



## A Proposed Predictive Model for Business Telemarketing Information Management

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### Abstract

Bank telemarketing is a prominent way of direct marketing approach in which the telemarketers ask possible clients by mobile phones for purchasing or subscribing to bank product or service. But the clients who are not interested in the offers or promotions by the bank telemarketing commonly face negative interaction owing to the thought of thinking the telemarketing as spam. Therefore, the recent developments of deep learning (DL) models can be used to realize the predictive models for bank telemarketing applications. This study develops an effective Archimedes Optimization with Deep Belief Network based Predictive (AOA-DBNP) for bank telemarketing applications. The proposed AOA-DBNP technique primarily undergoes pre-processing for transforming the data as to useful format. In addition, the AOA-DBNP technique involves the use of the DBN model for the prediction process and finally, the AOA is applied for tuning the hyperparameters of DBN technique. The utilization of AOA helps to optimally select the hyperparameters of the DBN model in such a way that the predictive performance gets improved to a maximum extent. To showcase the enhanced efficiency of the AOA-DBNP manner, a comprehensive comparative results analysis reported the better performance of the AOA-DBNP model.

**Keywords:** Bank telemarketing, Deep learning, Business section, Parameter tuning, Data mining

### 1. Introduction

The latest progressions in advanced innovation and the speeding up improvement of worldwide business sectors are totally changing customers' examples of living and spending [1]. Customers' inclination for contactless, distant cooperation channels has expanded, and they have become familiar with utilizing versatile innovation to get their ideal administrations and data nearly whenever and anyplace [2, 3]. To react to the present circumstance and gain a cutthroat monetary benefit while staying away from potential negative business results, organizations are endeavoring to offer types of assistance custom fitted to the computerized age while expanding the accommodation of contactless channels and the extent of direct showcasing. Henceforth, the significance of telemarketing is featured as a method for executing direct advertising methodologies, and the focal point of telemarketing is moving from inactive inbound calls to outbound calls, which are savvy and dynamic showcasing techniques. In the inbound technique, clients are urged to prefer items or administrations when they call a called community. Interestingly, in the outbound technique, a phone salesperson calls clients and welcomes them to prefer an item or administration. In this way, the improvement of innovation to precisely choose potential clients who are probably going to buy an item is significant [4-6].

Decision Support Systems (DSS) utilize the available data to make decisions. Several DSS sub-fields, like personal and smart DSS. Individual DSS is linked to restricted framework that supports an optimal

task of one supervisor, while smart DSS utilizes man-made cognitive procedures to help selections [7]. One more related DSS concept is Business Intelligence (BI) that comes under data mining, for instance, information distribution centers and data mining (DM) intends to help dynamic applying business data. Specifically, classification is a widely recognized DM process [8] and it intends to design a data driven approach which learns the basic ability which maps them into certain factors. Several classifiers are available in the past decades such as random forest (RF), neural network (NN), etc. Since they are adaptable in nature, the NN and RF will in general give precise expectations, but the derived approaches are difficult to be perceived by people. Be that as it may, these "discovery" models can be opened by utilizing an affectability investigation, which permits quantifying the significance and impact of specific contributions to the model yield reaction [9]. A few investigations have proposed different AI and deep learning (DL) forecast models to anticipate telemarketing achievement [10]. Notwithstanding, in light of the fact that the majority of these investigations examined the achievement of telemarketing techniques done by banks, the expansion of their outcomes to different monetary organizations, for example, protection and security organizations includes critical impediments.

This study develops an effective Archimedes Optimization with Deep Belief Network based Predictive (AOA-DBNP) for bank telemarketing applications. The proposed AOA-DBNP technique primarily undergoes pre-processing for transforming the data into useful format. In addition, the AOA-DBNP technique involves the use of the DBN model for the prediction process and finally, the AOA is applied for tuning the hyperparameters of DBN technique. The utilization of AOA helps to optimally select the hyperparameters of the DBN model in such a way that the predictive performance gets improved to a maximum extent. To showcase the enhanced performance of the AOA-DBNP approach, a comprehensive comparative results analysis reported the better performance of the AOA-DBNP model. In short, the paper contributions are given as follows.

- To design an effective Archimedes Optimization with Deep Belief Network based Predictive (AOA-DBNP) for bank telemarketing applications.
- Initially undergoes pre-processing for transforming the data into useful format.
- The AOA-DBNP technique involves the use of the DBN model for the prediction process
- Next, the AOA is applied for tuning the hyperparameters of DBN technique.
- The performance validation of the AOA-DBNP approach take place using benchmark dataset.

## **2. State of Art Predictive Models for Bank Telemarketing**

Selma [11] suggests an ANN method to forecast the achievement of telemarketing calls for marketing bank long-term deposits. To authenticate the presented method, they utilize bank selling information of 41188 phone calls. Moro et al. [12] proposed a DM method for predicting the achievement of telemarketing calls for marketing bank long-term deposits. It can be examined a huge set of 150 features connected to social-economic attributes, bank clients, and products. A semi-automated feature selection has been investigated in the modelling stage, implemented by the data previous to July 2012, and permitted to choose a decreased set of 22 attributes.

