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Comparative Performance Evaluation of Artificial Neural Network and Hidden Mackov Model for Predicting Substance Abuse Neuron Disorder Rate

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Abstract

Researchers in the past have adopted different techniques such as the traditional statistical models, hidden mackov models for forecasting into the distance future but this approach is becoming outdated and gradually reaching their limitation in application due to incomplete precision and accuracy, for the purpose of complete accuracy and precision, neural network model technology has been used in this application work where the problem domain mainly involves prediction model This study embraced the use of neural network model technology to forecasting precision for the control of Substance Abuse Neuron Disorder (SAND) rate. This enormous task methodology involve first the theoretical gathering of psychiatric life data from World Health Organization (WHO), then using different well-known neuron disorder diseases data were mathematically models and simulated in matrix laboratory tools with Artificial Neural Network (ANNM) and Hidden Mackov Model (HMM) as examples. Secondly, consider major variables upon which new model which is more realistically represents actual disease prediction is built. Three components are implemented: SAND; is a targeted non communicable disease with Routine surveillance, modeling the disease risk with historical data surveillance with contemporary environmental data; and Forecasting future risk with comparative evaluation using two predictive metrics models Mean Square Error (MSE), Standard Deviation (SDEV) as paramount tools in epidemiological surveillance. Average MSE and SDEV of HFSANDR for each periods was 0.7 and 0.8 which is close to (1.0) while that of AFSANDR performance was between 0.3 to 0.4 less than (0.5) which indicates the weakness of HFSANDR for prediction Finally the evaluation shows that ANN prediction model performs better than HMM with more than 18 percent in term of accuracy.

Keywords: Substance Abuse Neuron Disorder, Hidden Mackov Model. Artificial Neural Network Model, Epidemiological Surveillance. Forecasting

INTRODUCTION

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The epidemiology of Substances Abuse Neuron Disorder Rate (SANEDR) is characterized by routine social life styles, civilized epidemic waves. Most episodes SANED epidemic occurs in the tropical plus temperate Belt in the globe and has been caused mainly by social life styles (Drake 2025).

This study aim is to Design a forecasting system model for substance abuse neuron disorder rate, using artificial neural network and implement ANN learning algorithms of the trained data with Hidden Markov (HM) dynamic model for forecasting SANPER

Compare the conventional models as hiding markov, and ANN soft computing technique performance evaluation for prediction into distance future. SANED is a devastating non communicable disease occurring frequently during susceptible rates of up to 15000 per 100,000 people. Social life styles, unemployment, poor economy and coupled with political crises. Similarly, Neuron with respiratory diseases such as influenza and pneumonia might weaken the immune defenses and accelerates the mucosa damage. (Greenwood 2021)

Neurological disorders (NDS) are medically term as any disorders that alter the brain functionality, the spinal cord, and the nerves in the entire human body with structural, biochemical and electrical abnormalities resulting in a range of symptoms. Such disorders can occur as a result of structural, chemical, or electrical abnormalities within the nervous system. (Menelis.et al., 2021). Risk factors such as diet, drug abuse, education and other environmental components constituting the outcome of many neurologic or psychiatric disorders (Meyer Landenberg and Tost, 2022).

The central nervous system; the brain, the nerves, the spinal cord and the peripheral nervous system that branch out into other parts of the body is responsible for multiple bodily processes. (Greenwood. and Bradley 2021) Based on the nervous system part the neurological condition affects, a person may experience difficulties with the following: Movement, sensations, eating and drinking, swallowing, breathing, speech, learning, memory, mood. Headaches migraine, sinus headaches, cluster headaches and tension headache, Epilepsy and seizures occur when there is an emergency outbreak in the brain due to electrical activity seizures, Alzheimer's disease and dementia. (Marr John and.; Cathey 2023).The term "dementia" refers to a group of symptoms associated with a progressive decline in brain function, Parkinson's disease (PD) is a disease caused due to substances abuse by a loss of nerve cells within the part of the brain that controls movement and coordination, Stroke is the medical term for when the blood supply to part of the brain is cut off (Hertz, 2020).

