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AUTONOMOUS DECISION MAKING SYSTEM FOR THE UTILIZATION OF RENEWABLE ENERGY RESOURCES IN SMART GRIDS USING DEEP LEARNING

Vijayakumar AN [1], Karthik P [2], Pradeep K R [3]

[1] Research Scholar, Department of ECE, K S School of Engineering and Management, Bengaluru, India

[2] Professor, Department of ECE, K S School of Engineering and Management, Bengaluru, Karnataka, India

[3] Assistnt Professor, Department of AI&ML, BMS Institute of Technology andManagement, Bengaluru, India

Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India.

Abstract: In our day-to-day life, electricity has become the most necessary to lead an everyday life. Many researchers are working on practical methods and technologies for choosing the effective power source for the distribution to the smart girds. In this paper, Machine Learning (ML) andDeep Learning (DL) concepts have been used to predict the valuable source in different months of a year also the cost-effective in such situations. In this research work, optimizing the decision to choose the right start with optimized deep learning neural networks has been implemented. The results highlight the excellent responsiveness of optimized decisionsthrough the benefit of DNN.

Keywords: Machine Learning, Deep Learning, Smart Gird, Predictive measures, Solar Source, Wind Mill, and Thermal Sources.

1.INTRODUCTION

Deep Neural Networks(DNNs) stand the most efficiently used method in Deep Learning (DL). DNNs are the extensive form of the Artificial Neural Network (ANN),havinga higher number of layers to attainthedeepness of a network. DL algorithms characteristically learn the broad probability distribution for a dataset, clearly as in density calculation or implicitly as a combination. Most of the DL procedures are built on stochastic gradient descent optimization algorithms [29].Generally, they staywith a set of modules consisting of cost function, an optimization algorithm, a dataset, and amodel, to shape a Machine Learning (ML) algorithm. Existing DL enables supervised learning by a context that encompasses extra layers and added neurons to design a DNN that can instigatecurrentlyincreasingcomplicationrequirements. A specified large model and a vast training set can quickly map an input vector to an output vector. A feed-forward DNNs can efficiently accomplish this purpose. Still, for further regularization, optimization, and scaling, the DNNs can handle large input vectors forsubstantial length in time-series data,which must be specific.

Neural Network with deep learning modeling will be more productive for the non-linear data with extra hidden layers to the network [27],[28]. In medical image analysis, researchers adopt similar concepts to obtain the better and best performance, as shown in fig.1.

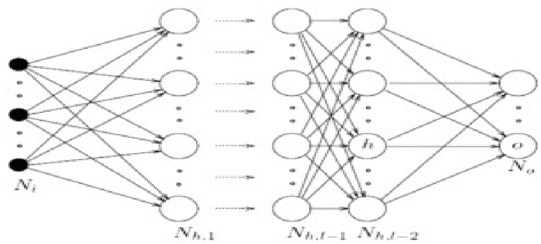

Fig.1. Deep Neural Network architecture

Deep-learning networks accomplish automatic feature extraction deprived of human interference, distinct from most customary machine-learning algorithms. This allowed evading the point of congestion for most data scientists to realize that deep learning is the only way to accomplish the task.