Hosseini [13] present a DSS based ML-BN for predicting the achievement rate of telemarketing calls for long-term bank deposits. Telemarketing is one of the popular communicating method of direct marketing, extensively utilized by financial organizations like banks to retail long-term deposits. During this work, they propose a BN method which forecasts the probability that possible clients subscribe to long-term deposits, i.e., regarded as output variables. The fundamental relationships between outcomes and client attributes have been recognized by the increased NB method, a familiar supervised learning model. The effect of all the client attributes on the probability of subscribing is forecasted. In [14], familiar methodology of SVM, DT, RF, and ANN classification were carried out.

In [15], an Intelligent Bank Market Management System (IBMMS) is designed for bank managers who like to handle effective marketing operations. IBMMS is the primary scheme proposed by integrating the power of DM method with the abilities of professional system. Furthermore, IBMMS comprises significant features which allow being intelligent: an inference engine, an advisor, and a knowledge base. With this method, a manager could effectively market campaigns and follows the decision schemes of individuals and clients; additionally, a manager could take decision which results in preferred respond by

clients. Pradap et al. [16] examine the application of DM techniques for predicting the consequence of the success of telemarketing calls to retail bank long-term deposits. A collection of four three DM methods such as NB, RF, and J48 classifiers were employed.

Feng [17] presented a dynamic ensemble election model, META-DES-AAP, for predicting the accomplishment of bank marketing of time deposits. Different from present ML based marketing sales predictive models focus on predictive performance, META-DES-AAP considered the maximization of standard profits and accuracy. In META-DES-AAP, considering the average profit and accuracy in the architecture of dynamic ensemble election with meta training, a multiobjective optimization method is developed for maximizing the average profit and accuracy for base classifier election. In [18], an IWOA method is presented for optimizing the weights among the competition and input layers of S\_Kohonen network. In this study, the inertia weight of WOA is proposed as to arbitrary factors based on nonlinear decline, later the random search patterns of Levy flight are presented into WOA method. Bolloju et al. [19] presented a method to integrate knowledge management processes and decision support with knowledge discovery systems. According to the presented algorithm, an integrated architecture has been developed to build enterprise decision support environment with model warehouses and marts as repository for acquaintance attained by several adaptations.

### **3. Design of Proposed AOA-DBNP Model**

In this study, a new predictive model using AOA-DBNP technique is derived for bank telemarketing applications. The proposed AOA-DBNP technique primarily undergoes preprocessing to transform the data into a useful format. Secondly, the DBN model is employed for the prediction process and finally, the AOA is applied to tune the hyperparameters of the DBN model.

#### **3.1 Process involved in DBN based Predictive Model**

At this stage, the DBN model receives the telemarketing data as input and performs the prediction process. DL is determined as multilevel learning of dissimilar depictions with a hierarchical method dependent upon lower-level features [20]. The central benefit of this technique is learning representation as a method of automated extraction of features from lower-level input. The DBN has been multilayer superposition of Boltzmann finite device which extracts the deep feature of the novel information. This method offers an effective method to learn (difficult method) by integrating simpler and numerous methods which were learned. Afterward learning the primary model, the output of layer (novel descriptions and show of original input information) is utilized as input to the 2nd layers (the constrained Boltzmann machine), and this method remains till each layer is trained. Fig. 1 illustrates the framework of DBN model.

