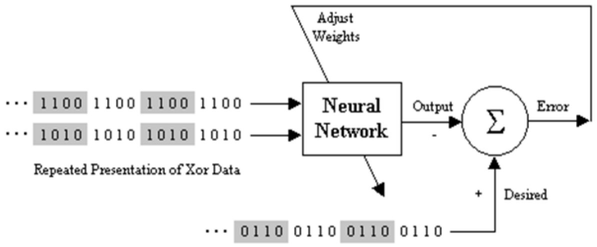

Fig. 2 The training process with back propagation [3]

B. Input and Output ANN during Training

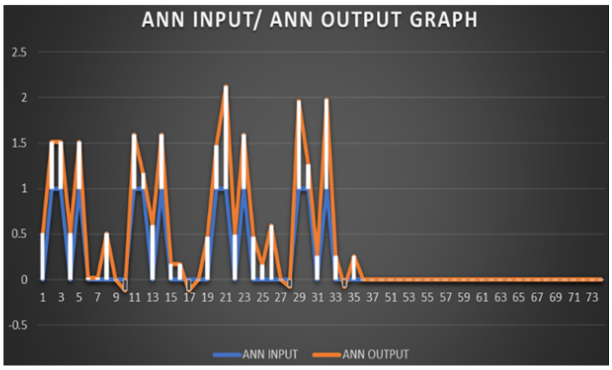

Fig. 3 The input and output for the ANN

The above graph depicts the rate of change from the input neurons through the two hidden layers to the output neurons, in the learning cycles. The transitions for four out of the six caches (A, B, E, and F) are compared according to the proximity of the locations, and graphs showed the same trend and patterns by the neurons which have the same susceptibility of fluid dynamics into groundwater reservoir. The input neurons are magnified by the adjusted weights in the hidden layers before the fluid dynamics patterns are recognized. This shows that the neurons are actually intelligent, in predicting the areas of low pressure with great fluid dynamics into reservoir.

C. Epoch Size of the ANN during Training

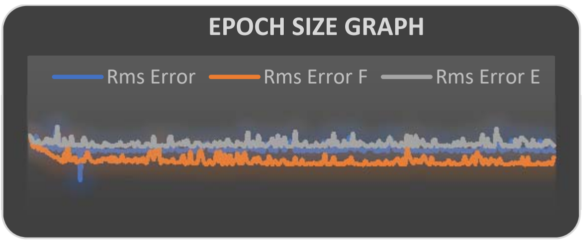

Fig. 4 Epoch size

This graph depicts the epoch size of the neurons at the learning cycles for the 300 epoch runs. This is the number of training samples presented to network between weights updates, when the sum of root-mean- squares errors for three locations A, E and F are compared. The reason why locations E and F are very high pressured regions is that the neurons are trying to avoid according to prediction of the neurons, while location A is not. Accordingly, we can see the same signatures for the two regions that are highly pressured, while location A has very low signatures as compared to the other two regions. In an online mode, the weights are updated after presentation of each training pair.

D. The Neural Network Architecture

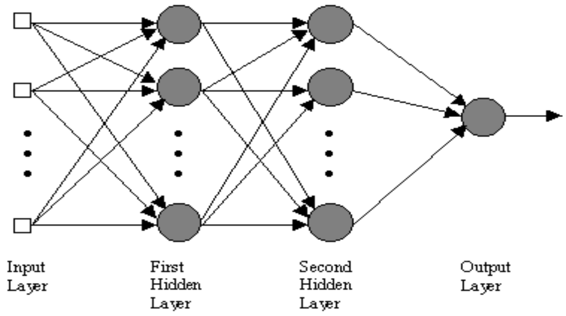

Fig. 5 Network architecture

The neural network used for the research assumes the above architecture, but in actual sense of this research, four inputs have been used and the two separate hidden layers of the order of three and four neurons in the middle preceding the output. The dotted lines show that there are more factors that can make an area to be unsuitable for groundwater management program, but the most important four have been focused for the purpose of the research.

For the purpose of this research, the training algorithm has been coded in C++ algorithmic language and the training was repeated with 300epoch to minimize the error and get a better output, which matched the threshold values in all the cases.

E. Model Analysis from Multiple Regressions

The model iterations from the SPSS software showed that the coefficients are statistically significant with reduced standard error maintained at 0.53(Appendix), which shows that the result is reliable to predict the coefficients as the bulk modulus of fluid dynamics that determines the flow pattern of the area under consideration.

IV. Results and Discussion

A. Flood Pattern Analysis

Fig. 6 shows the 2-D fluid dynamics and pressure pattern recognition map of the entire study areas as recognized by the neural network for non-linear classification. The neurons were able to detect and map out those regions that are highly pressured which cannot be used for sitting boreholes, with indication as pink pigments, the neurons predicted that those locations prevent groundwater motion. Therefore, they are pushed up by the resistance pressure to form a flood. Those areas that are marked with blue pigments constitute the low pressured regions where we expect the neurons to predict and map for groundwater conservation. The regions that are mapped with black pigments were also predicted by the neurons to be minor fractures and with good prospect for groundwater development. However, some of the regions have

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indications that in the future, fracture can occur, these are recognized by the neurons and are mapped with red pigments with their values ranging from 0.55 to 0.65 (i.e. $0.55 \le v \le 0.65$.). The 3-D pattern recognition map as confirmed by the neurons, gave a clearer picture that the areas mapped with sky blue pigments are high pressure regions which cannot be used to site borehole for water management, while those that are indicated with black pigments are the groundwater prospect region. Those with future tendency of being fractured are coded with light yellow pigment as recognized by the neurons.

