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A Grey Wolf Optimization Improved Deep Belief Network for Employee Attrition Prediction

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***Abstract** - The proposed study enables machine learning techniques to predict the probability of employee attrition. The study improves the accuracy of employee attrition prediction by developing an enhanced model using a Deep belief network or DBN. A deep belief network is a form of deep neural network made up of several layers of variables that are latent or hidden. This work uses the Restricted Boltzmann machine, which creates a stack of the network to analyze the pattern of the attrition dataset. The parameters involved in Deep Belief Network are fine-tuned by adapting a novel behavioral inspiration algorithm instead of random assignment of the values. The algorithm used here is the metaheuristic Grey Wolf algorithm which is an optimization algorithm that imitates the hunting behavior of Grey Wolves. Thus, it will increase the performance of the proposed model.*

Keywords - *Machine learning, Attrition prediction, Restricted Boltzmann machine, Grey Wolf Optimisation*

I. INTRODUCTION

Turnover of employees is a significant problem faced by organizations. Organizations are extremely concerned regarding the turnover of employees as the impact created by that is highly destructive. Apart from the expenses of a new hire, it also dampers the knowledge and experience accumulated by the organization. Hence it is highly desirable for organizations to depend on the current analytical techniques using machine learning for tackling the issue. The prediction of the possibility of attrition can support the organization. Even though promising technologies like Neural Networks are constructively implemented in many engineering and medical sciences, it is yet to be explored thoroughly for human resource management predictions. Hence the objective of this study is to predict the attrition of employees using advanced applications of neural networks and meta-heuristic technologies to further improvise the performance.

The proposed study improves the accuracy of employee attrition prediction by developing an enhanced model using a Deep belief network or DBN. A deep belief network is a form of deep neural network made up of several layers of variables that are latent or hidden. Deep learning algorithms incrementally learn features from data. Hence domain expertise and the use of deep-seated methods for the extraction of correlated features are not obligatory in this case. In the domain of artificial intelligence, the experiments with Deep Belief Network are highly significant [21]. This work uses the Restricted Boltzmann machine, which creates a stack of the network to analyze the pattern of the attrition dataset. Restricted Boltzmann Machines (RBM) automatically detect the patterns prevalent in the data by reconstructing the input. The two layers present in the RBM, called visible and hidden layers are nodes which are the input nodes and the modes which create information by the feature extraction from input nodes, respectively. The beauty of this technology is that the hidden patterns and correlations are automatically realized from the input data.

The parameters involved in the Deep Belief Network are fine-tuned by adapting a novel behavioral inspiration algorithm instead of random assignment of the values. The algorithm used here is a Meta-Heuristic Grey Wolfalgorithm which is an optimization algorithm that imitates the hunting behavior of Grey Wolves. The algorithm avoids the muddles created by the problem of local optima. The optimization of weights will enhance the performance of the proposed model [3].

The paper is structured as follows. The next section reviews the literature concerning the topic covered. The next section explains the proposed methodology adopted by the study. Results are compared and discussed in the further section, followed by the conclusion.

II. LITERATURE REVIEW

E. Emary et al., in their article, have explained the use of the Grey Wolf Algorithm for feature selection and are also comparing the efficiency of this algorithm with Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO). The dataset used by the authors is from the UCI Machine learning repository. The authors experimented and concluded that GWO (Grey Wolf Optimisation) shows a much better performance than GA and PSO [4].

Randall Sexton et al., in their article, are explaining about the use of the neural network for the prediction of employee turnover. The researchers are employing Neural Network Simultaneous Optimisation Algorithm (NNSOA) for training the Neural Network. It performs an accurate feature selection, and also the number of hidden nodes is automatically predicted by the algorithm [2].

The authors in their article explain the use of the Deep Belief Network algorithm for developing a method in identifying faults in the final products. The method named Tilear works based on a Deep belief network that trains Tilear using the signals that are generated from the samples which are of good quality. The samples are compared with the signals generated by Tilear. It was found by the researchers that Tilear performs better than Support Vector Machine [11].

Shu-Hao Yeh et al., in their study, use a deep learning algorithm for predicting corporate defaults. The daily stock returns of companies are taken as input data. The prediction models are trained using a Deep belief network. The research has found that the model developed using a deep belief network shows improved performance than Support Vector Machine [7].

Syed Atif Ali Shah et al. in their research are exploring the use of deep neural network in the prediction of the absenteeism of employees in the workplace. The proposed study has proved that this method achieved an accuracy of about 97.5% where as other traditional models were able to achieve only accuracy below 85% [12].

Dumitru Erhan et. al. in their study is explaining about the benefits of performing a pre-training which is unsupervised. The experiments conducted in the study support the use of pretraining in increasing the effectiveness of training [13].

III.PROPOSED METHODOLOGY

A. Architecture of the proposed method

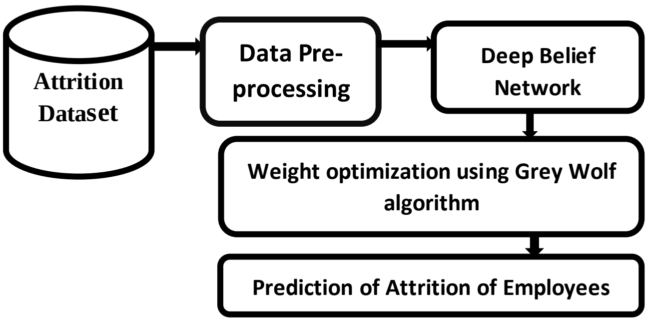

Fig 1: Architecture of the proposed method

The proposed method is using attrition dataset from Kaggle data repository. The data set selected has 34 attributes describing the variables used to explain the characteristics of employee. There are 1470 records in the dataset. The dataset is developed by IBM data scientists. The data is pre-processed by min-max normalisation method to reduce erroneous influence on classifier accuracy. In the study a generative graphical model deep belief network is used. The accuracy of the output is enhanced by the meta heuristic grey wolf optimisation.