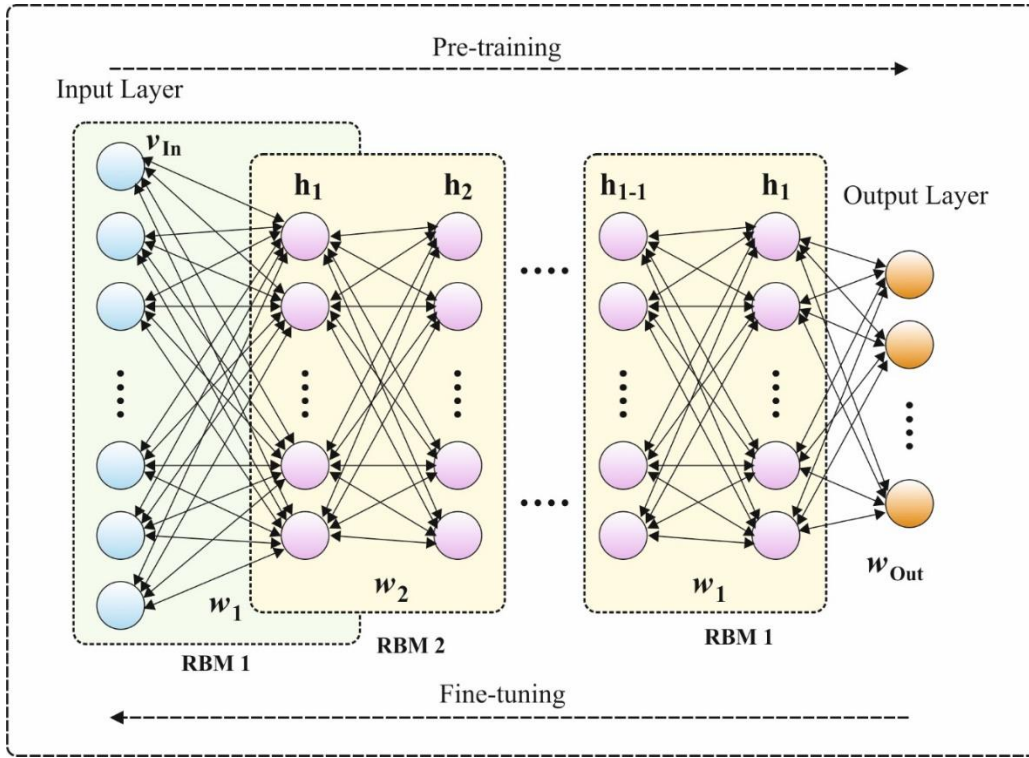


Fig. 1. Structure of DBN

Afterward learning the layer without an observer, the entire NN is separately adapted and trained with an observer, i.e., generally backward propagation. This pre-processing step detects a region in the weight space which enables the generalization to be designed and the overfitting to be decreased. It is noteworthy that over-fitting arises while the trained error is smaller however the testing error is higher. It can be noted that the hidden layer ( $L_h$ ) and visible layer ( $L_y$ ) defines the stochastic binary variable from the hidden and upper layers, correspondingly. Moreover, there are undirected biases and weights.

$$\rho(L_y, L_h) = F_p^{-1} \times e^{-E(L_y, L_h)} \quad (1)$$

In which,  $L_{y_i}$  &  $L_{h_j}$  represents the binary stage of hidden and visible units  $i$  &  $j$ , correspondingly and  $F_p$  defines the partition function i.e., attained by likely pair summation for visible and hidden units, viz.,

$$F_p = \sum_{L_y, L_h} e^{-E(L_y, L_h)} \quad (2)$$

In which,  $E(L_y, L_h)$  determines the energy of the combined formation of hidden as well as visible unit are given as follows:

$$E(L_y, L_h) = - \sum_{i=1} a_i L_{v_i} - \sum_{j=1} b_j L_{h_j} - \sum_{i,j} L_{v_i} L_{h_j} w_{ij} \quad (3)$$

Let,  $a_i$  and  $b_j$  be the biases in visible as well as hidden units, correspondingly, and  $w_{ij}$  indicates the weight amid hidden as well as visible units. In order to update the RBM weight,

$$\Delta w_{ij} = E_t(L_{y_i} L_{h_j}) - E_m(L_{y_i} L_{h_j}) \quad (4)$$

whereas,  $E_t(L_{y_i} L_{h_j})$  and  $E_m(L_{y_i} L_{h_j})$  represents the anticipation in the trained information correspondingly. But DBN is a stronger capacity in recognition, provided that an optimum framework for their layout is important. Lately, numerous studies have been proposed for improving the efficacy of DBN based metaheuristic model. In this work, they presented a novel method of metaheuristics to improve efficacy.

### 3.2 Process involved in AOA based Hyperparameter Optimization Model

For optimally tuning the hyperparameters involved in the DBN model, the AOA is employed to boost the predictive outcome [21]. As with other metaheuristic techniques, the AOA begins with any number of arbitrary populations of objects as candidates (immersed object). During this stage, objects are also adjusted with its arbitrary place from the fluid. A primary place of all the objects has been attained dependent upon the subsequent method:

$$x(i) = x_l(i) + rand \times (x_u(i) - x_l(i)) \quad i = 1, 2, \dots, N \quad (5)$$

where  $x(i)$  explains the  $i^{th}$  object, and  $x_l(i)$  and  $x_u(i)$  implies the low as well as upper limitations of solution spaces. Also place, the AOA initialization the following parameters using Eqs. (6)-(8):

$$V(i) = rand \quad (6)$$

$$D(i) = rand \quad (7)$$

$$A(i) = x_l(i) + rand \times (x_u(i) - x_l(i)) \quad (8)$$

Afterward initialized, the cost values of candidate are estimated and saved as  $V^{best}$ ,  $D^{best}$ , and  $A^{best}$  dependent upon the primarily created populations. Afterward, the candidates are upgraded utilizing the technique parameters. The upgrading of object acceleration was dependent upon its collision form by other neighbor objects. As follows, the mathematically expressed of this conception was described. In order to upgrade procedure, the volume and density of  $i^{th}$  object to iteration number  $t + 1$  is upgraded by the subsequent:

$$V^{t+1}(i) = V^t(i) + rand \times (V^{best} - V^t(i)) \quad (9)$$

$$D^{t+1}(i) = D^t(i) + rand \times (D^{best} - D^t(i)) \quad (10)$$

where,  $D^{best}$  and  $y^{best}$  stands for the density as well as volume linked with an optimum object created previously, and  $rand$  defines the arbitrary value which is distributed uniformly. Initially, the objects are collision, and then period, it can be tried to take for equilibrium state. The AOA utilizes term, named as transfer operator (TF), for reaching in exploration-exploitation as:

$$TF = \exp\left(\frac{t - t^{max}}{t^{max}}\right) \quad (11)$$

where,  $TF$  steps up slowly in period still attaining one,  $t$  and  $t^{max}$  demonstrates the iteration number and maximal iteration count. Similarly, a reducing feature of density ( $d$ ) uses the technique for providing global-local searching. It can be expressed as:

$$D^{t+1} = \exp\left(\frac{t^{max} - t}{t^{max}}\right) - \left(\frac{t}{t^{max}}\right) \quad (12)$$

where,  $D^{t+1}$  decreases with time that offers the capability for converging. It is term gives a suitable trade-off amongst exploration as well as exploitation from the technique. The exploration of technique was inspired dependent upon the collision amongst objects. It will have occurred if  $TF \leq 0.5$ . During this study, a random material (mr) has been chosen for updating the acceleration of object to round  $t + 1$  as:

$$A^{t+1} = \frac{D_{mr} + V_{mr} \times A_{mr}}{D^{t+1}(i) \times V^{t+1}(i)} \quad (13)$$