ANN Architecture Background

The foundation of ANN was to parameterized graphical model of human brain functions, the model consisting of networks with three prime architectures: Recurrent, Feed forward and Layered (Berneder et al, 2023). The recurrent architecture is more complex and it contains directed loop. The feed forward architecture does not contain the directed loops. The Layard architecture usually contains visible input and output layers and non-visible hidden layers. Feed-forward layered architecture is more commonly used in computational molecular biology. Each layer may contain one or many units. The units in the input layers are connected to units in the hidden layers which in turn are connected to units in the output layer. The connections are associated with weights. The number of units in layers is determined by the problem at hand. A good rule of thumb is that member of units is the hidden layer is equal to half of the sum of the member of input and output units (Hay kin, 2020).

ANNs are powerful because they are capable of modelling extremely complex biological functions yet that are relatively easy to use as they can learn from examples. Well-trained ANNs can predict complex biological patterns, structures and functions of newly discovered sequences. Depending on the type of data the structure prediction problem can be divided into two main categories; Classification and Regression. For example observed secondary structure data can provide discrete information for secondary structure clarification. (Moore, et al., 2019).

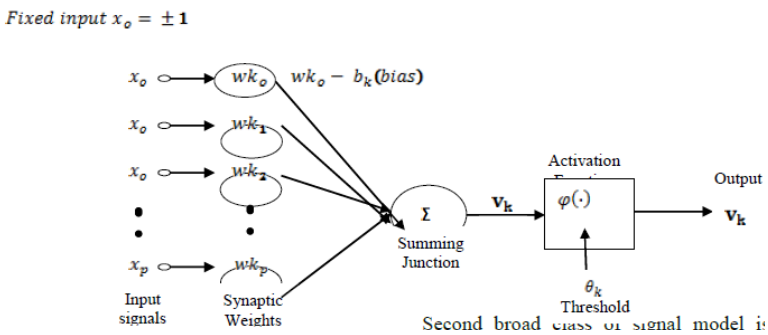

Figure 1. ANN Neuron Architecture for Mathematical Model.

The ANN Prediction Model in SANDER

There are several reasons in this work for applying a signal model; first a signal model provides the basis for a theoretical description of signal processing system which was be used to process the signal so as to provide a desired output.

Secondly, a signal model application here is indispensable in that they are potentially capable of letting one learn a greater deal about a signal source without having to have the source available. One can simulate the source and learn as much as possible when simulated. Finally signal model are important in that they often work extremely well in practice and enable one to realize the important practical system e.g. prediction systems, recognition systems, identification system in very effective manner.

Signal model are classified into the classes of deterministic models and the statistical model respectively (Rabihar, 2023). Deterministic model generally explore some known specific properties of the signal and in that case the generalization of the model is straight forward i.e. it required to estimate values of parameter of the signal models e.g. amplitude, frequency, phase of sine vector amplitude and rates of exponentiation etc.

Second broad class of signal model is a set of statistical model in which one tries to characterize only the statistical model to include Gaussian process, Poison process Markov process, and Hidden Markov process among others. The existing statistical model assumption is that the signal can be well characterized as a parametric random process and that the parameter of statistic in a precise well defined manner (Thomson et al. 2021)

Thirdly, a signal model is important in that they have reserve capability of enabling one to learn advance process of a signal source with no additional the source available. One can simulate the source and learn as much as possible when simulated.

Finally signal model are important in that they often in practice work excellently well and makes one to know the important practical system like prediction, recognition and identification systems etc in very effective manner.

Hidden Markov Prediction Models (HMPM) in SANDER

This is a statistics model parametric defining a modelled system being assumed to be a Markov Process (MP) with unknown parameters.(Hays 2019) The fact is to find the hidden parameters from the observable parameters such that the parameters of the model are given with aim of finding the most likely sequence of hidden states that could have generated a given sequence observe states. The regular Markov Model (MM) has the state directly shown to the observer such that the state transition probabilities are the only parameters and in contrast, HMM with no direct state visible where they are seen as an output token with each hidden state has a probability distribution i.e. emission probabilities over the possible observable token. Applicable as temporal pattern recognition and constitute a part of more complete solutions and used to speed up the processing of input sequences. (Rumelhart et al., 2019).)