B. Data pre-processing

The attrition dataset is comprised of various attributes with different range of values. The classifier accuracy can be exceedingly influenced by attributes with high value ranges, when used directly.Passing these raw values as input to any algorithm for further processing, the accuracy of results will be highly distorted. To overcome the influence of this incongruity, Min-max normalization is used which converts all the attributesto the same range between 0 and 1. A linear mapping relation has to be used for standardising the data before processing by the network. The Min-Max is characterized in the mathematical representation as follows.

$$att_i new = \frac{att_i - \min(att_i)}{\max(att_i) - \min(att_i)} \quad (1)$$

Where att_irefers to original attribute value and the min and max are the minimum and maximum value of the concerned attribute's entire record value.

C. Classification using Deep Belief Network

a) Deep Belief Network

In the proposed work, Deep Belief Network, a class of deep neural network with multiple layersof latent variables perform the classification of dataset for the prediction of attrition of employees. A neural network can be considered as a simulated version of human brain with many interconnected brain cells through which humans learn things, understand patterns and accordingly do decision making. A neural network simulating a human brain learns the actionsof its own accord. In neural network, neurons are organized as set of layers. When neurons receive input and it is transmitted, parameters like weight and bias are added. When the neurons receive the input, they are multiplied by weights and accordingly the selected neurons from the hidden layers are triggered and information reaches the output layer. Neural networks are involved in the learning process using the principles of feedback. The weights are modified in order to reduce the difference between the intended output and output produced by the network, while going backward [8][17].

A deep belief network has multiple layers of variables which are hidden units. Connections are established between the layer. But there is no connection between the units of each layer. The Deep belief network is more accurate with less amount of training time and the advantage of overcoming the problem of vanishing gradient. The problem of vanishing gradient occurs when the weights as well the biases of the layers are not effectively updated when it passesthrough each training session, leading to inaccuracy of the complete network [22] [23].

Deep belief nets work as model of probabilistic manner which has multiple stochastic layers and the variables are latent. The hidden units which are known as feature detectors are latent variables whose value is in binary format. The lower layers get top-down information from the direct connections with the above layers. The lowest layers unit state is denoted as data vector. The two important deep belief nets properties are:

- It is enriched with learning procedure of layer by layer, the dependency among the variables in the layer above and below are discovered using weight generation.

- Once the model completes its learning process, each layer's latent variables values are acquired by a single bottom-up passthe lowest layer will have the observed data and the generative weights are used in reverse.

In this work greedy learning is involved in learning about data and by treating latent variables values of each layer at a time to train and understand about data to train the next layer [15]. This learning procedure improves the discriminative performance which fine tunes all the weights of entire network to improve its process. This greedy learning procedure is unsupervised. But it provides a finest starting for the supervised training that follows. The model is trained layer by layer.

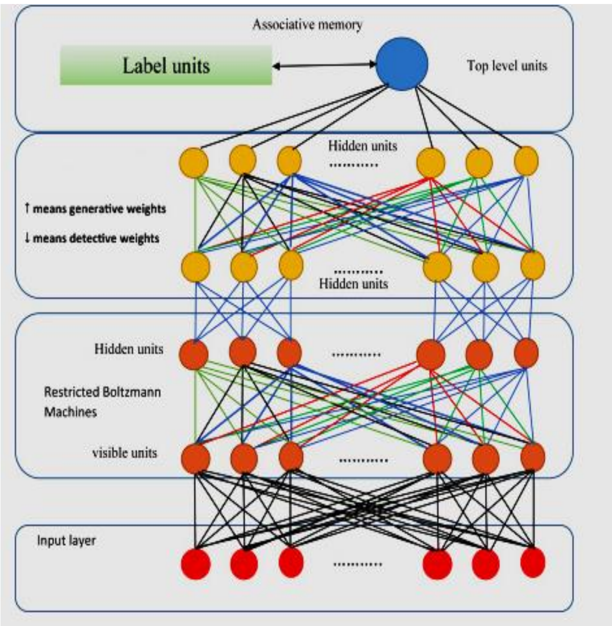

Fig. 2: Architecture of DBN

In conventional DBN, fine-tuning of variables to achieve desired output and backpropagation of the error derivatives are performed in the final layer. When the hidden layers are more in number in the network for huge volume of input data then back propagation performs better. This is accomplished by presence of feature detectors present in hidden layers which are initialisedby the process of learning a deep belief net that is responsible for designing the structure of the input data.[26]

Deep belief nets can be characterized as structure of simple learning phases each of which is constrained (Restricted) Boltzmann Machine (RBM) [14] [16]. RBM is comprised of a layer with visible units and hidden units which represents data and information about features which gain high correlation in data respectively [6]. The symmetric weights (*Wt)* are assigned to the connections among two layers using matrix formation. But there is no connection with in layer and activities of vector (*Vc)* of the visible and hidden units are conditionally independent, so that it is very easy to sample the vector (*h)* from the factorial posterior distribution on hidden vectors $fpd(h|vc,Wt)$. The main idea in deep belief nets is the fact that the weights are learned using the RBM for both $fpd(h|vc,Wt)$ and $fpd(vc|h,Wt)$. The visible vectors V's probability is represented as

$$fpd(vc)=\sum_h (h|Wt)p(vc|h,Wt) \quad (2)$$

In the first step the training vector is initialised used the visible units. Then the hidden units are updated using the equation

$$P(hid_j = 1| V) = \sigma(bs_j + \sum vis_i w_{ij}) \quad (3)$$

$$P(vis_i = 1| H) = \sigma(as_i + \sum hid_j w_{ij}) \quad (4)$$

Where σ = the sigmoid function and $bs_j$is used to represent the bias of hid_j and as_i is used to represent the bias of vis_i.

