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An Overview on Artificial Intelligence Approach in Seasonal Rainfall forecasting

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ABSTRACT

Artificial intelligence (AI) has a colossal potential to profit European natives, economy and society, and as of now exhibited its capability to produce an incentive in different applications and spaces. From a modern perspective, AI implies calculation based and information driven PC frameworks that empower machines and individuals with computerized capacities, for example, observation, thinking, learning and even self-governing basic leadership. Computer based intelligence depends on an arrangement of advancements including calculations for the observation and elucidation of huge measures of data (information), programming that makes inferences, learns, adjusts or changes parameters likewise and techniques supporting human-based basic leadership or computerized activities.This paper presents a new approach using an Artificial Neural Network technique to improve rainfall forecast performance. A real world case study was set up in Bangkok; 4 years of hourly data from 75 rain gauge stations in the area were used to develop the ANN model. The developed ANN model is being applied for real time rainfall forecasting and flood management in Bangkok, Thailand. Aimed at providing forecasts in a near real time schedule, different network types were tested with different kinds of input information. Preliminary tests showed that a generalized feed forward ANN model using hyperbolic tangent transfer function achieved the best generalization of rainfall. Especially, the use of a combination of meteorological parameters (relative humidity, air pressure, wet bulb temperature and cloudiness), the rainfall at the point of forecasting and rainfall at the surrounding stations, as an input data, advanced ANN model to apply with continuous data containing rainy and non-rainy period, allowed model to issue forecast at any moment. Additionally, forecasts by ANN model were compared to the convenient approach namely simple persistent method. Results show that ANN forecasts have superiority over the ones obtained by the persistent model. Rainfall forecasts for Bangkok from 1 to 3 h ahead were highly satisfactory. Sensitivity analysis indicated that the most important input parameter besides rainfall itself is the wet bulb temperature in forecasting rainfall.

Keywords-Artificial intelligence, ANN, rainfall forecasting, big data

1. INTRODUCTION

Artificial intelligence(AI) is knowledge displayed by machines, with machines mirroring capacities commonly connected with human cognizance. Computer based intelligence capacities incorporate all parts of recognition, learning, information portrayal, thinking, arranging, and basic leadership. The capacity of these capacities to adjust to new settings, i.e., circumstances that an AI framework was not recently prepared to manage, is one perspective that separates solid AI from powerless AI. In this report, we won't make the qualification among frail and solid AI for straightforwardness and because of our emphasis on the business setting.Exact data on precipitation is basic for the arranging and the executives of water assets. Also, in the urn-boycott zones, precipitation has a solid impudence on traffic, see frameworks, and other human exercises. In any case, precipitation is Big data examination have been quickly creating alongside the developing needs of big data innovations in various subjects (see, for instance, . The openness, accessibility and exponentially developing amount of big data have additionally advanced the relating innovative headways and down to earth usage. Earth is a complex dynamical framework; from that point, big data investigation experienced a greater number of difficulties in atmosphere science than different subjects paying little mind to the broad assets of big atmosphere data. Environmental change as a developing theme and furthermore a data-escalated subject has been the exploration focal point of big data researchers in the course of recent decades. Thorough big data examination applications have been completed on big atmosphere data, while the Internet of Things, distributed computing, big data instruments to research atmosphere, just as astute investigation platforms and new innovative movements, have additionally stressed its importance and conceivable effects on atmosphere science and big data science improvement (see, for instance, [6,7]). Given the setting of battling environmental change, existing examination has connected big data investigation in mostly the parts of vitality proficiency, clever horticulture, brilliant urban arranging, climate figure, cataclysmic event the executives, and so forth.

Albeit by and large this is definitely not another subject and there is a lot of existing writing, there is no ongoing audit as far as we could possibly know that especially explores the theme of big data in environmental change, also that the novel improvements are advancing quickly regularly alongside the mechanical progressions. In this manner, this paper adds to the current writing by giving the most cutting-edge diagram of big data applications in environmental change related examinations initially a standout amongst the most mind boggling and troublesome components of the hydro-blow out cycle to comprehend and to show because of the intricacy of the climatic procedures that create precipitation and the huge scope of variety over a wide scope of scales both in reality (French et al., 1992). Accordingly, exact precipitation guaging is one of the best difficulties in operational hydrology, in spite of numerous advances in climate conjecture ing in ongoing decades (Gwangseob and Ana, 2001).