This model is explored to predict the hidden relationship between input and outputs. It is one of the most alternative research one in the field of information system, the technique can be used in simulating the SANPER epidemic rate forecast by sampling a small subset of known information to reduce the effect of uncertainty and noise. HMM does not improve result as one might have expected. (Adepoju and May .2023). The HMMs are not stable to be used for a training tool on data having enormous factors influence it request due to weakness of HMM. A neural network is an alternative powerful data models tool capable to capture and represent complex input and output relationships.

COMPUTATIONAL METHOD

This study employed data collection and simulation in matrix laboratory using Back propagation Algorithm for the models implementations with the following data set

Table 1. Computational parameters.

Types of Data Sets	Size of Data Sets
Train Data	6000
Validation Data	3000
Test Data	1000
Total	10000

Back propagation Algorithm

The main idea of the back propagation algorithm in this work is to minimize the error, which is the difference between the expected value and the output of the model (Tagharini, 2021).

All weights in between the neurons are adjusted until the error gets an acceptable value. Training of a neural network with a back propagation algorithm is a bi- directional way operation; where inputs are forwardly propagated through the input layer where sigmoid activation function is used to threshold the resultant product (weight and input) while errors are propagated backwards by computing the error each unit is assigned for as defined the pseudo code for the back propagation training algorithm as:

i. *Randomly choose the initial weights*
ii. *While error is too large and each training pattern (presented in random order)*
iii. *Apply ANSANDR to input to the network*
iv. *Calculate the output for every neutron from the input layer, through the hidden layer(s) to the output layer*
v. *Calculate the error of the ANSANDR outputs*
vi. *Use the ANSANDR output error to compute error signally for pre-output layer*
vii. *Use the error signals to compute weight adjustments*
viii. *Apply the weight adjustments*
ix. *Periodically evaluate the network performance.*

Hidden Markov Model for SAND Epidemic rate forecasting

Hidden Markov Model for SAND epidemic rate forecasting model (HMM) is a conventional statistical approach of SAND epidemic ratio forecasting. They dominate the regression and the time series forecasting (RTSF) since the data set can easily be made available, we made use of this on the same SAND epidemic rate data we used for the SAND epidemic regression forecast model and compare their result together.

1. *Create a feed-forward network n: inputs, nL hidden units, and no output units*
2. *Initialized all weights to small random values (e.g. between -0.1 and 0.1)*
3. *Until termination conditions is met*
4. *For each training sample vectors (x,t), do*
5. *Compare the output Ou for every unit of x 6. For each output unit kO calculate δk = Ok (1- ok) (tk – ok)*
6. *For each hidden unit h, calculate δh= oh (1-oh) ∑ δkwkh k Downstream (h)*
7. *Update each network weight Wji as follows*
   $Wji \leftarrow Wji + Wji$
   where $Wji = \eta\sigma jxji$
   $$\%\ Accuracy = Sum\frac{(At-Ft)}{N} \quad (1)$$

PERFORMANCE MEASUREMENT

The methods applied to meet the performance of AFSANDR and HFSANDR are mean squared error and standard deviation. These are some of the indicators that measure the performance of models. The model with similar mean squared error and standard deviation is a better model. AFSANDR and HFSANDR Accuracy Forecast (AF) were computed together with MSE and SDEV as follows:

AFSANDR [**AF**] :=
SDEV (predicted value) – SDEV (actual value)*100 **SDEV** actual values (2)
HFSANDR accuracy forecast = **SDEV** (predicted value) – **SDEV** (actualvalue) (3)
The **MSE** was computed as $\frac{(\Sigma \mathbf{FE})^2}{\mathbf{N-1}}$ (4)
SDEV is standard deviation = $\boldsymbol{\sigma}$
$=\sqrt{\mathbf{E}\,(\mathbf{X}-\mu)\mathbf{2}}$ (5)
Where:
$\sum$ = sum of
FE = Forecast errors = Actual value – predicted value
N = Number of Predictors
σ = Standard deviation
μ = Mean value of expected values
X = Predicted values
E= Average value of

The results of MSE, SDEV and percentage accuracy of both models for all years are depicted in table one, two and three. The Forecasting of substance abuse neuron disorder epidemic rate into distance future using both model are illustrated in figure two, three and four and this is done taken (year 2026 as the base period.

