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Bank Telemarketing Analysis Using Bayesian And Non-Bayesian Neural Network

Prince Gupta[1], Kartike Malhotra[2], Rashmi Tiwari[3]

[1,2,3]Computer Science Engineering, HMR Institute of Technology and Management, New Delhi, India

Abstract**:** Deep learning refers to Artificial Neural Networks (ANN) with multiple layers. These networks are inspired by human brains and contain billions of neurons like human brain for communication. There are various types of architectures of Neural Networks and among all two of them is Multilayer perceptron and Bayesian Neural Network. Multilayer Perceptron is a feed forward neural network with more than three layers. Whereas, Bayesian Neural Network is an extended version of this Multi-layer perceptron neural network that use Bayes theorem to describe the uncertainty in weights so that uncertainty in predictions can be estimated which are not estimated by simple multi-layer perceptron. In this paper Multilayer perceptron neural network having 7 layers and Bayesian neural network having 7 layers is implemented and compared on Bank Telemarketing dataset. Finally, Accuracy, ROC-AUC curve, Binary cross entropy, and KL-divergence loss are used to compare both the models.

Keywords: Neural Networks, Bayesian Neural Networks, Multi-Layer Perceptron, Bank telemarketing, probability distribution, classification.

I. INTRODUCTION

Marketing is a business in which customers are made aware of a product of a company through various media such as email, phone. It helps in selling of the product, letting customers know about the product and also determine the need of the product. At the end, the overall goal is to increase the sales of the product, get financial benefits, and improve the reputation of the company.

This whole marketing process generates lots of data and this data is of utmost importance in today's world. Using it in an effective way can create a huge impact on the business by improving the performance of the business. To improve performance and customer experience, an organization can capture and analyze the customer data. The main aim of analysis is to increase the sales and services for the business.

Telemarketing is form of direct marketing in which salesperson approaches the customer via phone call or email to promote their services or products. It is cost effective way and keeps the customers up to date. Telemarketing is the backbone for selling product or service in the banking sector. Thus, to keep the performance of the bank up to the point and also to help the bank in crisis time, analysis of the customers data of the bank is important. To do so data mining techniques can be used.

Nowadays classification and prediction techniques of data mining have become crucial in banking sector for analysis of customer data. These two techniques can be applied using machine learning models like logistic regression, decision tree classification, support vector machine, Naïve Bayes and deep learning models such as neural networks various architectures can be used.

For bank telemarketing analysis although many machines learning models and deep learning models have been built but all of them failed to capture the uncertainty in predictions and also, they lead to overfitting. Thus, the main objective of this paper is to capture the uncertainty in predictions for more accurate predictions which other models cannot do so that bank can choose among the other models and the model proposed in paper to identify the most responsive customers before the marketing campaign and predict the customers' behavior and identify the customers that will take the term deposit and those that will not more effectively.

In the paper, to fulfill the above objectives, two deep learning models are used and compared. The two deep learning models used and compared are Multi-layer Perceptron (MLP) Neural Networks and Bayesian Neural Networks. The Bayesian neural network is used to gain uncertainty in predictions which other models cannot do and MLP is used to show the difference of uncertainty predictions between the two.

The paper is divided into 8 sections. Section 2 includes the literature review that has been done. Section 3 –includes the description of neural network (Multi-layer perceptron), Bayesian neural network, and its various training methods. Section 4 – Methodology Used explains about the methodology used for implementation and also it is being explained about the structure of MLP and Bayesian neural network used in implementation. Section 5 describes the Results obtained. Section 6 explains the conclusion obtained from the results and finally the paper ends with the last topic i.e. References.

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II. LITERATURE REVIEW

In this section previous research work that has been done for classification for this dataset is explained along with previous work that has been done on Bayesian Neural network is explained.