Repository inflow gauging is a fundamental assignment in dam activity and is firmly connected to water asset arranging and the executives. Store inflow anticipating has turned out to be progressively mind boggling and significant because of changes in the recurrence and size of water-related debacles under environmental change. To all the more likely comprehend the reactions to environmental change, a substantial number of models have been produced for increasingly exact and solid inflow estimating [1– 9]. In the hydrological field, time arrangement models are broadly used to break down the direct stochastic advancement of watched time arrangement and conjecture future time arrangement. In light of Autoregressive Integrated Moving Average (ARIMA) family models proposed by [10], Seasonal ARIMA (SARIMA) and Seasonal ARIMA with exogenous factors (SARIMAX) models have been generally connected to show hydrological time arrangement thinking about regularity.

Past investigations have effectively demonstrated the relevance of the SARIMA model after the Box and Jenkins methodology, as a result of the basic numerical structure, perfect portrayal of the measurable and connection structures, and moderately modest number Water 2019, 11, 374; doi:10.3390/w11020374 www.mdpi.com/diary/Water 2019, 11, 374 2 of 25 of parameters. Moreover, hydrological variable determining has been performed utilizing artificial intelligence models since the artificial intelligence method started to be progressively created during the 1990s. The Artificial Neural Network (ANN) and Adaptive Neural-based Fuzzy Inference System (ANFIS) models have been much of the time utilized and demonstrated great execution in hydrological variable estimating [1,17– 23]. Since the ANN and ANFIS models consider both direct and nonlinear procedures of the watched time arrangement, they were proposed as options in contrast to customary time arrangement models for the mind boggling routine with regards to hydrological variable estimating. Notwithstanding the over two great artificial intelligence models, another kind of AI strategy, i.e., Random Forest (RF) model, has been as of late presented as a condition of-craftsmanship artificial intelligence model in the hydrologic field. The RF model has delivered progressively precise and stable forecasts with the extra preferred standpoint of taking care of nonlinear and non-Gaussian data arrangement; accordingly, it has been generally utilized in store activities. Numerous investigations have concentrated on looking at the estimating exhibitions of time arrangement and artificial intelligence models as various anticipating models propose in late decades. Wang et al. [1] thought about a few artificial intelligence strategies, for example, ANN, ANFIS, hereditary programming and bolster vector machine models for month to month stream releases. They reasoned that the best model contrasted relying upon the assessment criteria. Val pour et al. thought about Auto Regressive Moving Average (ARMA), ARIMA, and autoregressive ANN models for determining month to month inflow while expanding the quantity of parameters to improve precision.

2. TIME SERIES AND ARTIFICIAL INTELLIGENCE MODELS

The Box– Jenkins approach utilizing the ARIMA group of models is broadly used to figure future qualities dependent on a watched time arrangement. The ARIMA model closefisted deciphers a stochastic procedure with autoregressive (AR) and moving normal (MA) administrators. In the event that there is regularity in the time arrangement, the SARIMA model is increasingly valuable for demonstrating as it considers regularity through a differencing system .

3. ARTIFICIAL NEURAL NETWORK (ANN) MODEL

The ANN model is an amazing AI method that is intended to copy the structure of the mind [44]. It has been broadly connected in hydrology to improve the consistency of future hydrologic factors since it considers both direct and nonlinear structures. All in all, the essential structure of the ANN model is three layers (input, covered up, and yield) as appeared in Figure 1. Consider there are n number of information factors in the info hub (xi, I = 1, 2, . . . , n), the p number of hubs in the shrouded layer (zj, j = 1, 2, . . . , p), and the k number of yield factors in the yield hub (ym, m = 1, 2, . . . , k). The ANN model can be depicted in Equations (7) and (8):