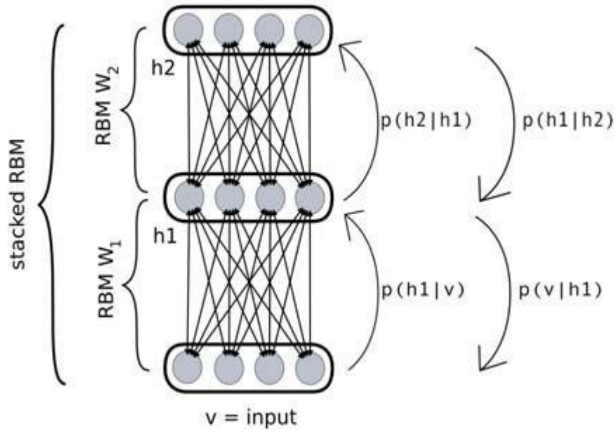

Fig. 3: Stacked RBM

The second step of updating the visible units is mentioned the reconstruction step. The hidden units are again updated using same equations given above. Then the weights are updated as the difference between the original and reconstructed values.

$$Upd(wij) = wij + L\ (vis_i\ hid_{j\ (data)} - vis_i\ hid_{j(reconstruction)}) \quad (5)$$

Here L represents the learning rate.

Once the process of training an RBM is executed, next RBM is stacked above which takes its input from the previously trained layer [18]. Again, new RBM is trained and the process is repeated until the threshold is obtained.

b) Grey Wolf Optimization Improved Deep Belief Network using based Employee Attrition prediction

1) Grey Wolf Optimization (GWO)

The grey wolf optimization imitates the hierarchy of grey wolves and their hunting behaviour for their food. There are four different kinds of grey wolves they are alpha, beta, delta and omega, it is sorted in a descending order of highest to lowest ranking. To achieve optimization three important processes are considered, prey searching, encircling and attacking the prey. The hierarchy of grey wolf are arranged as alpha, beta and omega. The alpha wolves are more responsible in decision making they can be a female or a male. Their decisionsare dictated to the entire pack, as they live in a pack of 5 to 12 members. They follow a very restricted social dominant hierarchy, and at the same time democratic strategy is also observed within their pack [4][24].

The next level in the hierarchy is beta grey wolves, which helps the alpha wolves to take proper decision, they are the candidate of the alpha wolves. They command the other wolves and plays the role of advisor and discipliner for the pack. It reinforces the command passed by the alpha wolves and it gives feedback to them [20].

Omega grey wolves are at the lowest ranking in the hierarchy, they are the scapegoat they should obey all other dominant wolves. They are allowed at the end to eat the prey. They maintain the dominance structure, in their absence whole pack will face the internal fighting issue [25].

There are two types of searches followed by wolves. Exploitation is the search in the local space for a solution that is optimum. The process of encircling the prey and after that attacking the prey are considered as exploitation. In exploration phase the wolves do a searching in the global space to get hold of the prey.

In the proposed work the parameters involved in influencing the deep belief network to classify the employee attrition is not assigned in the random manner during learning or training phase. The intelligence of the hunting behaviour of the grey wolves are induced in deep belief network for searching the fittest value to be assigned for the parameters in feature descriptor nodes of Deep Belief Network to produce the more accurate results in detection of employee attrition at right time.

The mathematical formulation of grey wolf optimization is characterized as follows

Once the location of prey is searched and found, the wolves encircle them. The position of the prey is detected and based on the best position; the search agents do adjustment in their positions.

$\overrightarrow{MD} = |\overrightarrow{CV} * \overrightarrow{PP}(t) - \vec{P}(t)|$(6)

To move the particular element towards best location $\overrightarrow{MD}$ is computed at the iteration t, the prey position vector is represented as $\overrightarrow{PP}(t)$ and the $\vec{P}(t)$ signifies the position of the grey wolf and the coefficient vector is $\overrightarrow{CV}$.

$\vec{P}(t+1) = \overrightarrow{PP}(t) - \overrightarrow{ATT} * \overrightarrow{MD}$(7)

$\overrightarrow{ATT} = 2 * \vec{a} * \overrightarrow{rd_1} - \vec{a}$(8)

$\overrightarrow{CV} = 2 * \overrightarrow{rd_2}$(9)

$\vec{a}$ = 2 – (2 it/maxitr) (10)

where it is the present iteration and maxitr is the maximum number of iterations

Hence the value of $\vec{a}$decreases from 2 to 0 when the number of iterations increases and $\overrightarrow{rd_1}$and$\overrightarrow{rd_2}$arerandom variables minimized through prespecified iterations.

During the hunting, the strategies are represented with the following equations.

$\overrightarrow{MD\alpha} = |\overrightarrow{CV}1 * \overrightarrow{P\alpha} - \vec{P}|$(11)

$\overrightarrow{MD\beta} = |\overrightarrow{CV}2 * \overrightarrow{P\beta} - \vec{P}|$(12)

$\overrightarrow{MD\delta} = |\overrightarrow{CV}3 * \overrightarrow{P\delta} - \vec{P}|$(13)

$\overrightarrow{MD\alpha}$, $\overrightarrow{MD\beta}$,$\overrightarrow{MD\delta}$are the vectors specifying the distances which are modified between the other wolves and the wolves representing alpha, beta and delta. The adjustment of distance vectors is guided by the co-efficient vectors calculated using formula specified in equation (9).