RESULTS

During training the Matrix Laboratory, window is open and shows training programs and permit one to discontinue training at any point by clicking stop training. This instance used the training x function. When the validation error reaches for six iterations, this training stopped which occurred at iteration 112. When clicking performance in the training window, you can see a Linear Regression (LR) representation between the network outputs and the corresponding targets were performed. The figure five displays the result after training is completed.

A close Look at the sample figures the values of both models AFSANDR and HFSANDR are close but AFSANDR values are closer to actual values than HFSANDR values. This means that AFSANDR offers a superior forecast than HFSANDR In the same vein, observing figure six initially which depict the result of validation of substance abuse neuron psychosis The Y-axis displays the increment in the validated data value for the susceptibility cases of substance abuse neuron epidemic rate while the x-axis displays the computation result of the data rate. In cell the epidemics validation value showed the highest peak substance abuse neuron disorder rate levels of uncertainty and instantaneously nature of substance abuse epidermis compared to computational values as we can see this in various graphs, where the validation curve of compete with the actual computation which indicates the steady growth in the occurrence rate. In figure. Seven which depicts error improvement, the current error rate progression computations were 2.50, 2.25, 2.00, 1.75, 1.50 and 1.25... 0.00, with a marginal constant deference of 0.25 as compare to Error improvement rate 0.00055, 0.00050, 0.00045, 0.00040, 0.00040 and 0.00035 with a marginal steady deference of 0.00005 for the years. A close look at table two, the average MSE and SDEV of HFSANDR for each periods was 0.7 and 0.8 which is close to (1.0) while that of AFSANDR performance was between 0.3 to 0.4 less than (0.5) which shows the weakness of HFSANDR's prediction for all the years and the neuron disorder epidemic, the percentages accuracies of one higher than HFSANDR. For example the sum total for neuron disorder rate for all periods in the years, AFSANDR showed and accuracy of 87.8063%, while for HFSANDR was 64.392%. This is evidence that AFSANPDR is better than HFSANPDR. Table four Figure four producing various magnitudes of neuron disorder rate values prediction where each model could be compared jointly with actual data set and their target output.

Comparison between ANN (RBP) network and HFSANDR The performance with conventional methods and the training network as compared together defines the objective of the training network and by using predicted transforming value obtained from the predicted network. Value and error are shown in table two and table three respectively and its corresponding graph is shown in figure two and three. Total sum square error (TSSR) of the training set with testing and the total sum of the percentage accuracy for both AFSANDR and HFSANDR. Was 83.62% and 64.30% respectively, while the corresponding MSE and SDEV value of AFSANDR and HFSANDR for the period 6 and 7 are 0.417 and 0.4169 as against 0.7066 and 0.7359 respectively and 0.300 and 0.322; 0.771 and 0.775 respectively The Regression coefficients of both ANN and the HMM linear model were respectively 0.99 and 0.63

Table 2. Percentage accuracy for AFSANDR and HFSANDR.