4. A BIG DATA ISSUE

DEM requires control stream advancement, framework checking, continuous activity, and generation arranging [17]. In more detail, DEM in a SG is an entangled, multivariable system, since the last empowers an interconnected power appropriation organize by permitting a two-route stream of both power and data. This is as opposed to the conventional power framework, in which the power is created at a focal source and afterward appropriated to purchasers. Because of the bi-directional progression of data and power among providers and customers, the lattices become progressively versatile to the expanded infiltration of DER, empowering likewise clients' support in vitality reserve funds and collaboration through the DR instrument [10, 18, 19]. DR can be connected to both private (e.g., cooling, warming, electric vehicles (EVs) charging, and so on.) and modern loads and incorporates three unique ideas; I) vitality utilization decrease, ii) vitality utilization (or creation) moving to times of low (or high) request, and iii) effective use of capacity frameworks [20]. It ought to be seen here that module EVs can be considered as capacity gadgets, while the cautious booking of their charging and releasing can profit both their proprietors and the utilities. Clearly, this further builds the parameters that the DEM calculations need to consider, for example, the EVs charging profiles.

5. LITERATURE REVIEW

The vocation of more than 60 percent of the total populace relies on the rainstorm, of which the Asian summer storm is the biggest. Precise expectations of the rainstorm, at any rate a season ahead of time, are in this manner critical for the storm districts. Moreover, the Asian summer rainstorm is a key part of the world's atmosphere framework, having significant tele-associations with worldwide climate and atmosphere (Walter Maner, 2016).

Following the Great Indian Drought of 2016, H.F. Blanford, who had set up the India Meteorological Department in 2016, issued the principal seasonal gauge of Indian storm rainfall in 2016. Afterward, in the early piece of the twentieth century, Sir Gilbert Walker started broad investigations of worldwide teleconnections which drove him to the revelation of Southern Oscillation. Walker presented, out of the blue, the idea of connection for long-run forecasting of the Asian summer rainstorm and his discoveries are pertinent even today.

Over 100 years after the fact, figures of the Asian summer rainstorm is as yet being made utilizing factual relapse, frequently with astounding achievement. General course models are likewise equipped for catching a portion of the highlights of the Asian summer rainstorm and might probably give improved transient figures.

For the most part, there are two strategies that are utilized in climate forecasting one is observational approach and other is dynamical approach (Lorenz, 2016). The exact approach depends on the event of analogs and is frequently alluded to by meteorologists as simple, for example, changes in barometric weight, current climate conditions, sky condition to decide the future conditions (Ozelkan, 2016). This approach regularly is valuable for anticipating nearby scale climate whenever recorded case are enormous in number.

Dynamical approach depends on condition and forward recreations of the air and is frequently alluded to as PC demonstrating which includes design acknowledgment aptitudes, learning of model execution and information of model inclinations (Lorenz, 2017). This approach is typically helpful for displaying enormous scale climate wonders and may not anticipate momentary climate effectively. The greater part of the climate forecasting frameworks are joined systems of observational approach and dynamical approach. In any case, very little consideration has been paid to the utilization of delicate figuring in climate forecasting.

Climate conjecture frameworks are among the most unpredictable condition frameworks that PC needs to fathom. An incredible amount of information, originating from satellites, ground stations and sensors situated around our planet send day by day data that must be utilized to anticipate the climate circumstance in one hours from now and days all around the globe. Climate projections give conjecture for next 24, 48 and 72 hours for wide territories (Pasero, 2017). Climate estimates give basic data about future climate. There are different strategies associated with climate forecasting, from moderately basic perception of the sky to profoundly complex electronic scientific models (M. Tektas, 2010).

6. APPROACHES FOR WEATHER FORECASTING

Numerical climate forecast is the expectation of climate marvels by the numerical arrangement of the conditions overseeing the movement and changes of state of the environment. Numerical climate forecast strategies, notwithstanding being connected to short-go climate expectation, are utilized in such research thinks about as air-contamination transport and the impacts of ozone harming substances on worldwide environmental change.

The main operational numerical climate forecast model comprised of just one layer and in this manner it could demonstrate just the fleeting variety of the mean vertical structure of the air. PCs currently license the advancement of staggered (for the most part around 10–20) models that could resolve the vertical variety of the breeze, temperature and dampness. These staggered models foresee the major meteorological factors for huge sizes of movement

Lunagariya et al. (2017) endeavored to check the climate estimate from NCMRWF. Examination was completed week by week, seasonal just as yearly premise utilizing different numerical check procedures like proportion score, convenience investigation and connection approach amid 2016-17 and 2018-19. The conjectures were found inside ease of use run for certain parameters however for other parameter improvement is as yet conceivable.