The new position vectors are obtained using the following method

GWα = $\overrightarrow{P\alpha} - \overrightarrow{ATT}1 * (\overrightarrow{MD\alpha})$(14)

GW_β = $\overrightarrow{P\beta} - \overrightarrow{ATT}2 * (\overrightarrow{MD\beta})$(15)

GW_δ = $\overrightarrow{P\delta} - \overrightarrow{ATT}3 * (\overrightarrow{MD\delta})$(16)

The average of these positions is calculated as the final position.

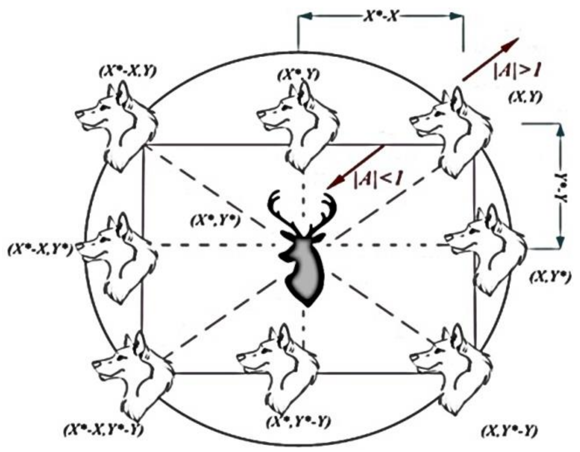

Fig 4: Grey Wolf Optimization [13]

If $|\overrightarrow{ATT}|$ <1 then the exploitingbehaviour of attacking the prey simulated, it means the optimized value is determined to assign for the parameters in the DBN. Else if $|\overrightarrow{ATT}|$ >1 it characterizes that the wolf is spacing from the prey exhibiting exploration as its behaviour. It means it searches for the global optimization to find the best value when their neighbouring values are not appropriate.

The complete process explained about Grey Wolf Optimization can be represented as a flowchart as given below.