Hany. Elsalamony, et al [1] proposed Bank Direct Marketing on the basis of Neural Network. Customers are the focus of bank telemarketing, and it is tough for humans to classify such a large amount of data. This was used to create captivating decision-making patterns and methods. Data mining is a wonderful strategy for solving such a challenge, both in terms of performance and accuracy. Different classification models were examined in this work based on past and new research. The performance of this model on real-world data was measured using a novel technique called Multilayer Perception Neural Network (MLPNN), which combined characteristics from C5.0. It examined techniques for boosting efficiency by highlighting the aspects that influence success measurement. The system's performance was assessed using criteria such as classification correctness, comprehension, and specificity.

J. Wei et al in [2] have implemented three models – two machine learning models and one deep learning model for bank telemarketing dataset. They have done the implementation in two steps. In the first step they have analyzed and preprocessed the dataset. Feature scaling, data encoding, and handling missing values were the three steps they have done in the first step. In the second step the three models were implemented. The three models adopted for prediction were – Decision tree, Support vector machine, and Neural Network. For decision tree, CART algorithm was used. BFGS algorithm was used for Neural Network. For Support vector machine, simple sequential minimal optimization algorithm was adopted. Time, accuracy, precision, and AUC were used to evaluate the three models. From the results obtained by them, out of all three models, decision tree gave best results. The accuracy, precision and AUC obtained for decision tree was 100% and also the time taken by Decision tree was least. Out of remaining two, neural network and support vector machine, neural network gave better results in terms of accuracy, precision, AUC but the time was 4.4 times more than SVM.

Sergio Moro et al used an approach namely Data-Driven in [3] for Prediction of the Success of Bank Telemarketing. Crises in terms of finance was seen when data was calculated from the year of 2009 to 2014. About 150 elements were included in the data, including product name, job type, campaign, and customer name, among others. On this dataset, a semi-automatic approach was used to pick the features, which reduced the dataset to 22 features. Different algorithms, such as neural networks and decision trees, were compared. During the evaluation process, it was discovered that Neural Networks gave great results in classifying clients. Two more models were added to the neural network to highlight certain essential characteristics like call direction and bank agent experience. For the managers, these results and models were crucial.

A. Sabber [4] in has implemented Bayesian Neural Network to combat the problem of insufficient data and to find out the parameters responsible for earthquake rupture and to estimate the uncertainties in related to earthquake rupture. He used a dataset having around 2000 instances for training and testing of the model. F1 score is used by him for results. The results obtained by him showed that the test F1-score of BNN (0.8334), is 2.34% higher than plain NN score.

G. Diodato et al in [5] implemented a Bayesian Neural Network for cellular image classification and analysis of uncertainty. They have done the implementation to show the two advantages of Bayesian neural network – first possibility of discardation of highly uncertain predictions to guarantee high accuracy. Second, identification of unfamiliar patterns in the data that correspond to outliers. To demonstrate the two advantages they have used biomedical imaging dataset on which they have applied Bayesian neural networks with variational inference. Confidence score is being used to measure the performance of the network. The results obtained showed that Bayesian neural network proved to be better than standard neural network for biomedical image classification.

A. Back et al [6] have implemented Bayesian Neural Networks for forecasting of financial asset. They have used and compared three techniques for training of Bayesian neural network i.e. – Dropout, Variational Inference and Markov Chain Monte Carlo. From the results obtained, they concluded that Dropout and Variational Inference provided strong regularization but their predictive uncertainties are not promising, whereas Markov Chain Monte Carlo provided strong regularization as well as promising predictive uncertainties that could improve the results.

III. TRADITIONAL NEURAL NETWORK AND BAYESIAN NEURAL NETWORK

A. Neural Network

Neural networks are deep learning models inspired by human brains. The way human brains consist of millions of neurons for communication, neural networks also communicate the similar way using neurons of the neural network. Several neurons called as nodes are arranged in layered manner in a neural network [7]. The three basic layers of neural network which every neural network has are: Input Layer, Output layer and Hidden Layer [8,9].