2. RELATED WORK

In this work, the authors have experimented with the effectiveness of decentralized smart grid control. This work elaborates in detail about the heterogeneous networks for the individual nodes. The results are linear for basin analysis, in parallel averaging the time and increasing the delay will benefit the grid effectively [1], [2].This research focuses on generating renewable energy in decentralized production and then integrating the sources to the grid with proper delay intervals spontaneously [10]. The DSGC simulation gives a solution to the frequency stabilization even in the unstable states with power fluctuations. The results are impressive in the Gaussian White noise situations, too [11]. The author works onpower distribution from the grid to the sub-stations. Spontaneously decision on choosing the source for the distribution [8],[9]. This work mainly focuses on maintaining the grid's stability by altering the topology slightly; it results in better performance in the North European Power system. This work focuses on improving the electric power generation, distribution, transmission, and utilization using the neural network concepts to forecast the load requirements [3]. This article proposed a novel method by implementing artificial systems to overcome the problem of predicting the load based on the time series. This system is implemented for the short-term forecasting of the load [12]. The ANN-based model can create a reliable and predictive controller to optimize the design using backpropagation [13], [7]. Agent-based deep learning and machine learning models have been developed for continuous and discrete reinforcement algorithms to analyze the demandsupply to optimize the utilization [4]. Mainly, it works to minimize the energy cost in the microgrids for short-term and long-term storage in batteries using hydrogen storage concepts using solar energies [14]. A lot of surveys have been done on deep learning effectiveness to implement in the smart grids, and a case study also shows that the deep learning or machine learning methods can be more effective than the conventional techniques [5], [15]-[18]. SDN was used to detect the problem in the grid, and the performance was enhanced using deep learning concepts [6]. Some surveys have on renewable energy, and their techniques have also been discussed [19]-[23]. Author discussed Unsupervised and Supervised Learning based Classification Models for Air Pollution Data [24], Identification of Harmful animal detection using Image Processing Technique[25], Novel Approaches to Improve the Production of Cost-

Effective Software Artifacts [26], we proposed Deep Learning Self-directed Decision Making System for the Consumption of Renewable Energy Resources in Smart Grids.

3. PROPOSED METHODOLOGY

The main objective of this procedure is to identify and designthe grid systems for solar energy production and consumption, havingwith the conflicts and variationsthat are dynamically included bythe assembly, which helps to know how the contributors respond to deviations. This methodology works to monitor thespecific property of the grid based on its frequency,i.e.,alternate current (AC) calculated upon the number of cycles per secondHertz (Hz)

The electrical signal frequency works with the concept of "increase in time of surplus generation and decrease in a shortfall of production,"helping to provide the essentialdata about the smart grid.

3.1 WORKING OF THE PROPOSED MODEL

In the proposed model,the grid uncertainty is predicted.Based on the binary classification technique subjected to the balanced againstunbalanced. But the performance relies on substantial interpretations. Here MLtechnique is implanted ina resulting way:

- A given set of input parameters is inputted into the original,intelligent grid model;
- The smart grid model progresses this input and yields a binary output as balanced' or 'unbalanced" based on thebinary classification technique.
- The above steps are accomplished 'n' severaltimes.

a) System Architecture

The system architecture of Optimized DNN for Smart grid is as shown in Fig..2. they containfourstagesthat undergo the following steps.

1. Dataset information.
2. Exploratory Data Analysis (EDA).
3. Optimized DNN classification method.
4. Performance of the algorithm with visualization