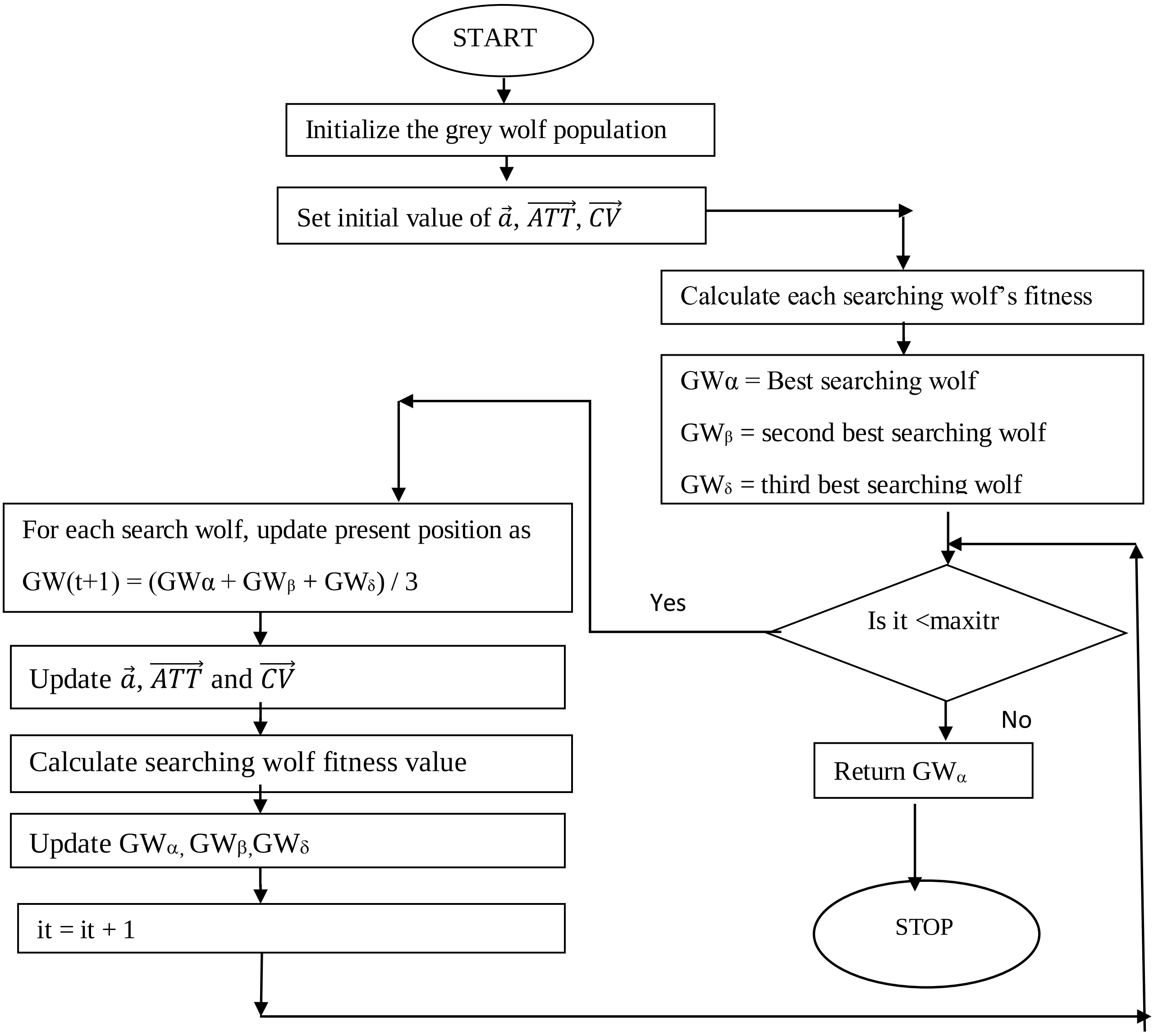

Fig 5: Flow chart for GWO

In each step, the fitness of each search agent is calculated, which shows the closeness of each solution with the optimum solution. Alpha will be the best, followed by beta and delta. The positions of the search agents are updated. The coefficient vectors, $\overrightarrow{CV}$, $\overrightarrow{ATT}$ and $\vec{a}$ values are updated. Again, fitness values are calculated and Alpha, Beta and Delta are also updated. This process continues until the number of iterations are completed.

2) Algorithm for Grey Wolf Optimization

Initialize the grey wolf population $P_{GW(I} = 1..n)$
Set the initial value to $\vec{a}$, $\overrightarrow{ATT}$, $\overrightarrow{CV}$
Calculate each searching wolf's fitness
GW_α // best searching wolf
GW_β // second best searching wolf
GW_δ = // third best searching wolf
While (it < max-itr)
For each search wolf
Position of present wolf search is updated using the formula
$GW(t+1) = \frac{GW_1 + GW_2 + GW_3}{3}$
Update $\vec{a}$, $\overrightarrow{ATT}$ and $\overrightarrow{CV}$
Calculate searching wolf fitness value
Update GW_α, GW_β, GW_δ
it=it+1
return GW_α

2.3 Summary of the complete methodology of the Grey Wolf Optimization Improved Deep Belief Network for Employee Attrition Prediction

The data is collected from the Employee Attrition dataset. The dataset is divided as test set and training set. The units in every layer, number of layers, t number of epochs, number of training and test data and number of hidden layers are given as input.

Normalize input dataset using the equation

Min-Max(EDS($Att_{i=1..n}$)) = = $\frac{att_i - \min(att_i)}{\max(att_i) - \min(att_i)}$

Where EDS represents entire data set

The parameters in the Deep Belief Network are estimated by normally applying a greedy layer wise model, which is the pre training phase. This phase affords an optimal start for the coming supervised training.

A supervised learning is executed with conventional Deep Belief Network.

In order to enhance the weight value, the Grey Wolf Optimisation function is called.

With the optimised weight value. the training of supervised learning model is done. The supervised learning of deep belief network is refined with the optimised weights and the cycle continues until the prescribed number of iterations.

The output is the detection of presence or absence of employee attrition

This is followed by the testing.