The input layer neurons receive the input data and process and propagate this data to the hidden layer. By translating the data into a more summary format, the hidden layers apply the activation function and learn complicated characteristics of the data. Then the output obtained by hidden layers is passed to the output layer neurons to get the final results of prediction or classification [8].

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There are various types of Neural Network architectures and each of them can be applied to applications such as speech recognisition, image recognisition, natural language processing, social network filtering, forecasting, prediction, etc according to the purpose [10,11]. Some of the Neural Network architectures are: - Perceptron (a neural network that has only the two basic layers i.e. input and output), Feed forward neural network [12] (a type of neural network that has all the three basic layers but information is only forward propagated and weights are static). Multi-layer perceptron [12] (a type neural network that has an input layer and an output layer but more than three hidden layer. Also, it allows backpropagation of information for better results).

A.A Multi-Layer Perceptron

Multi-Layer Perceptron is a type of feed neural network with more than three layers and with a feature of backpropagation allowed as shown in Figure 1

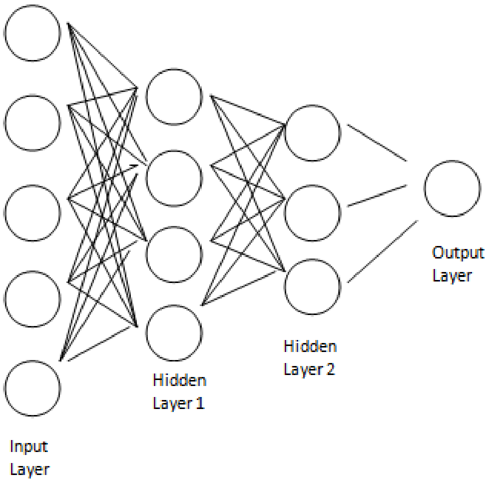

Figure1. Architecture of MLP

The training of Multilayer perceptron [12] is done in 3 steps:
1. Forward Propagation
2. Calculation of Loss
3. Backward Propagation

In the forward propagation the inputs are multiplied with weights and bias is added at every layer. This all is done at hidden layer. When the output from last hidden layer is passed to output layer, the predicted output and actual output are compared and loss is calculated which is backpropagated to the network to update the weights and then again the updated weights are multiplied with the inputs and bias are added and then again output is obtained at output layer an compared with the actual output. The whole process is repeated till the loss between the actual and predicted output is minimum [12].

B. Bayesian Neural Network

As discussed in above section, in traditional neural networks, a dataset is available to train a model and weights are manipulated externally to minimize the loss function. The weights are estimated using maximum likelihood estimation ($e^{-\text{loss function}}$) and assigned a single value or point estimate [13,14]. In addition to weights, sometimes parameters required to design a model are determined using this method of estimation. But this makes the model susceptible to overfitting [15], as it starts learning from the noise along with irregular and uncommon entries in the dataset. This method of estimation (maximum likelihood estimation) ignores several uncertainties (it doesn't take into account certainty of results, all it cares about is giving results) that may be present in the weights and even classify unseen or abrupt data into wrong categorization [17]. The solution to overcome this problem is to use posterior inference.

Bayesian Neural Networks (BNN) is a modified version of neural Networks that use posterior inference. BNN is based on the Bayesian paradigm which has two simple and uncommon characteristics: (a) probability is a computation of faith in the occurrence of events, and (b) prior probability influences posterior probability [13][15]. Thus, the generic definition of BNN states, that - BNN is a stochastic artificial neural network trained using Bayesian inference. BNN is a hybrid model of neural networks and probabilistic modelling and can naturally address traditional NNs issues [18,19], such as – irregularization (overfitting or underfitting), model selection, and comparison, that also without any cross-validation of data set.