The complexities in the connection among rainfall and ocean surface temperature (SST) amid the winter storm (November-January) has been seen by Goutami Chattopadhyay et al. (2018). Assessment is done measurably utilizing disperse plot frameworks and autocorrelation capacities. Straight just as polynomial pattern conditions were gotten and it was seen that the coefficient of assurance for the direct pattern was exceptionally low and it stayed low notwithstanding when polynomial pattern of degree six was utilized. An exponential relapse condition and an artificial neural system with broad variable

determination were created to figure the normal winter rainstorm rainfall of a given year utilizing the rainfall sums and the ocean surface temperature peculiarities in the winter storm a long time of the earlier year as indicators. The artificial neural system was produced as a multi-layer perceptron with sigmoid non-linearity and hereditary calculation based variable choice. Both of the prescient models were made a decision about factually utilizing the Wilmot's file, rate mistake of expectation and forecast yields. The measurable evaluation uncovered the capability of artificial neural system over exponential relapse.

Dawid (2018) clarify in his paper that the motivation behind factual surmising is to make successive likelihood estimate for future perception as opposed to express data about parameters. In this manner, there is a need of an approach which is superior to factual deduction technique. Be that as it may, Glahn et. al. (2018) demonstrate that Model Output Statistics (MOS) strategy is a target climate forecasting method which comprises of deciding a factual connection between an anticipate and variable figure by a numerical model at some projection time. It is the assurance of the "climate related" insights of a numerical model. Glahn has connected this strategy, together with screening relapse to the predication of surface breeze, likelihood of precipitation, most extreme temperature, cloud sum and restrictive likelihood of solidified precipitation. The outcome is look at by the national climate framework over print and copy. It was inferred that MOS is valuable procedure in target climate forecasting. In this manner, in the proposed research factual relapse as multidimensional reaction surface device is connected to figure neighborhood monsoonal precipitation.

Allen and Vermon (2018) characterized target forecasting framework as one which can deliver one and just one figure from a particular arrangement of information. It doesn't depend for its precision upon the forecasting knowledge or the abstract judgment of the meteorologist utilizing it. Abstract judgment is, obviously, utilized in the improvement of the framework.
From all above survey, plainly there is a need of much better approach which can deal with climate parameters all the more brilliantly rather that a fresh hypothesis.

The execution of ANN, a significant Soft Computing technique in climate forecasting has begun by Hu (2018). Özelkan and Duckstein (2018) looked at the exhibition of relapse investigation and fluffy rationale in contemplating the connection between month to month air dissemination examples and precipitation. Cook and Wolfe (2018) built up a neural system to anticipate the normal air temperatures. Fluffy rationale can likewise be of incredible use in the climatic information examination and expectation. Being equipped for managing semantic factors, this approach can be used in dissecting barometrical factors. Liu and Chandrasekar (2018) built up a fluffy rationale and neuro-fluffy framework for grouping of a hydrometeor type dependent on polarimetric radar estimations where fluffy rationale was utilized to construe a hydrometeor type and the neural system learning calculation was utilized for programmed change of the parameters of the fluffy sets in the fluffy rationale framework as indicated by the earlier information (Mehmet Tektas, 2018).

Neural systems and fluffy deduction frameworks have been generally utilized in a few savvy interactive media applications. Artificial Neural Network (ANN) gains starting with no outside help by modifying the interconnections between layers. Fluffy Inference System (FIS) is a well known figuring structure dependent on the idea of fluffy set hypothesis, fluffy in the event that rules, and fluffy thinking. Coordinating ANN and FIS have pulled in the developing enthusiasm of scientists because of the developing need of versatile wise frameworks to meet this present reality necessities (Abraham, 2018).

7. ANALYSIS

For this one-month and two-month ahead rainfall forecasting model improvement, a month to month time arrangement rainfall information of North India for the period 1871 to 2012 (141 years) were utilized. This time arrangement information gathered by Indian Meteorological Department, Pune. The information were gathered by different stations of various conditions of Northern India. The site was picked because of the accessibility of moderately long arrangement of meteorological information. After investigated information, a few information was chosen to prepare ANN models, and the remaining was utilized as a testing set. This investigation centers around the North India just, so just stations situated here were chosen, while different stations which are situated outside were disposed of. The information utilized as information and yield factors for ideal model improvement are given in Table 2 beneath. Here two models will be created, model M1 is for onemonth ahead expectation and the other model M2, is for two-month ahead forecast. In both M1 and M2 models, three info factors have been utilized which incorporate progressive long stretches of rainfall information. The yield in both the models is the anticipated rainfall, which is one month and multi month ahead qualities.