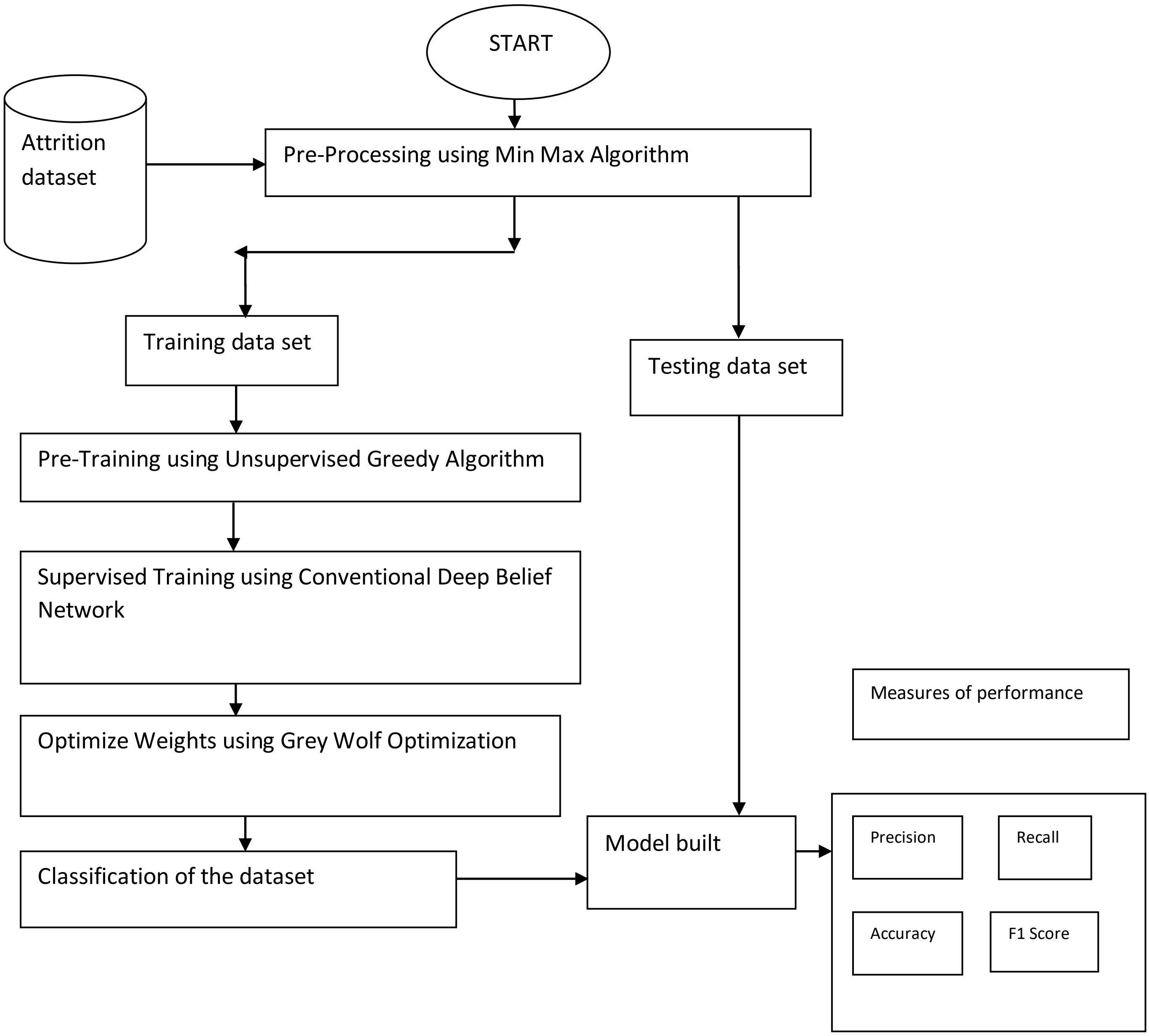

Fig.6: Flow chart of GWO improved Deep Belief Network

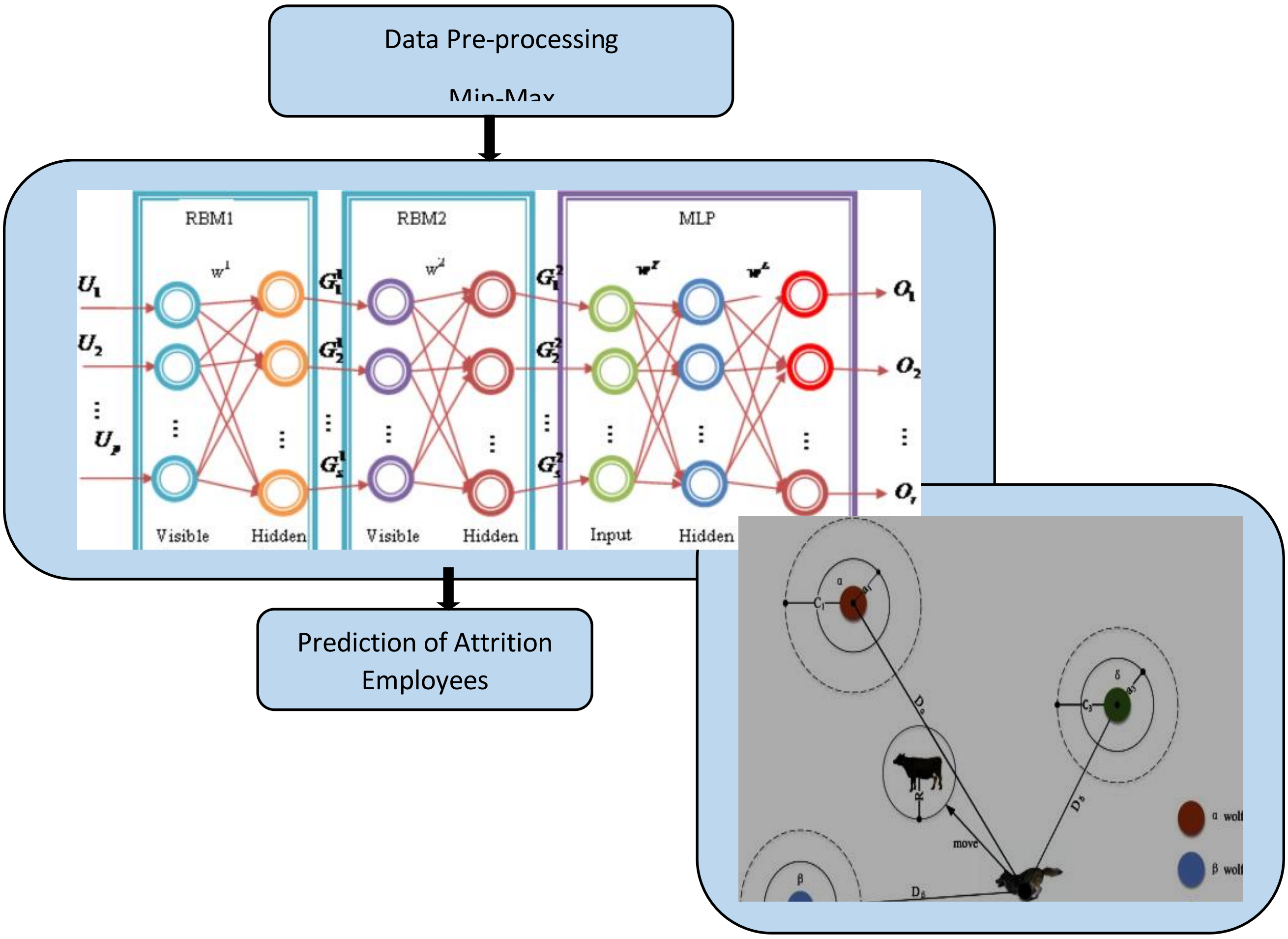

Fig 7: GWO enhanced DBN

D. Measures of performance

The algorithm is run using unlabelled test data for the classification as employees with attrition and employees without attrition. An algorithm is considered effective when it gives maximum accuracy in prediction calculated using measures like True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). True positive is a measure of the observations which are rightly recognized as positive whereas True Negative is a measure of the observations which are rightly recognized as negative. False positive is a measure of the observations which are actually negative but shown as positive and False Negative is a measure of observations which are actually positive but shown as negative.