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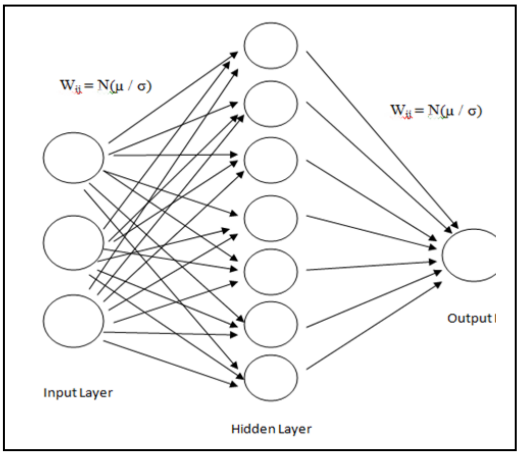

Figure2.Architecture of Bayesian Neural Network

The architecture shown in above figure figure.2 is almost same as traditional neural networks. It has same input layer, hidden layer and output layer as traditional neural network except one difference. Unlike traditional networks, where unknown weights are assigned a true value and known data is treated as random variable, the Bayesian neural network uses the contradictory approach of treating the unknown parameters as random variables and these are determined based on the data set available [16]. The unknown weights in the model are estimated based on the data set available and are assigned probability distribution. This estimation of parameters is done using the inverse probability method, which is known as Bayes theorem. This theorem allows the representation of distribution over the weights in terms of probabilities [13].

In BNN, a prior is utilized to determine the parameters, which is later used as an input to the neural network. BNN classifies data in terms of probabilities with probability distribution attached to each layer, whereas traditional neural networks follows optimization scheme for classification with each layer having fixed weights and biases that determine the output.

This probability distribution describes the uncertainty in weights and can be used to estimate uncertainty in prediction. Since weights and output are probability distribution so to get final single value of prediction, expected value of all posterior probability distribution is calculated.

So thus when an unseen data is given to BNN, it refuses to classify it and does correct classification. All this is done by BNN through Bayes theorem.

If w=weight and d=data, then Bayes theorem for posterior inference of weights can be stated as:-

$$P(w/d) = \frac{P(w)\,P(d/w)}{P(d)} \qquad (1)$$

Where: -

P (w/d) = posterior probability = probability of weights given the observed data

P (w) = prior probability of weights,

P (d / w) = likelihood = weights that maximize the probability of observed data

P (d) = marginal likelihood = probability of observed data with all possible weights

B.A Methods to Train Bayesian Neural Network

1. Laplace Transformation

The most difficult and expensive work in Bayesian is to calculate this integral as written below. It requires following integration over all possible value of weights given that assume a Gaussian distribution [15]:-

$$P(d) = \int P(d/w)\,P(w)\,dw \qquad (1)$$

Thus, Laplace approximation is used for this calculation. But usage of this method to calculate posterior distribution thus requires calculation of marginal likelihood and also Integration over all weights which is practically impossible and very expensive [15] thus various alternative approaches such as Variational Inference (VI), Markov Chain Monte Carlo (MCMC) is used.

2. Markov Chain Monte Carlo

Monte Carlo Markov Chain is a sampling method that allows sampling a posterior distribution without knowing all of the distribution's mathematical properties with finite resources [15][20]. MCMC combines two words Monte Carlo and Markov Chain.

Monte Carlo is a practice of estimating the properties of distribution by examining random samples from distribution. For example – To calculate mean and standard deviation of distribution, random samples are drawn from the distribution and

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then calculate the mean of those samples.
Markov Chain is used to generate the random samples by sequential chain like process. Each random sample is used to generate next random sample.
In Bayesian Neural Networks, MCMC allows to calculate posterior probability that cannot be calculated directly using formulas. Instead MCMC generate samples from a given posterior distribution to calculate posterior distribution [20].
There are various algorithms for implementing MCMC. But they have some limitations such as high rejection rate, slow for larger and complex datasets.