Models	Test Year	Period Month/Year	MSE	MSED	SDVE	% Accuracy	% Difference
AFSANDR HFSANDR	1	Jan – Dec 2026 01/01-30/12/2026	0.1645 0.6700	0.5055	0.1643 0.6603	78.99% 61.09%	17.90%
AFSANDR HFSANDR	2	Jan – Dec 2027 01/01-30/12/2027	0.2570 0.8571	0.6001	0.2607 0.8564	75.10% 58.22%	16.88%
AFSANDR HFSANDR	3	Jan – Dec 2028 01/01-30/12/2028	0.1830 0.7847	0.6017	0.1810 0.7850	81.61% 56.55%	25.06%
AFSANDR HFSANDR	4	Jan – Dec 2029 01/01-30/12/2029	0.1815 0.8333	0.6518	0.2821 0.8281	63.84% 67.03%	3.19%
AFSANPER HFSANPER	5	Jan – Dec 2030 01/01-30/12/2031	0.3591 0.7368	0.3777	0.3562 0.7361	54.80% 51.20%	3.60%
AFSANDR HFSANDR	6	Jan – Dec 2032 01/01-30/12/2032	0.4176 0.7066	0.2890	0.4169 0.7359	83.62% 64.30%	19.32%
AFSANDR HFSANDR	7	Jan – Dec 2033 01/01-30/12/2034	0.300 0.775	0.4750	0.322 0.771	69.77% 61.40%	8.37%
AFSANDR HFSANDR	8	Jan – Dec 2035 01/01-30/12/2035	0.2516 0.8541	0.6025	0.2514 0.8431	76.00% 59.60%	16.40%
AFSANDR HFSANDR	9	Jan – Dec 2036 01/01-30/12/2036	0.1755 0.8324	0.6569	0.1760 0.7934	74.20% 63.60%	10.60%
AFSANDR HFSANDR	10	Jan – Dec 2037 01/01-30/12/2037	0.0857 0.6630	0.5773	0.0853 0.6613	87.46% 69.80%	17.76%
AFSANDR HFSANDR	11	Jan – Dec 2038 01/01-30/12/2038	0.2611 0.5490	0.2879	0.2662 0.5634	83.74% 65.12%	18.62%
AFSANDR HFSANDR	12	Jan – Dec 2039 01/01-30/12/2039	0.4556 0.8844	0.4288	0.4560 0.8721	75.00% 56.30%	18.70%
AFSANDR HFSANDR	13	Jan – Dec 2040 01/01-30/12/2040	0.4533 0.6321	0.1788	0.4612 0.6332	69.56% 58.71%	10.85%
AFSANDR HFSANDR	14	Jan – Dec 2041 01/01-30/12/2041	0.6101 0.7604	0.1503	0.6110 0.7584	74.28% 56.86%	18.42%
AFSANDR HFSANDR	15	Jan – Dec 2042 01/01-30/12/2042	0.3961 0.6412	0.2451	0.3991 0.6418	66.47% 51.21%	15.26%
AFSANDR HFSANDR	16	Jan – Dec 2043 01/01-30/12/2043	0.5872 0.6591	0.0719	0.5879 0.6631	71.01% 63.81%	17.20%

Table 3. Mean square error (MSE) accuracy for AFSANDR and HFSANDR models.

Test_Year	**1**	**2**	**3**	**4**	**5**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
ANNSAND	0.16	0.25	0.18	0.18	0.35	0.41	0.30	0.25	0.17	0.08	0.45	0.61	0.39	0.58
HMNSAND	0.67	0.85	0.78	0.83	0.73	0.70	0.77	0.85	0.83	0.66	0.63	0.76	0.64	0.65

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Table 4. Standard deviation (SDEV) accuracy for AFSANDR and HFSANDR models.

Test_Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
ANNSAND	0.16	0.26	0.18	0.28	0.35	0.41	0.32	0.25	0.17	0.05	0.26	0.45	0.46	0.61	0.39
HMNSAND	0.66	0.85	0.78	0.82	0.73	0.73	0.7T	0.84	0.79	0.66	0.56	0.87	0.63	0.75	0.64

Table 5. Percentage prediction accuracy of the models.

Test_Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
ANNSAND	78.99	75.10	81.61	63.84	54.80	83.62	69.77	76.00	74.20	87.46	83.74	75.00	69.56	74.28	66.47
HMNSAND	61.09	58.22	56.55	67.03	51.20	64.30	61.40	59.60	63.60	69.80	65.12	56.30	58.71	56.86	51.21

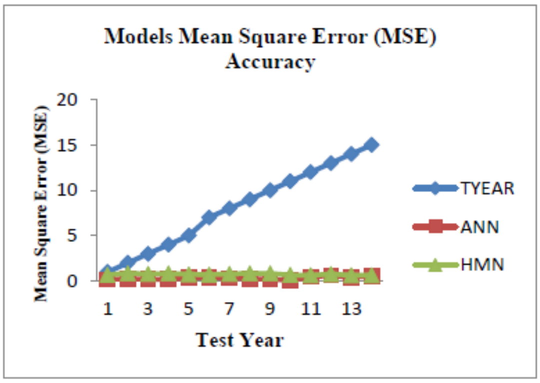

Figure 2. Mean Square Error (MSE).