IV. DATASET DESCRIPTION

This work is implemented using the employee attrition dataset with 34 attributes and 1470 instances. The dataset contains fields denoting age, daily rate, distance from home, job satisfaction, monthly income, job role, marital status, job involvement, environment satisfaction to name a few. The algorithm is coded using python in Jupyter Notebook.

V. RESULTS AND DISCUSSION

This section analyses the performance of the proposed Greywolf optimization improved deep belief network for employee attrition detection using the measurement parameters as given.

Precision gives a measure of how many those who were predicted to have attrition are actually records where attrition is there.

Precision=TP/(TP+FP) (17)

Recall specifies how many correct predictions for attrition were made from the records where attrition is there.

Recall= TP/ (TP+FN) (18)

Accuracy denotes the number of correct predictions done.

Accuracy=(TP+TN) / (TP+FP+TN+FN) (19)

F1 score is calculated as the harmonic mean of precision and recall

F1 score = (2 * recall * precision) / (recall + precision) = 0.92 (20)

The performance of the GWO-DBN is compared with the conventional classification models. It is compared with simple and Deep Belief Network (DBN) where there are no additional enhancements and also Artificial Neural Network (ANN). The measures of performance clearly demonstrate the improvement of the model by the introduction of the metaheuristic optimisation algorithm.

The below figure shows the count plot of attrition data

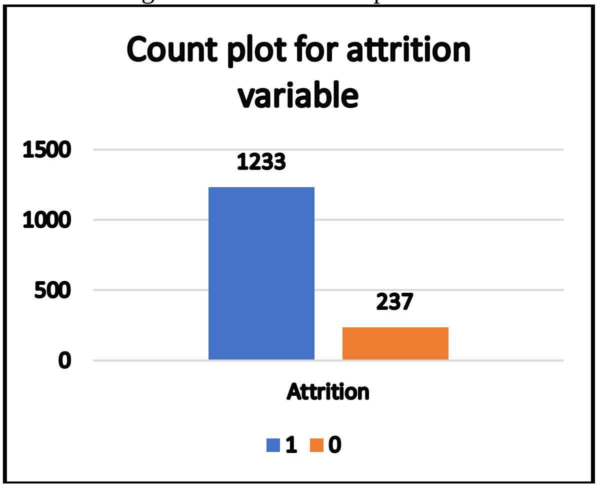

Fig 8 : Count plot for attrition data

Table 1 : Comparison of performance of algorithms

Algorithm	Accuracy	Precision	Recall
GWO-DBN	0.97	0.92	0.92
DBN	0.88	0.87	0.86
ANN	0.79	0.75	0.74

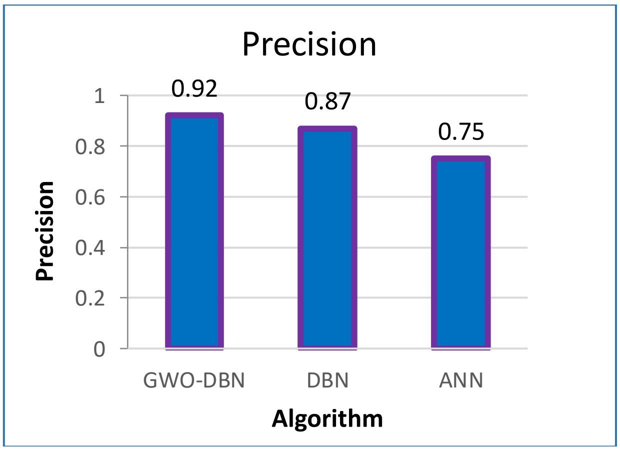

Fig9: Comparison based on precision

The figure illustrates comparison of three different classification models for employee attrition detection based on precision rate. The improved deep belief network produces highest precision value compared to DBN and ANN. The reason is GWO-DBN adapts the intelligence of grey wolf optimization which finetunes the parameters involved in improving the learning process and enhance attrition classification. The hunting behaviour of grey wolf is used to assign optimized value to increase its detection rate.

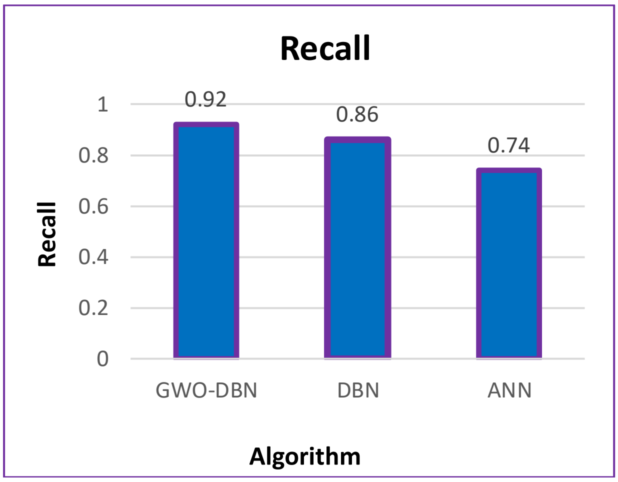

Fig.10: Comparison based on recall

The figure explores the recall value generated by three classification models namely grey wolf optimization improved deep belief network, conventional deep belief network and artificial neural network. The behavioural and metaheuristic model grey wolf optimization greatly influence the classification performance of Deep Belief Network by symmetrically assigning values to the parameters and thus, it produces highest recall rate for attrition classification. The other conventional models assign parameter value in a random manner and using back propagation it adjusts the values iteratively. Hence their performance is lesser than GWO-DBN in employee attrition detection.