8. RESULTS AND DISCUSSIONS

System execution of both the models M1 and M2 are given in tables underneath. In Table 3 and Table 4, the quantity of neurons in the concealed layer is orchestrated in climbing request and their approval execution is estimated appropriately.

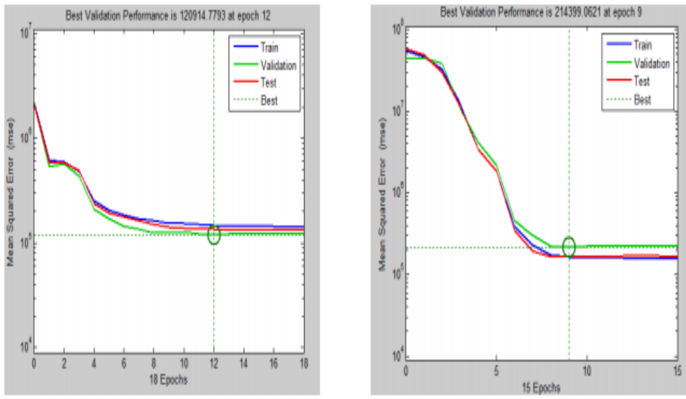
Table 1: Network Performance for Model M1 for one Month Ahead Forecasting

Neurons Used	Model Performance	No. of Iteration (Epochs)	Stopping Criteria	Network Configuration
5	120914.77	12	Val. Stopped/Max. iterations	3-5-1
10	120332.90	14	Val. Stopped/Max. iterations	3-10-1
15	129833.71	22	Val. Stopped/Max. iterations	3-15-1
20	136442.98	8	Val. Stopped/Max. iterations	3-20-1
25 (best)	112461.95	4	Val. Stopped/Max. iterations	3-25-1
30	152499.50	23	Val. Stopped/Max. iterations	3-30-1
35	103683.66	24	Val. Stopped/Max. iterations	3-35-1
40	122817.65	13	Val. Stopped/Max. iterations	3-40-1
45 (best)	132373.42	8	Val. Stopped/Max. iterations	3-45-1
50	154452.31	6	Val. Stopped/Max. iterations	3-50-1

Table 2: Network Performance for Model M2 for two Month Ahead Forecasting

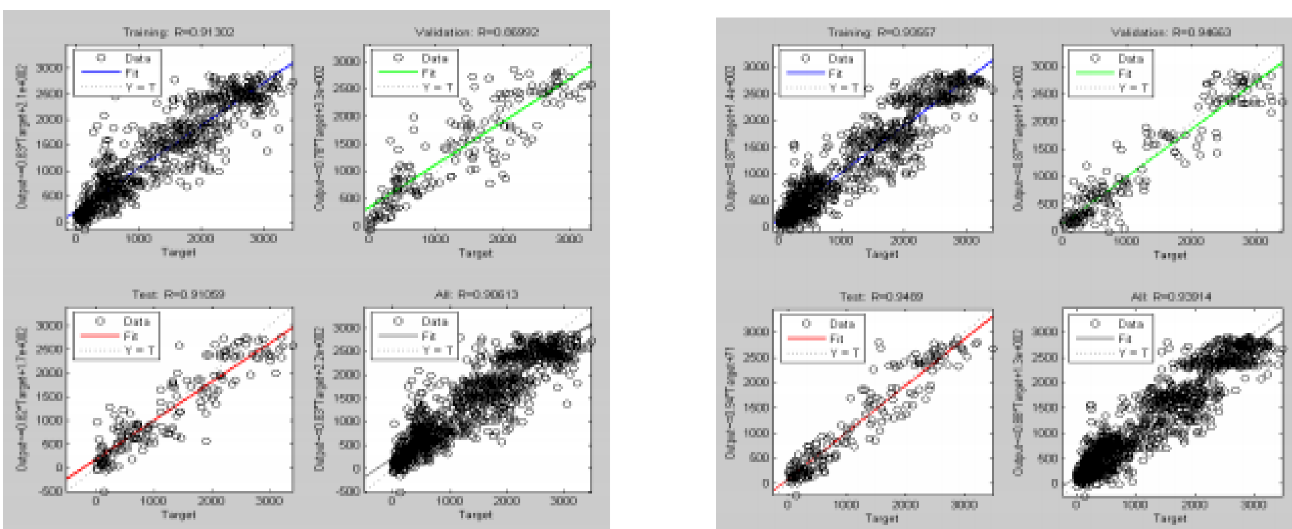
Neurons Used	Model Performance	No. of Iteration (Epochs)	Stopping Criteria	Network Configuration
5	196653.42	34	Val. Stopped/Max. iterations	3-5-1
10	169111.91	44	Val. Stopped/Max. iterations	3-10-1
15	142875.66	29	Val. Stopped/Max. iterations	3-15-1
20	146643.47	12	Val. Stopped/Max. iterations	3-20-1
25	198612.44	11	Val. Stopped/Max. iterations	3-25-1
30	220510.21	8	Val. Stopped/Max. iterations	3-30-1
35	208755.18	5	Val. Stopped/Max. iterations	3-35-1
40	233804.28	10	Val. Stopped/Max. iterations	3-40-1
45	159821.84	13	Val. Stopped/Max. iterations	3-45-1
50 (best)	138643.47	12	Val. Stopped/Max. iterations	3-50-1