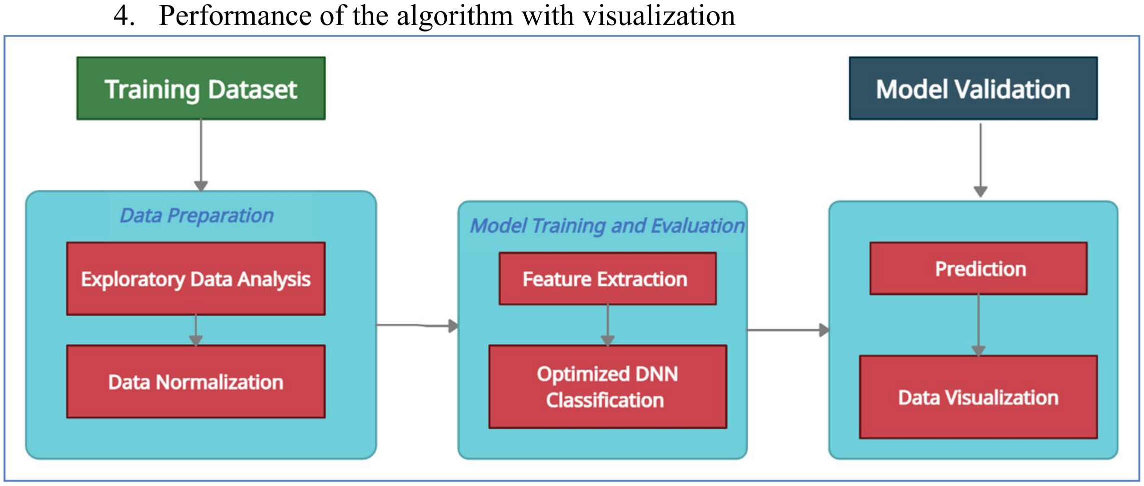

Fig 2: Architectureof the Optimized DNN smart grid model

i) Datasetinformation

The dataset chosen for this method is obtained from the solar grid based on the results from reproductions of grid reliability.The dataset size is 15,000 4 different energy stations such as Solar power, wind power, generator, and water energy resources containing 12 features and two dependent variables.

Here the model consists of the features connected toentire power stability, the response time of the production, and energy ratedefiance.

Based on the dataset properties,the following techniques have been implemented in this work:

1. Keras sequential model Deep Neural networks (DNN) method is implemented.
2. The DNN architecture is based on the number of hidden layers, the variation of epochs, and theoptimization technique.

Table 1. represents the sample data sets for the solar power generation, wind power, generators, and water resource taken for a month randomly weekly three days. By keeping this as a base, the complete data set have been obtained, and then we have predicted how effectively the generation and trustworthy for the power distribution to the grids.and there are Dependent variables that include

1. Differential Equation output: the extreme part of the typical differential equation root to find out positive and negative values to find out wether the system is linearly 'unbalanced'or'linearly balanced' respectively.
2. Binary: categorical label mentioned as 'balanced' or 'unbalanced'states.

ii) EDA

EDA is performed to check and understand the dataset's characteristics, which helps determine whether the data is in a stable/unstable state and checking any missing values. This helps for data preprocessing, which is achieved through the following steps.

Missing value treatment and Normalization

By updating the data of 12 features from the used dataset andbased on the count of data trials, mean, min, max , and standard deviationvalues are found out leading to the Normalization serving to get rid of the missing values and to update the values of columns in the dataset to a standard scale.

Split data for training and testing

With this regard, out of 15000 datasets for each of 4 different energy stations, training data and testing data aresplited in the ratio of 80% and 20%, so that training data counts to 12000 and testing data counts to 3000.

iii) Optimized DNN classification method.

The ***Optimized DNN classification*** technique uses DNN classifier approach having Keras Sequential model for setting the DNN classifier. For the applied method, a linear stack of layers tries to categorizeand anticipate the input shape.This is reflected in a sequential structure, inthe order of actions forusing the DNN, 12 input node-set units of the data, four hidden layers each consisting of pattern 12,24,24 and 12 units, and one output layer of single node, in together having aoverall of 85 nodes and 1,308 edges as shown in Fig 3.

The ***Activation function***generates the backpropagation for the gradients with the errors helping to update the biases and weights as shown in Equation. 1 and 2

$$V = activation\ function \sum(weights * inputs) + bias(1)$$

$$V_{pred} = w(1)x + b(1) \qquad (2)$$

Where,$V_{pred}$is the vector output of hidden layer-1,$w(1)$be the vector weights given to 12 units of neurons in hidden layer-1 till hidden layer-4, b1 and b2,$b(1)$are the vectorized form of general linear function.