While  $D_{mr}$ ,  $y_{mr}$ , and  $A(i)$  implies the density, volume, and acceleration of random materials. The exploitation term of technique was inspired as considering no collision amongst objects. It will have occurred if  $TF > 0.5$ . During this study, upgrading of objects are recognized by the subsequent:

$$A^{t+1}(i) = \frac{D^{best} + V^{best} \times A^{best}}{D^{t+1}(i) \times V^{t+1}(i)} \quad (14)$$

where,  $A^{best}$  refers to the optimal object accelerations. The next step is for normalizing the acceleration for evaluating the modified percentage as:

$$A^{t+1}(\bar{i}) = u \times \frac{A^{t+1}(i) - \min(A)}{\max(A) - \min(A)} + l \quad (15)$$

where,  $A^{t+1}(i)$  indicates the step in which all the agents are altered,  $l$  and  $u$  denote the normalized limitations which are fixed to  $[0.9, 0.1]$ , correspondingly. During the next step, if  $TF \leq 0.5$ , the place of an object numbers  $i$  to the succeeding round has been attained by the subsequent:

$$x^{t+1}(i) = x^t(i) + c_1 \times rand \times A^{t+1}(\bar{i}) \times D \times (x^{rand} - x^t(i)) \quad (16)$$

where  $C_1$  represents the constant equivalent to two. Otherwise, if  $TF > 0.5$ , the place to objects is upgraded as:

$$x^{t+1}(i) = x^{best^t} + F \times c_2 \times rand \times A^{t+1}(\bar{i}) \times D \times (T \times x^{best} - x^t(i)) \quad (17)$$

where,  $c_2$  implies the constant value equivalent to 6.  $T$  improves with time from the range  $[c_3 \times 0.3, 1]$  and gets a defined percentage in the optimum place. This percentage improves slowly for decreasing the variance amongst the present and optimum places for providing an optimum balance amongst exploration as well as exploitation.  $F$  determines the flag for altering the motion way as:

$$F = \begin{cases} +1, & \text{if } P \leq 0.5 \\ -1, & \text{if } P > 0.5 \end{cases} \quad (18)$$

where,

$$P = 2 \times rand - c_4 \quad (19)$$

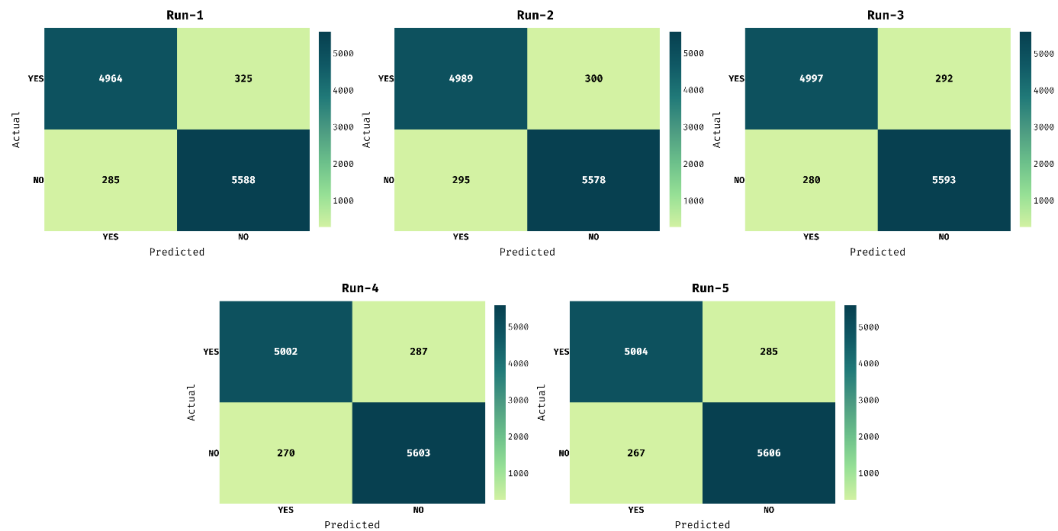
Eventually, the value of all objects is estimated utilizing the cost function and returns the optimum solution when the end state is met.

#### 4. Results and Discussion

The AOA-DBNP model is validated using benchmark bank telemarketing dataset and the details are given in Table 1.

**Table 1 Dataset Description**

Description	Dataset-1
No. of Instances	11162
No. of Features	16
No. of Class	2
No. of Yes Samples	5289
No. of No Samples	5873
Data sources	[22, 23]



**Fig. 2. Confusion matrices of the AOA-DBNP technique**

Fig. 2 portrays the confusion matrices offered by the AOA-DBNP model under five runs. On test run 1, the AOA-DBNP model has classified 4964 instances into YES class and 5588 instances into NO class. Along with that, on test run 3, the AOA-DBNP model has classified 4997 instances into YES class and 5593 instances into NO class. In line with, on the test run 5, the AOA-DBNP model has classified 5004 instances into YES class and 5606 instances into NO class.

The classification results analysis of the AOA-DBNP model under distinct test runs is demonstrated in Table 2 and Fig. 3. The results portrayed that the AOA-DBNP model has resulted in improved classification performance over the other techniques.