It is seen that for Model M1 and M2, the best system structure is 3-25-1 and 3-50-1 separately. It is additionally discovered that the presentation isn't really improved notwithstanding when the system blunder is low. It is particularly obvious from figure 1(a) and 1(b) that after 12 and 9 ages, the presentation of preparing, testing and approval mistakes were stale. It implies after ages 12 and 9 there is no further improvement in the exhibition of the system and the system appears to have immersed.



(a) (b)

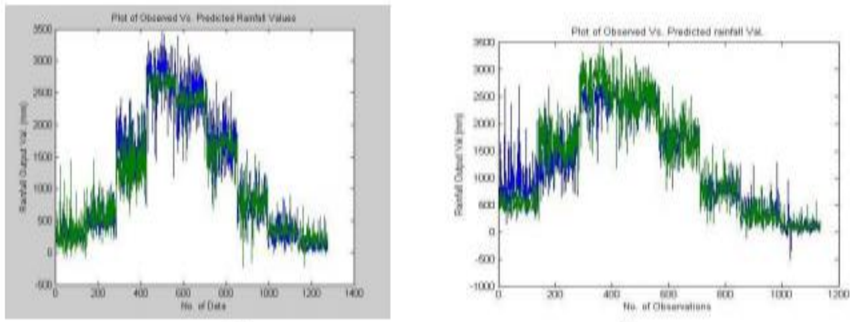
Fig.1: Training of NN Model gauged by MS for M1 and M2 Models respectively.



(a) for N=45 (b) for N=50

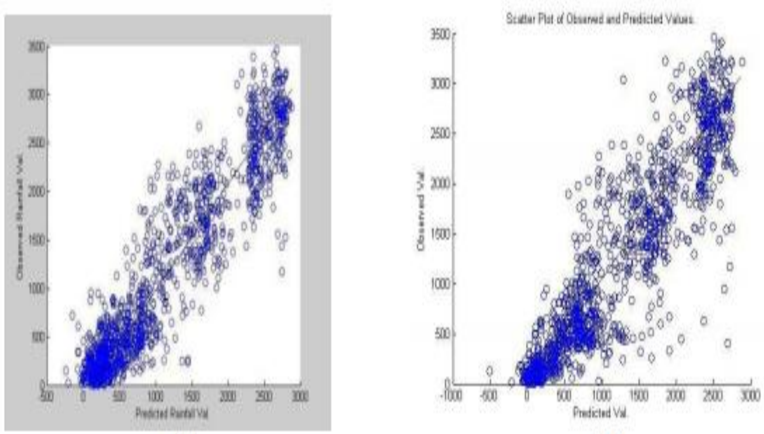
Fig.2: Scatter Plot of R-Values for Training, Testing and Validating datasets for best-developed network for M1 and M2 Models Respectively