3. Variational Interference

Variational Inference (VI) is a technique that uses approximation method to calculate the posterior distribution. It converts the problem of computation of posterior distribution into optimization problem [13]. The main purpose of Variational inference is to provide the marginal likelihood for model selection and to provide approximate solution of posterior probability [15].
In variational inference a distribution like normal distribution or Gaussian distribution, Q is assumed and the parameters passed to it are adjusted such a way that this assumed distribution, Q is as close as possible to exact posterior distribution, P. To measure the closeness between Q and P, KL divergence is used.
If w represents the weights, d represents the data, $Q(w/\theta)$ is the assumed probability distribution, $P(w/d)$ is the true posterior probability, and θ is the parameter that is to be adjusted to minimize the KL divergence then this is the following KL function between the two distributions:-

$$KL(Q(w/\theta) \parallel P(w/d)) = \int Q(w/\theta) \log \frac{Q(w)\,dw}{P(w/d)} \quad (1)$$

This equation on solving integrand can be further expanded as:

$$= KL(Q(w/\theta) \parallel P(w/d)) - \exp(\log(P(d/w)) + \log(P(d)) \quad (2)$$

$$= -ELBO + \log(P(d)) \quad (3)$$

The ELBO function is optimized using various optimizing algorithms to minimize the KL divergence between the distributions Q and P [15]. Optimizing algorithms are algorithms used to reduce the loss by changing weights and learning rate of the neural network. Various optimizing algorithms available are – Stochastic gradient descent, Adam, RMSprop and many more.
In the paper, variational inference is used for training of Bayesian Neural Network using the pytorch library and the optimizer used is Adam (combination of stochastic gradient descent with momentum and RMSProp).

IV. METHODOLOGY USED AND EXPERIMENTAL DESIGN

Various classification methods have been used in past such as Logistic regression, Decision tree classification, Naïve Bayes, Random-forest classification, Support Vector machine for bank telemarketing analysis.
In the paper, Bayesian approach of Neural network that is Bayesian neural network and a Multi-Layer perceptron Neural network is used for bank telemarketing analysis to classify the customer as 'Yes' for customers who have taken the term deposit and 'No' for customers who have not taken the term deposit. The dataset used is taken from Kaggle. This dataset is a marketing campaign dataset in which phone calls were made to the customers to make them do term deposit in the bank. So the results of the phone call that is whether the customer does the term deposit or not and other details regarding the customer are recorded and converted into database for analysis. The dataset is based on real information of a bank. It is taken from Kaggle. It has 45212 instances and 17 attributes as follows – age, job, marital, education, default, balance, housing, loan, contact, day, month, duration, campaign, pdays, previous, poutcome, y. The first 16 attributes are the feature variables and the last variable (y) is the target attribute. The target attribute contains two values 0 and 1, 0 to show that the term deposit is not purchased and 1 to show that the term deposit is purchased. Figure.3. shows diagrammatically the methodology used.

Following are the steps followed for the implementation-
1. The dataset is downloaded and obtained from the Kaggle
2. Various methods for pre-processing such as handling missing values, handling the outliers, handling the useless attributes are used.
3. Various graphs are then made to analyse the dataset.
4. Then, the dataset is splitted into training and testing set.

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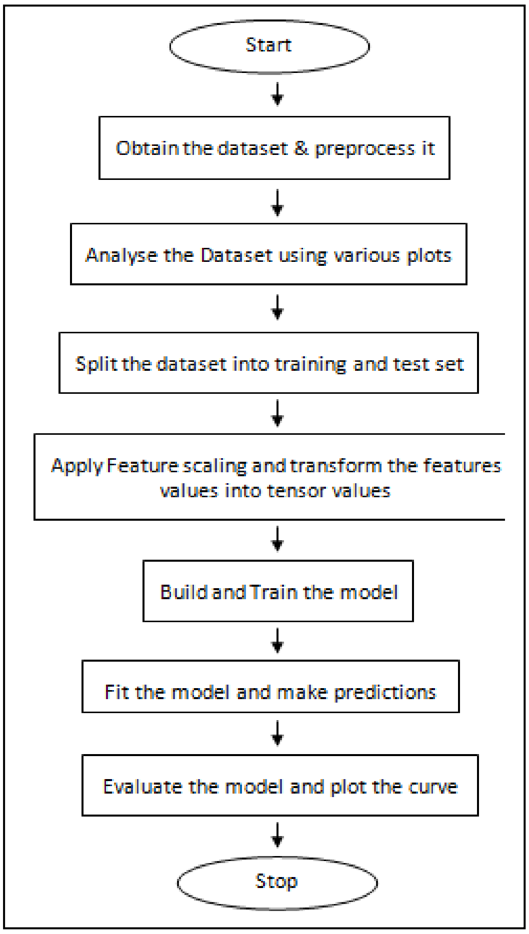