**Table 2 Classification results analysis of the AOA-DBNP technique**

No. of Runs	Precision	Recall	Accuracy	F-Score	Kappa
Run-1	0.9457	0.9386	0.9454	0.9421	0.8675
Run-2	0.9442	0.9433	0.9467	0.9437	0.8754
Run-3	0.9469	0.9448	0.9488	0.9459	0.8564
Run-4	0.9488	0.9457	0.9501	0.9473	0.8852
Run-5	0.9493	0.9461	0.9505	0.9477	0.8867
<b>Average</b>	<b>0.9470</b>	<b>0.9437</b>	<b>0.9483</b>	<b>0.9453</b>	<b>0.8742</b>

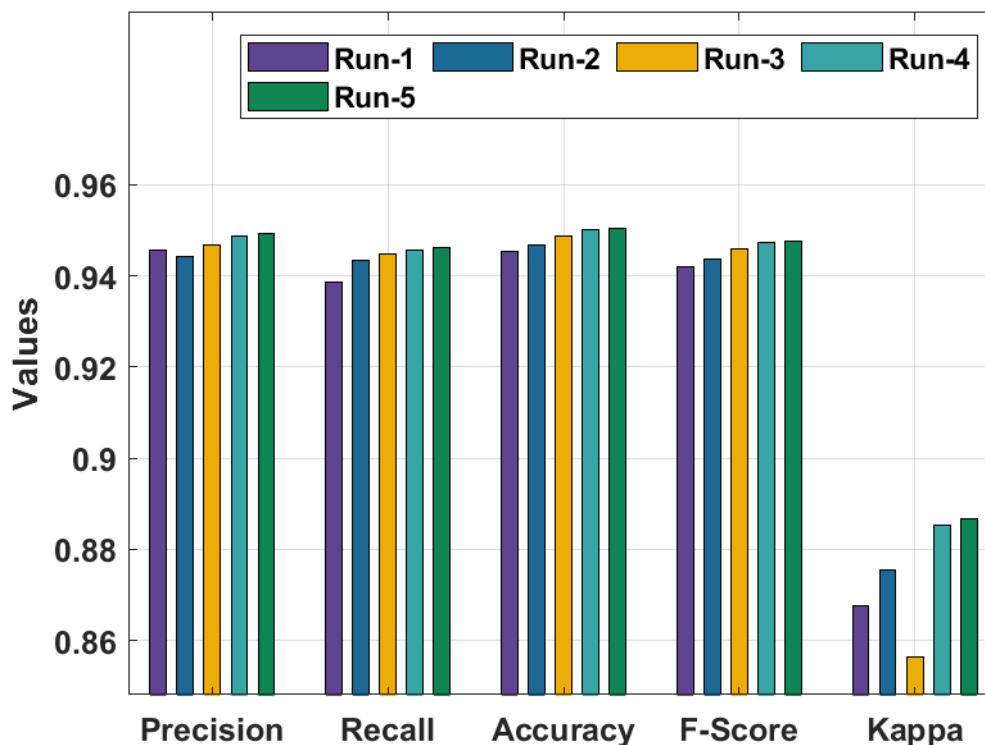


Fig. 3. Overall classification results analysis of the AOA-DBNP technique

For instance, with run-1, the AOA-DBNP model has attained  $prec_n$ ,  $rec_l$ ,  $acc_y$ ,  $F_{score}$ , and kappa of 0.9457, 0.9386, 0.9454, 0.9421, and 0.8675 respectively. Furthermore, with run-2, the AOA-DBNP model has attained  $prec_n$ ,  $rec_l$ ,  $acc_y$ ,  $F_{score}$ , and kappa of 0.9442, 0.9433, 0.9467, 0.9437, and 0.8754 respectively. Concurrently, with run-3, the AOA-DBNP model has attained  $prec_n$ ,  $rec_l$ ,  $acc_y$ ,  $F_{score}$ , and kappa of 0.9469, 0.9448, 0.9488, 0.9459, and 0.8564 respectively. Simultaneously, with run-4, the AOA-DBNP model has attained  $prec_n$ ,  $rec_l$ ,  $acc_y$ ,  $F_{score}$ , and kappa of 0.9488, 0.9457, 0.9501, 0.9473, and 0.8852 respectively.