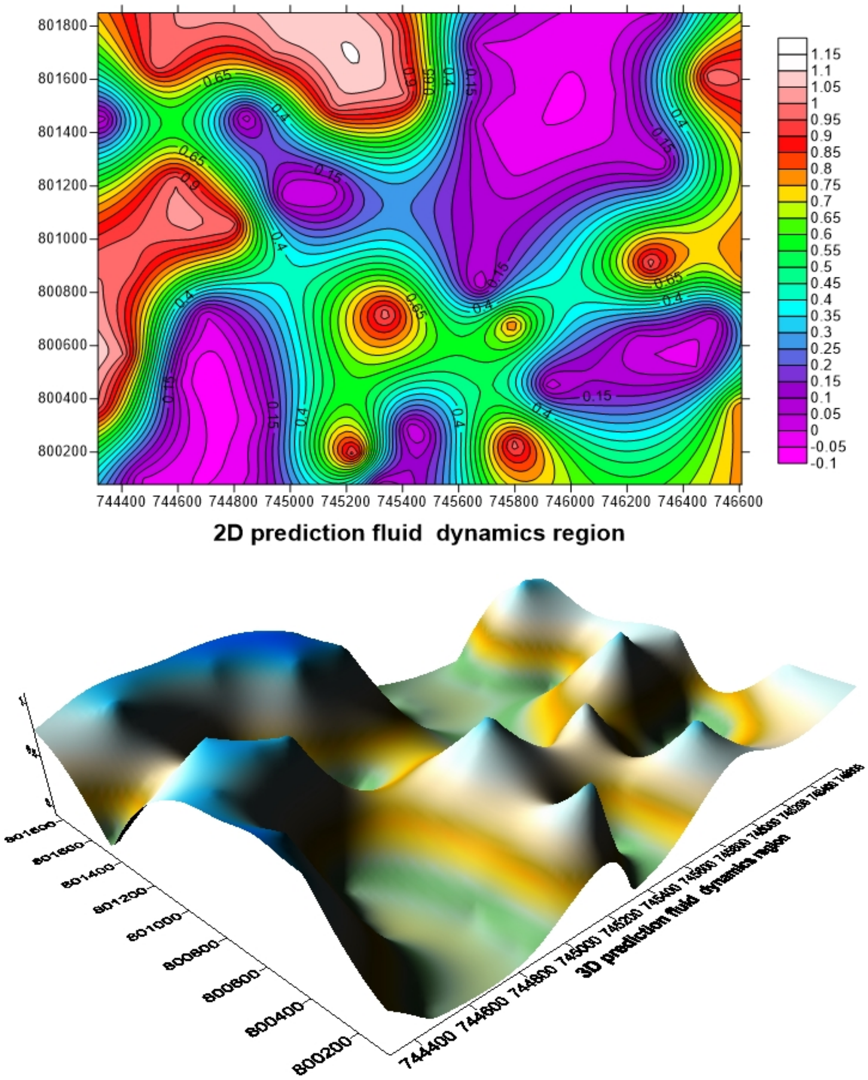

Fig. 6 2-D and 3-D pattern recognition map

B. Color Prediction and Intensity of the Neurons

Fig. 7 depicted the color intensity as recognized by the neural network, which is also in line with the explanations in the 2D map in Fig. 6.

V. Conclusion

The application of Neural Network has been tested in the prediction of fluid dynamics of the regions in the studied area; the pattern recognition map showed a very good fit of the neural in predicting the likely regions of how the flow channels behave in respect of the groundwater reservoirs formation. The neural also predicted those areas in future that are likely to be fractured due to certain tectonic disturbances and weathering activities in geological time frames and they are mapped with red pigments. The neural predicted some regions to be avoided for sitting boreholes and giant structures and are marked with pink pigments. However, in all the cases, the configuration used in the neural network proved successful and can be used to solving environmental problems relating to reservoir modeling of the neural pattern recognition. The errors in the each of the 300 epoch runs are appreciable and in the order of about 0.05 tolerances level, and very good in the adjustments of the neural weights.

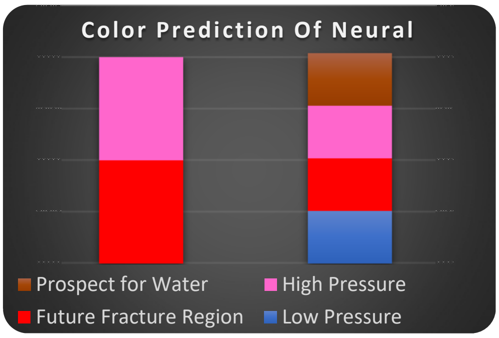

Fig. 7 Pressure severity of ANN

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