Figure.3 Workflow of Methodology Used

5. The splitted dataset is then undergone through SMOTE technique for handling imbalancing of the data.
6. Then feature scaling is applied to normalize the data. Then these normalized data values are transformed into tensor values.
7. The model is then built, trained and applied on the splitted and transformed dataset.
8. Then apply the model on testing data and classifications are made to classify the clients on the basis of status of their term deposit.
9. Finally, the performance of the model is evaluated using Accuracy, Mean Squared Error, and KL divergence value. A ROC plot is lastly made to visualize the performance.

A. Structure Of MLP Used

Seven-Layer multilayer perceptron Neural Network is used in the dissertation for the purpose of classification of customers as the one who have taken term deposit and the one who have not taken term deposit.

The architectural layers are depicted in the graphic below figure 4. The input layer of the MLP receives the data. The dot product of the input and weights is computed after passing through the input layer, and an activation function is implemented to the hidden layer.

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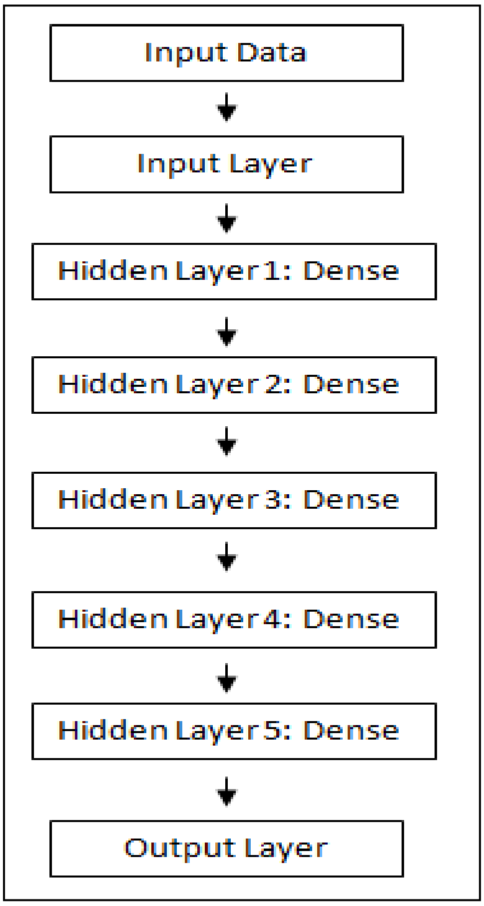

Figure 4. Structure of Multi-Layer Perceptron Model

Similarly, the output from previous hidden layer is moved to next hidden layer and same two processes are done.
Finally, the output from the last hidden layer will be passed to output layer where it goes through either backpropagation in which sigmoid function is applied to convert the values between 0 and 1 so that binary cross entropy loss can be calculated or may be a final output is obtained if the output is optimized at its best.

B. Structure Of BNN Used

Seven Bayesian layers Bayesian Neural Network is used in the dissertation for the purpose of classification of customers as the one who have taken term deposit and the one who have not taken term deposit. The diagram above figure 5 shows the layers of the architecture used.