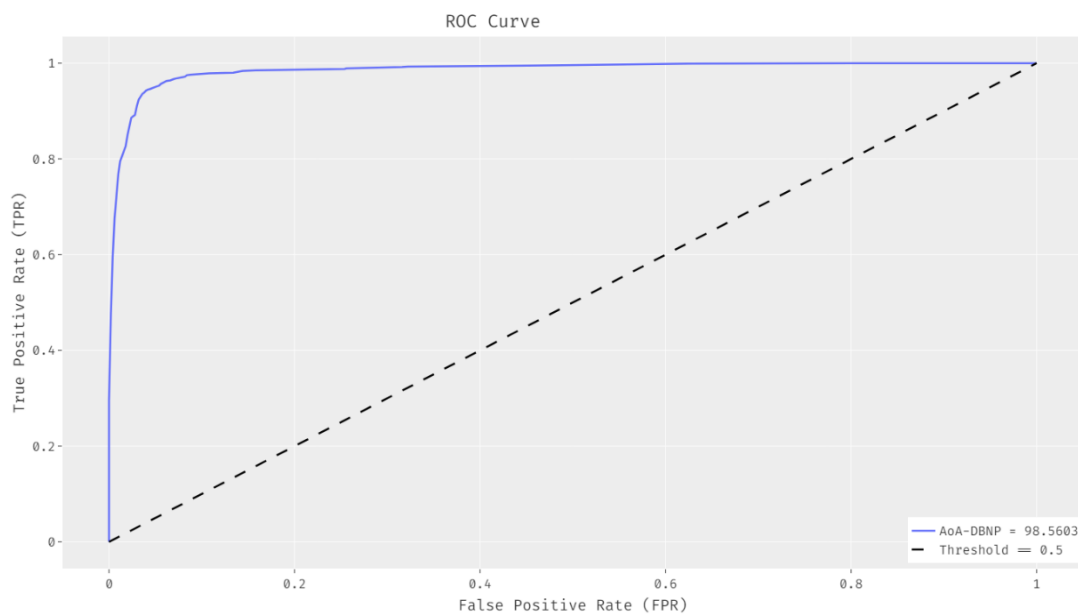


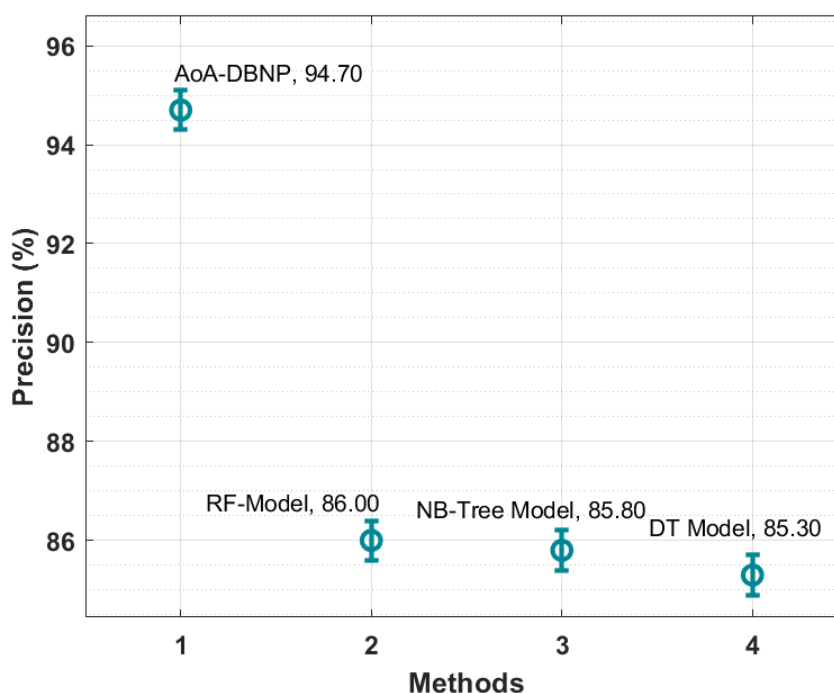
Fig. 4. ROC analysis of the AOA-DBNP technique

Fig. 4 demonstrates the ROC analysis of the AOA-DBNP model on the test dataset. The figure portrayed that the AOA-DBNP AOA-DBNP technique has accomplished outperforming performance with the maximum ROC of 98.5603.

Finally, a detailed comparative study of the AOA-DBNP with existing techniques takes place in Table 3. Fig. 5 exhibits the brief precision analysis of the AOA-DBNP with recent approaches. The figure depicted that the DT and NB-Tree models have accomplished lower precision of 85.30% and 85.80% respectively. At the same time, the RF model has resulted in a moderate precision of 86%. However, the proposed AOA-DBNP technique has gained improved outcomes with a higher precision of 94.70%.

**Table 3 Performance Evaluation of Different Classifiers on Applied Dataset**

Methods	Precision	Recall	Accuracy	F-Score	Kappa
AoA-DBNP	94.70	94.37	94.83	94.53	87.42
RF-Model	86.00	85.80	85.76	85.80	71.54
NB-Tree Model	85.80	85.60	85.63	85.60	71.27
DT Model	85.30	85.00	84.99	85.00	70.03



**Fig. 5. Comparative precision analysis of AOA-DBNP technique**

Fig. 6 showcases the comprehensive recall analysis of the AOA-DBNP with recent algorithms. The figure exhibited that the DT and NB-Tree models have accomplished minimum recall of 85% and 85.60% correspondingly. Simultaneously, the RF approach has resulted in a moderate recall of 85.8%. Finally, the presented AOA-DBNP technique has achieved increased results with a higher recall of 94.37%.

Fig. 7 demonstrates the detailed accuracy analysis of the AOA-DBNP with recent methods. The figure depicted that the DT and NB-Tree systems have accomplished lower accuracy of 84.99% and 85.63% respectively. Likewise, the RF model has resulted in a moderate accuracy of 85.76%. But, the proposed AOA-DBNP methodology has gained improved outcomes with higher accuracy of 94.83%.