Table 1: Represents the sample data sets for the solar power generation, wind

Samp	**SOLAR POWER**													
	WEEK1			**WEEK2**			**WEEK3**			**WEEK4**				
	Day 1	**Day 2**	**Day 3**	**Day 1**	**Day 2**	**Day 3**	**Day 1**	**Day 2**	**Day 3**	**Day 1**	**Day 2**	**Day 3**	**Differential**	**Binary**
1	2.4	2.9	4.9	1.8	2.6	-	-	-	0.3	0.59	0.2	0.8	-	balan
2	9.4	9.5	4.9	2.9	3.2	-	-	-	0.4	0.77	0.3	0.7	0.033	unbal
3	2.7	5.0	2.8	5.8	3.6	-	-	-	0.3	0.30	0.4	0.4	-	balan
4	9.3	2.2	7.4	3.3	3.6	-	-	-	0.6	0.34	0.0	0.8	-	balan
5	8.4	8.4	6.8	9.2	3.4	-	-	-	0.5	0.16	0.4	0.8	0.053	unbal
6	4.4	4.7	6.1	9.5	4.2	-	-	-	0.8	0.35	0.7	0.3	0.055	unbal
	WIND POWER													
1	5.2	8.1	7.2	3.4	2.9	-	-	-	0.2	0.65	0.9	0.9	0.066	unbal
2	3.8	8.2	4.7	2.6	3.9	-	-	-	0.7	0.86	0.2	0.8	0.040	unbal
3	3.8	6.1	8.5	4.3	5.2	-	-	-	0.7	0.63	0.2	0.3	0.034	unbal
4	6.5	1.7	5.5	5.4	2.8	-	-	-	0.7	0.93	0.5	0.1	0.021	unbal
5	3.7	1.0	4.2	8.8	3.6	-	-	-	0.4	0.15	0.2	0.7	-	balan
6	2.1	8.5	8.4	3.3	3.2	-	-	-	0.9	0.07	0.5	0.1	-	balan
	GENERATORS													
1	1.4	9.7	7.1	2.5	3.8	-	-	-	0.7	0.65	0.2	0.3	-	balan
2	4.4	3.9	9.6	3.1	3.1	-	-	-	0.3	0.74	0.7	0.7	0.028	unbal
3	6.3	6.4	9.5	5.5	5.2	-	-	-	0.3	0.22	0.6	0.1	0.022	unbal
4	4.4	7.1	0.9	7.7	5.2	-	-	-	0.3	0.11	0.1	0.7	-	balan
5	3.3	4.8	1.8	9.8	4.7	-	-	-	0.0	0.23	0.2	0.9	0.007	unbal
6	1.0	9.9	1.2	6.5	3.7	-	-	-	0.5	0.82	0.7	0.3	-	balan
	WATER RESOURCE													
1	7.2	3.0	8.6	2.1	4.5	-	-	-	0.7	0.98	0.7	0.1	0.047	unbal
2	4.1	0.8	3.2	0.6	4.8	-	-	-	0.5	0.64	0.8	0.9	-	balan
3	4.5	2.4	5.6	2.5	3.4	-	-	-	0.2	0.56	0.1	0.9	-	balan
4	6.1	6.3	9.8	3.9	3.9	-	-	-	0.7	0.61	0.2	0.4	0.047	unbal
5	3.3	2.9	1.2	6.8	4.3	-	-	-	0.5	0.28	0.5	0.3	-	balan
6	7.8	2.1	9.5	2.9	3.3	-	-	-	0.4	0.52	0.5	0.5	0.002	unbal