The input is fed to the Bayesian Neural Network where it first goes through the Bayesian layer 1. Bayesian Layer is nothing but just a simple linear input layer like that of neural network that extract features but except that it works on the concept of probability modeling for weights as explained in previous chapters. Then the output obtained from Bayesian layer 1 is fed to Relu layer 1. The Rectified Linear Unit (ReLU) is a non-linear activation function that zero out any negative values in the input from Bayesian layer 1. It increases the network's non-linearity. Other activation functions, such as sigmoid and hyperbolic tangent, can be substituted for ReLU, although ReLU is the most widely utilised. The Bayesian layer and Relu layer in combination are working as hidden layer. The output obtained from Relu layer 1 is further fed to next layer and similarly the other layers process the input fed to them.
Finally at the output, sigmoid function is applied to convert the output values between 0 and 1 so that binary cross entropy can be used as a loss function or may be a final output is obtained if the output is optimized at its best.

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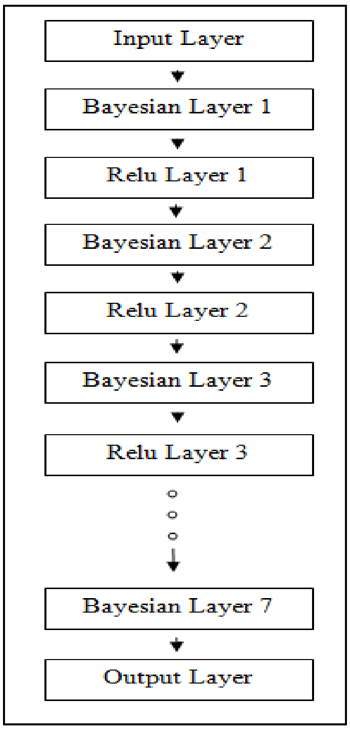

Figure 5. Structure of Bayesian Neural Network Used

C. Performance Metrics Used

The efficiency of MLP and Bayesian Neural Network models trained is measured using five performance measures.

1) Accuracy
2) ROC-AUC Curve
3) Binary Cross Entropy Loss
4) KL Loss

V. EXPERIMENTAL RESULTS

A. Accuracy

Table1. Accuracy Obtained

S.no.	Model Name	Accuracy Obtained
1.	Multi-Layer Perceptron	77.70
2.	Bayesian Neural Network	83.50

B. AUC Values

Table2. AUC Values Obtained

S.no.	Model Name	AUC value
1.	Multi-Layer Perceptron	0.76
2.	Bayesian Neural Network	0.79

C. Binary Cross Entropy Loss

Table3. Binary Cross Entropy Loss Obtained

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S.no.	Model Name	BCE Loss
1.	Multi-Layer Perceptron	1.24
2.	Bayesian Neural Network	0.14

D. KL Loss

Table4. KL Loss Obtained

S.no.	Model Name	KL Loss
1.	Bayesian Neural Network	0.19

VI. CONCLUSION

In the past few years, many real-life problems emerged such as activity recognition, speech recognition, face recognition, and many more. All these applications require large amount of data to achieve desirable performance, but every time large data is not available and thus limited data is to be used. Bayesian neural networks works perfectly well with limited data also. They are used to avoid the problem of overfitting and to predict the uncertainty of results which traditional neural networks like multi-layer perceptron cannot do.

From the results obtained, it can be seen that the accuracy of Bayesian Neural Network is 83.5% and that of Multi-Layer Perceptron is 77.7%. From the values it can be seen that the accuracy of Bayesian neural network though is not much higher but still it is 5.8% higher than Multi-Layer Perceptron. The AUC values obtained are even higher for Bayesian Neural Networks (0.790) instead of Multilayer Perceptron (0.766) showing Bayesian performed better than Multilayer Perceptron (traditional neural networks). Finally, the binary cross entropy loss obtained for Bayesian neural network is less as compared to Multilayer perceptron thus showing Bayesian neural network to be better.

Thus, from the above results it can be concluded that Bayesian neural networks performed better than Multilayer perceptron for Bank telemarketing analysis.

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