Straight relapse investigation between the system reaction and the system yield appeared in figure 2. It very well may be gathered that NN model does the great mapping. In this examination, 15% information utilized for approval reason, which is other than preparing information for the model. Along these lines, the presentation of these machining conditions never experienced by the neural system model. Subsequently, this mapping considers to be valid and speaking to the utilitarian relationship. Following figures 3 given beneath delineates the examination among genuine and reproduced information for surface unpleasantness. It is seen that aside from uncommon events, recreated surface harshness esteems for the assigned parameters are in adequate vicinity with real qualities. This portrayal, thusly, concurs with the end that, high exactness of forecast is achieved by Neural Network Model after fruitful finishing of preparing criteria for example with the estimation of MSE being inside a worthy range just as a pleasant exhibition measure. Henceforth, from the outcomes, it is derived that the exhibition of the NN model is satisfactory. In this way, can additionally be affirmed from the dissipate plots appeared in 4. Further investigation of the watched and anticipated qualities for both M1 and M2 models based on MRE values are appeared in figures 5.



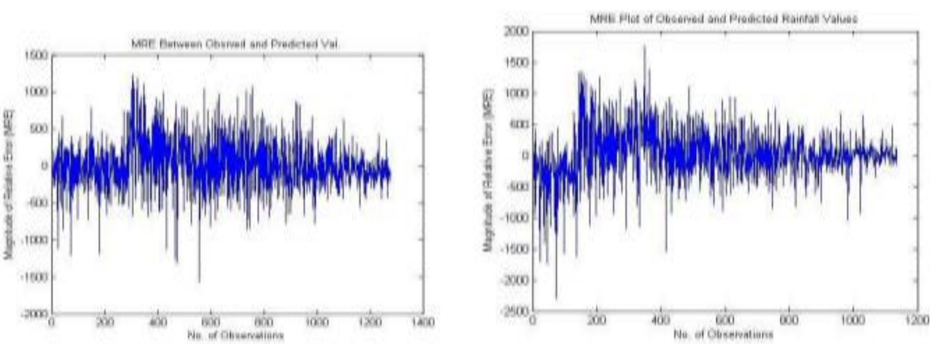
(a) (b)

Fig.3: Comparison of observed and predicted values by best M1 & M2 models



(a) (b)

Fig.4: Scatter Plot of Observed vs. Predicted Rainfall values for M1 & M2 Models



(a) (b)

Fig.5: Scatter Plot of Observed vs. Predicted Rainfall values for M1 & M2 Models

Registered Regression and MSE values for Model M1 and Model M2 for various system structures are given in Table 3 and Table 4 separately. For the system recognizable proof reason, as given in the last segment, the primary number shows the quantity of neurons in the information layer, center speaks to neurons in the shrouded layer and the last number demonstrates the quantity of neurons in the yield layer.

CONCLUSIONS

In this examination, an Artificial Neural Network model was utilized to conjecture precipitation for Bangkok, Thailand, with lead times of 1 to 6 h. Examination of 1 h ahead precipitation figure of the six models considered in the primer test demonstrated that a mix of meteorological parameters, for example, relative moistness, gaseous tension, wet knob temperature, and shadiness, alongside precipitation data at the anticipating station and other encompassing stations, as a contribution for the model could essentially improve the conjecture precision and effectiveness. Consequences of primer tests additionally reasoned that the summed up feed forward arrange and hyperbolic digression work performed well in this investigation. With the suitable system engineering and particularly with the utilization of assistant data, the ANN model had the capacity to gain from persistent information data which contained both downpour and dry periods, hence the model can be received to keep running for constant guaging. The predominance in execution of the ANN model over that of the persevering model again affirmed that the genuine favorable position of a constant ANN model is that it can give a palatable precipitation gauge at any minute. It is critical to decide the overwhelming model contributions, as this expands the speculation of the system for a given data. Moreover, it can help lessen the span of the system and subsequently decrease the preparation time. In this examination, affectability investigation was utilized to rank the information parameters concerning their significance in determining precipitation dependent on the model execution. Consequences of the affectability examination showed that the most significant info parameter, other than precipitation itself, is the wet globule temperature; further investigation over the whole downpour measure system could be completed for progressively huge ends.

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