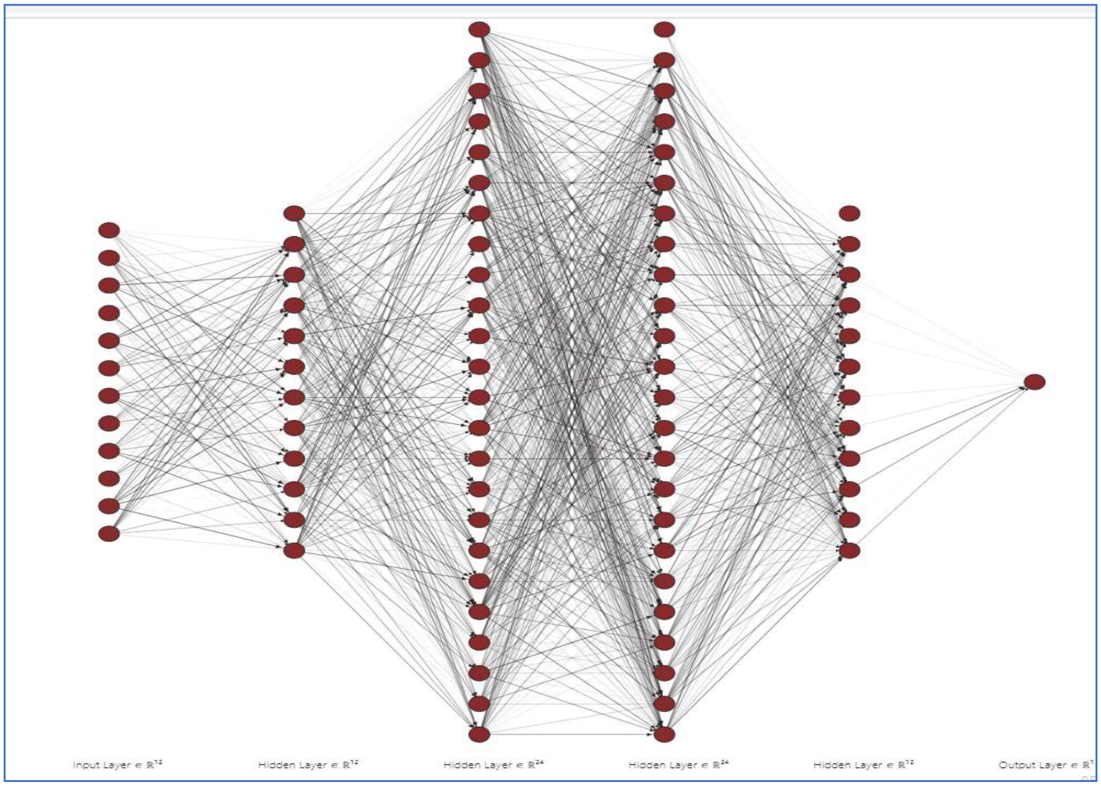

Fig 3: sequential structure the DNN Model

Rectified linear unit (ReLU)is a non-linear activation function in DNN added to the hidden layers,serving to shape an effective functionthatactivates the neurons in multiple layers, as shown in Eqn.3

$$R(x) = max(0, x) \qquad (3)$$

Where., if $x < 0$, $R(x) = 0$and if x≥٠,$R(x) = x$

It also quickens the union of stochastic gradient descent as related to sigmoid activation functions.

Grid Search Cross-Validation (CV) Algorithmisimplemented forestimation prediction. The parameters of the prediction are used to predict the methods that are optimized by the Grid Search CV method toa parameter grid.

- ***Step 1:*** Fit values individually to the parametersselectedwith the Batchsize of 50 and the epoichs of 50along with the optimizer ADAM which provided the most acceptable combination where the importance of parameters arestatic to decrease the time and memory consumption.
- ***Step 2:*** Implement 10-fold CrossValidation (CV) individually to the parameter's group, added with the estimator, that outputs the tentypes of scores individullay for parameter group.

Compiling the network involves training the DNN classifier ina set of optimization method and gradient descent [31]. Binary Cross Entropy is used along with the ADAM optimizer [32]to curtail the loss,,heplingthe function to have less value of Mean Square Error function.To have the finest momentum, aminorrefinement of hyperparameters is done by calculating the exponentially weighted average of precedinggradients, variables GE_w and GE_b earlier to bias correction and $GA_{w^{correct}}$ and $GA_{b^{correct}}$ done with bias correction. Based on it, the Adam optimization technique is implemented with bias correction as shown in the below Equations 4to9 and updating the parameters of and Update parameters w and b.