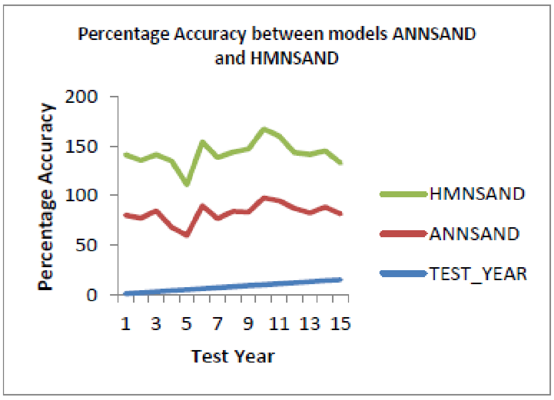

Figure 4. Percentage Accuracy between models ANNSAND and HMNSAND.

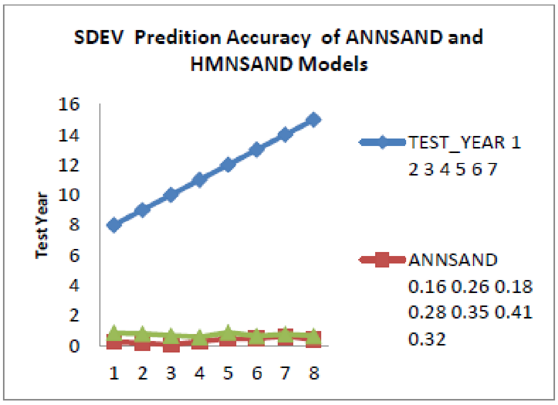

Figure 3. Percentage Accuracy between models ANNSAND and HMNSAND.

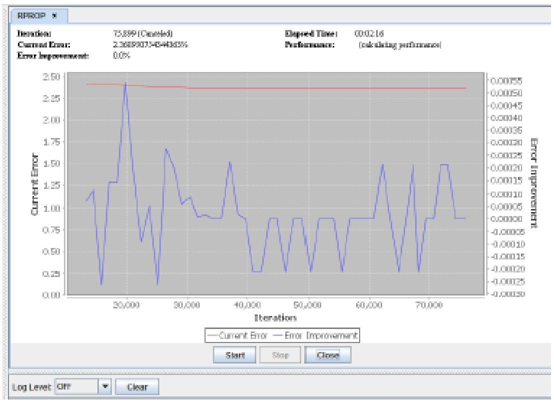

Figure 5. Model Screen Short for ANN Result and Validation.

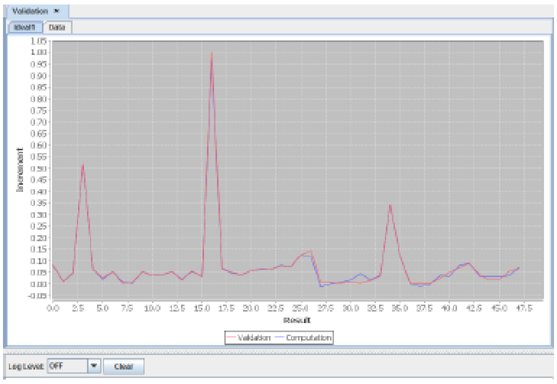

Figure 6. Mat Lab Model Training.

SUMMARY AND CONCLUSION

Summary

From the evaluation analysis the tables and figures, it shows that Artificial Neural Network Model is more potentially, inherently fault tolerate and capable of robust computation than the HMM counterpart. Its performance has does significantly improved under adverse operating condition such as disconnection of neurons, noisy and missing data in this work. (Bell and Ribar, 2023). The adoption of ANN implementation in this work has also able to contribute very extremely well to the enhancement of accuracy of health care delivery biometric data and to others where applicable..

Its implementation in this work is less susceptible to the problem of model miss peculation as compared to the parametric models having the capability to learn complex system with incomplete and corrupted

Conclusion

The percentage total accuracy for both AFSANDR and HFSANDR. Were 83.62% and 64.30% respectively, while the corresponding MSE and SDEV value of AFSANDR and HFSANDR for the period 6 and 7 are 0.417 and 0.4169 as against 0.7066 and 0.7359 respectively and 0.300 and 0.322; 0.771 and 0.775 respectively. It is evidence that AFSANDR model maintains better prediction accuracy than the counterpart HFSANDR model.

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