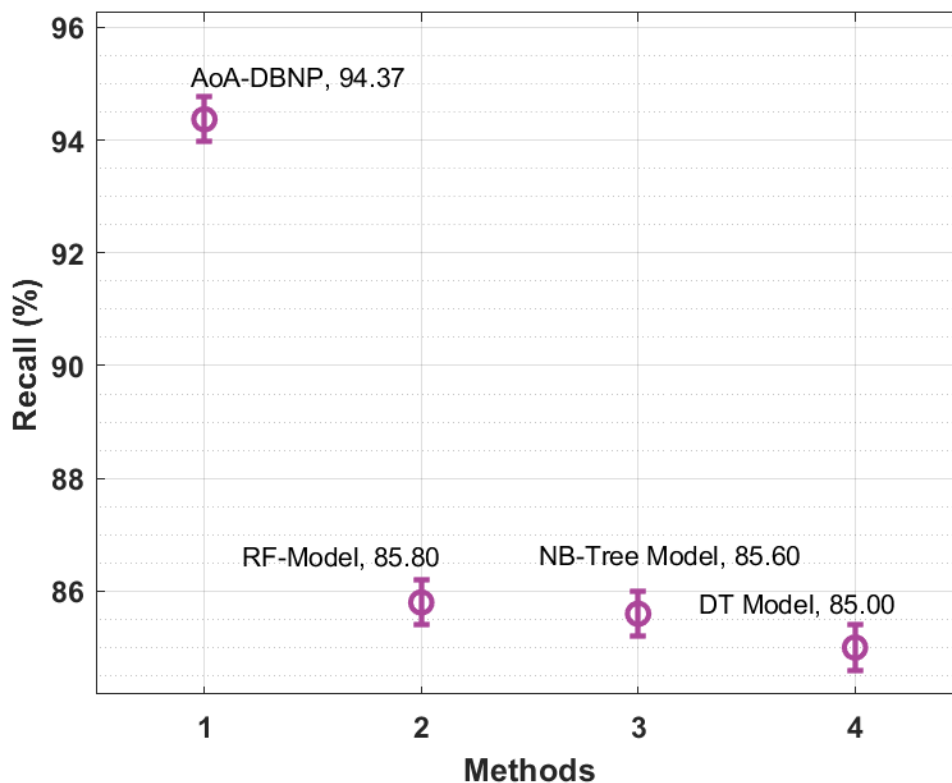


Fig. 6. Comparative recall analysis of AOA-DBNP technique

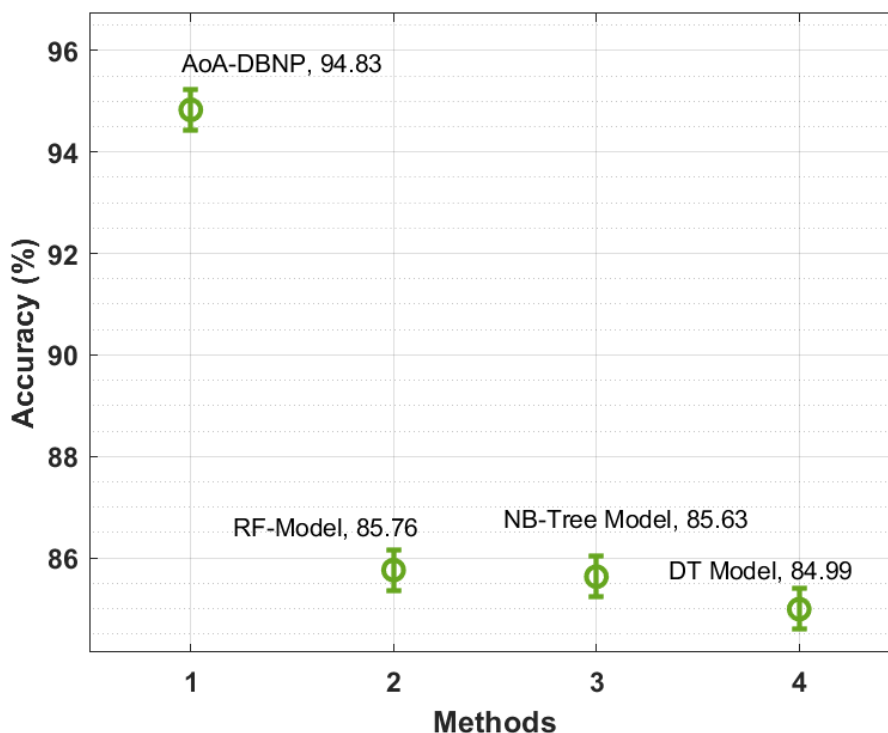


Fig. 7. Comparative accuracy analysis of AOA-DBNP technique

Fig. 8 depicts the brief F-score analysis of the AOA-DBNP with recent approaches. The figure outperformed that the DT and NB-Tree models have accomplished reduced F-score of 85% and 85.60% correspondingly. Followed by, the RF model has resulted in a moderate F-score of 85.8%. At last, the projected AOA-DBNP technique has obtained maximum result with the superior F-score of 94.53%.