$$GE_{w^{correct}} = \frac{GE_w}{\left(1-\beta_{1i}\right)} \quad (4)$$

$$GE_{b^{correct}} = \frac{GE_b}{\left(1-\beta_{1i}\right)} \quad (5)$$

$$GA_{w^{correct}} = \frac{S_w}{\left(1-\beta_{2i}\right)} \quad (6)$$

$$GA_{b^{correct}} = \frac{S_b}{\left(1-\beta_{2i}\right)} \quad (7)$$

$$weight = weight - LR * \left(GE_{w^{correct}} \Big/ \sqrt{(SG_{w^{correct}} + \varepsilon)} \right) \quad (8)$$

$$bias = bias - LR * \left(GE_{b^{corrected}} \Big/ \sqrt{(SG_{b^{correct}} + \varepsilon)} \right) \quad (9)$$

Where epsilon ε is anactualvalue to evade dividing by zero,β_1 and β_2 are hyperparameters are used tonormalize two weighted averages exponentially using the default values $\beta_1 = 0.9$ and $\beta_2 = 0.999$.

iv) Performance of the algorithm with visualization

Fit networkshapes the DNN classification model for training and fine-tuning the dataset. In training data, fit method is implied to have the best Batchsize and Epoch, where Epoch requires one forward pass and one recessive pass for all the training set, specified over the count of iterations and keys, based on the Batch Size.

The evaluationand prediction of the testing data set is based on the above evaluation metrics definedinthe smart grid DNN model which isoptimal and free from underfitting and overfitting. The graph is shown below in Fig. 4,5,6, and7showsOptimizedDNN classifier models Summarization history for accuracy and loss for both the training and testing of four smart gird data sets thataccomplishgood with reduced error loss and maximum accuracy in each iteration of epochs vs.accuracy and epochs and loss.

Fig 4: Summarization history for accuracy and loss for Smart grid1-Solar Power

Fig 5: Summarization history for accuracy and loss for Smart grid1-Wind Power

Fig 6: Summarization history for accuracy and loss for Smart grid1-Generators

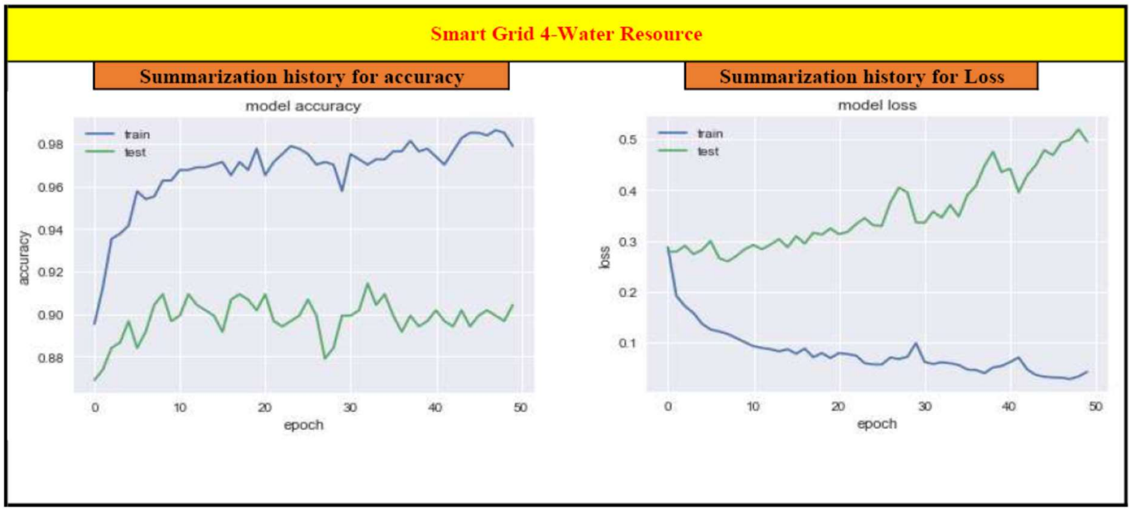

Fig 7: Summarization history for accuracy and loss for Smart grid1-Water Resource

3.2EVALUATION AND PREDICTION

Evaluation and prediction of the Optimized DNN model is done to identify the performance scorebased on evaluation metrics as shown below.