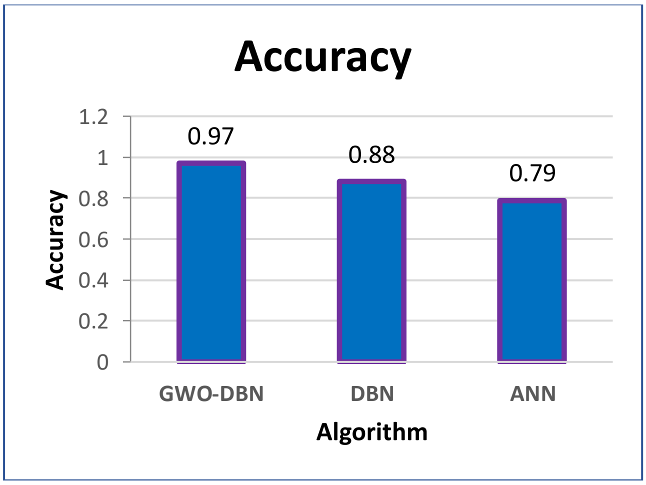

Fig. 11: Comparison based on accuracy

The figure explores that the improved deep belief network which achieves more accuracy in employee attrition classification. The other two classification models DBN and ANN produce less accuracy because the parameters used in fully connected layer is not symmetric as it is assigned in a random manner using back propagation by comparing with their expected output and observed output.

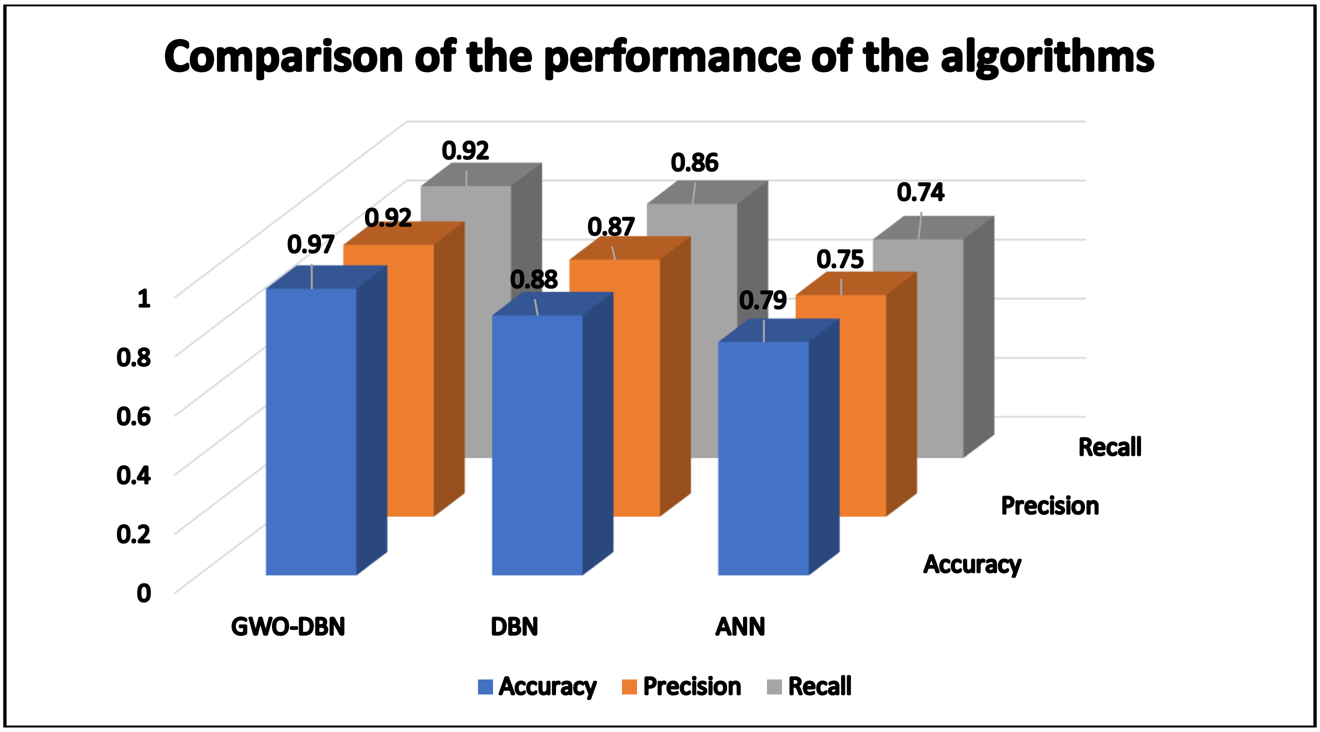

Figure 12: Comparison of performance of the algorithms

The above figure demonstrates that the DBN enhanced with the metaheuristic inspirational algorithm Grey Wolf Optimisation is performing well compared to traditional ANN as well as DBN which is not enhanced with GWO. In terms of the performance parameters accuracy, precision and recall, GWO-DBN achieves best results. The hunting behaviour of grey wolf is being used here in order to detect the values leading to result. The conventional methods assign parameters in a random manner. In GWO-DBN eliminates the use of random parameters.

VI. CONCLUSION

In the study, an enhanced model is proposed using Deep Belief Network for the prediction of attrition of employees in the organization. Attrition is a major challenge faced by organizations. Hence an accurate algorithm for prediction is highly appreciable. The efficiency of the Deep belief network is enhanced by the use of the meta heuristic Grey Wolf Optimisation for fine tuning of parameters used. Prediction efficiency of Deep Belief Network is improved with the addition of the novel inspiration algorithm which is measured with the performance parameters as Accuracy, Recall and Precision. The result is also compared with ANN. The results are visually presented in graphical form.

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