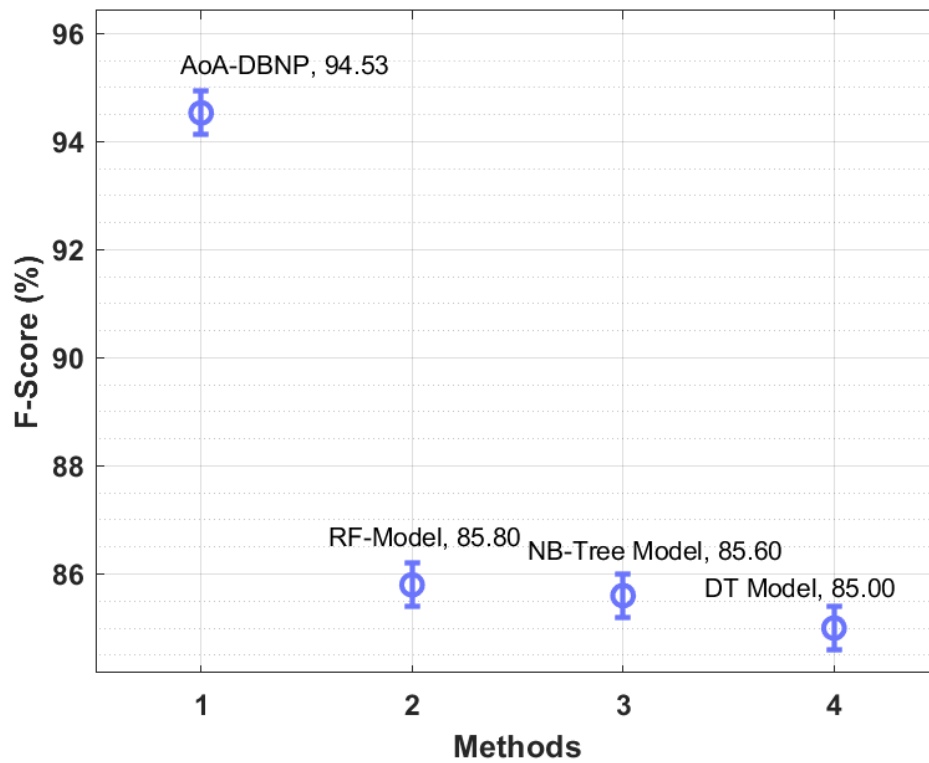


Fig. 8. Comparative F-score analysis of AOA-DBNP technique

Fig. 9 portrays the brief kappa analysis of the AOA-DBNP with recent techniques. The figure displayed that the DT and NB-Tree models have accomplished lesser kappa of 70.03% and 71.27% respectively. Concurrently, the RF method has resulted in a moderate kappa of 71.54%. Lastly, the presented AOA-DBNP system has reached a higher outcome with a higher kappa of 87.42%.

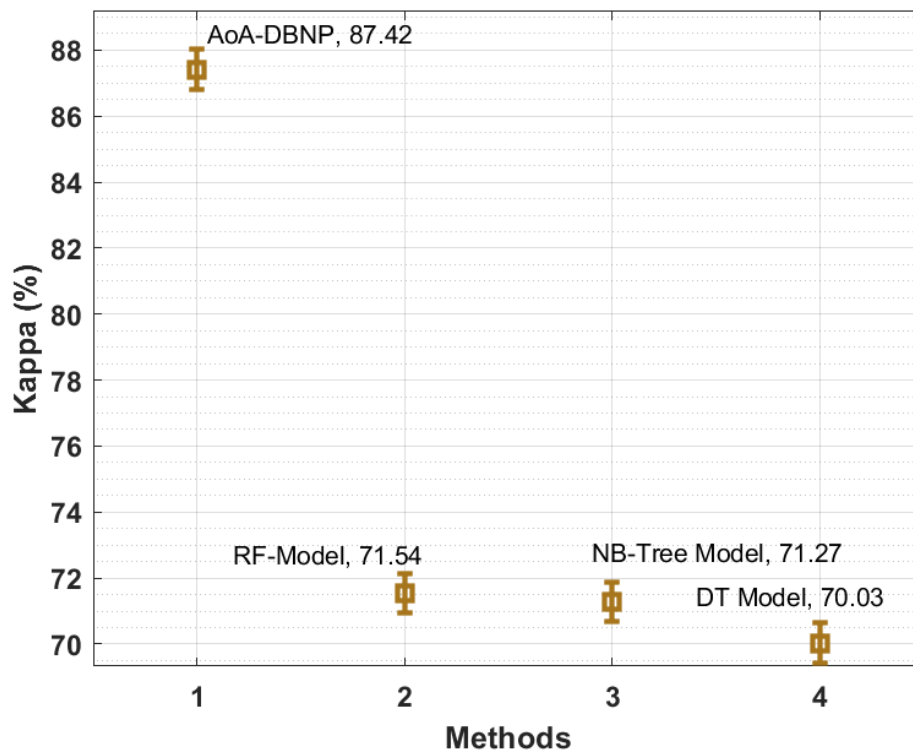


Fig. 9. Comparative Kappa analysis of AOA-DBNP technique

## 5. Conclusion

In this study, a new predictive model using AOA-DBNP technique is derived for bank telemarketing applications. The proposed AOA-DBNP technique primarily undergoes pre-processing to transform the data into a useful format. Secondly, the DBN model is employed for the prediction process and finally, the AOA is applied for tuning the hyperparameters of DBN technique. The utilization of AOA helps to optimally select the hyperparameters of the DBN model in such a way that the predictive performance gets improved to a maximum extent. To showcase the enhanced performance of the AOA-DBNP approach, a comprehensive comparative results analysis reported the better performance of the AOA-DBNP model in bank telemarketing applications compared to recent approaches in terms of several measures. In future, hybrid DL models can be derived instead of DBN model to boost the predictive outcome.

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