Confusion Matrix: The output is ahown in mtarix format thatstates the specific performance forthe testing model with3000datasets, displaying the predicted class (balanced or unbalanced) of the Smart grid Data set as shown in Table 2,here the validation split is of 0.33.

Table 2: Confusion Matrix of the testing data attained by Optimized DNN classificationSmart grid Model

<table>
<tr><th colspan="7">Data set size (15,000)</th></tr>
<tr><td rowspan="3"></td><td colspan="3">Validation Split is 0.33</td><td>TP</td><td>FP</td><td rowspan="3"></td></tr>
<tr><td>Train data</td><td>80%</td><td>12000</td><td rowspan="2">FN</td><td rowspan="2">TN</td></tr>
<tr><td>Test Data</td><td>20%</td><td>3000</td></tr>
<tr><td>Smart Grid Types</td><td>Architecture</td><td>Folds</td><td>Epochs</td><td colspan="2">Confusion Matrix</td><td>Accuracy</td></tr>
<tr><td rowspan="2">SOLAR POWER</td><td rowspan="2">12-24-24-12-1</td><td rowspan="2">10</td><td rowspan="2">50</td><td>1723</td><td>192</td><td rowspan="2">87.16%</td></tr>
<tr><td>193</td><td>891</td></tr>
<tr><td rowspan="2">WIND POWER</td><td rowspan="2">12-24-24-12-1</td><td rowspan="2">10</td><td rowspan="2">50</td><td>1819</td><td>123</td><td rowspan="2">90.97%</td></tr>
<tr><td>148</td><td>910</td></tr>
<tr><td rowspan="2">GENERATORS</td><td rowspan="2">12-24-24-12-1</td><td rowspan="2">10</td><td rowspan="2">50</td><td>1786</td><td>134</td><td rowspan="2">89.54%</td></tr>
<tr><td>180</td><td>901</td></tr>
<tr><td rowspan="2">WATER RESOURCE</td><td rowspan="2">12-24-24-12-1</td><td rowspan="2">10</td><td rowspan="2">50</td><td>1787</td><td>145</td><td rowspan="2">89.67%</td></tr>
<tr><td>165</td><td>903</td></tr>
</table>

Based on the confusion matrix, metric score is calculated to find performance of the optimized DNN classificationSmart grid model for Smart grid types.

Accuracy rate is ratio of the number of accurate forecasts to the overall number of input samples as shown in eqn10

Accuracy = TP + TN / TP + TN + FP + FN (10)

Where FP=False Positive Rate, TP =True positive Rate, FN=False Negative Rate, TN=True Negative Rate

3.3 RESULTS AND DISCUSSION

The Optimized DNN classifier model is built with skit learn, Keras and Tensorflow libraries on Jupyter notebook. Performance evaluation is predicted with output as "balanced" or "unbalanced". The architecture and the hyperparameters of the particular dataset are directed to the most acceptable prediction performance on the test set.

Distinct features of this optimized DNN for smart grid control is stated below:

1. As the dataset is undergone preprocessing, the accuracyrate of the testing set confirms that anOptimized DNN model is the best method for a Smart grid.
2. The augmented number of epochs during fitting also plays a substantial role for the testing set, yielding better prediction accuracy;
3. The usage of a test dataset with3,000 observations endorsedmeaningfullyforbetteroutcomes.

4 CONCLUSION

In this research work, we have presented DNN algorithms for optimizing the decision for choosing the right source to the smart grid for distribution. Here we have focused on the cost, stable/balanced quantity generation in the choose period. Our proposed architecture uses the DNN method to predict the decision in selecting the source to the grids. In this project, we have used four different sources like diesel generators, solar plant, wind mill generation and thermal power plant. The cost also will impact in choosing the source in any given period. Our predictive algorithms are more potential in selecting the appropriate source to the grid as well the effective generation of the source. Our predictive methods achieve almost above 85% of efficiency. Based on this response the power distribution can be more cost effective and be more productive. Further we are planning to develop a model integrated model for various sources and improve the overall performance of the utilization effectively.

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