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Landslides Identification through Conglomerate Grey Wolf Optimization and Whale Optimization Algorithm

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Abstract

The research aims to develop a prediction model to identify landslide through Deep Neural Network (DNN) for predicting the hazard assessment and mitigation of landslide-related losses. It is essential to identify landslide for preventing from affecting the population with significant socioeconomic damage and high economic losses in developing countries. While evaluating the performance of traditional DNN, it is apparent that changes in weights influence the output performance. In this basis, the research aims to involve optimization techniques to identify optimal weights parameters. The involved optimization techniques are Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), and the proposed conglomeration of GWO and WOA (CGW). The performance of the proposed technique shows the better performance over other comparative techniques. The developed proposed model predicts the types and size of landslide effectively with 97.75% accuracy.

Keyword: *landslide, Deep Neural Network, Grey Wolf Optimization (GWO), Whale Optimization Algorithm, conglomeration of GWO and WOA (CGW).*

Landslides Identification through Conglomerate Grey Wolf Optimization and Whale Optimization Algorithm [1]

Rajesh B[2]

Introduction

Landslide is a local natural phenomenon, popularly understood as the "mass displacement of earth, debris, and rocks" that can be triggered by hydrological, topographic, and geophysical reasons [1]. However, anthropogenic activities such as mining and construction, as well as natural events including heavy rainfall, earthquake, volcanic eruption, and marine erosion can also trigger landslides [2]. The World Bank reported that nearly 3.7 million square kilometres of world's land area is highly prone to landslides which could put at risk about 300 million human lives [3]. As pointed out by many researchers the complexity of mainly the natural but also the man-made processes that are considered responsible for the evolution of landslides, makes it difficult to predict the spatial and temporal occurrence of landslides [4].

After nearly one and half decades later, these figures must have changed; however, because of the lack of consistency in the landslide reports, it is very midcult to come up with an exact number of the landslide incidences and the fatalities. These inconsistencies in the reports could be because of the varied nature of landslides; for example, landslides could be seismic only or triggered by rainfall, rock-slides, floods, or hurricane. In a recent study, the authors provide a good discussion of the discrepancies in landslide reports [2]. Furthermore, the authors report that between only 2004 and 2016, a total of 4862 landslide events occurred globally, with high impacts in the Central and South America, Caribbean Islands, East Africa, Turkey, Iran, European Alps, and Asia [2].

The Himalayan Arc across Indian and south-eastern China has experienced the highest landslide events, followed by areas of Laos, Bangladesh, Myanmar, Indonesia, and the Philippines [2]. India, has experienced severe naturally triggered landslides in the 21st century. In 2001, nearly 40 individuals died in the Amboori of Kerala state of India; in 2013, a landslide occurred in Kedarnath of Uttarakhand state of India and more than 5000 people died; and in 2014 in the Pune of Maharashtra state of India, over 100 individuals were found to be missing

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after the landslide [6,7]. Depicts the locations of landslide events in India and the fatalities that occurred at such locations—an estimated 12.6% of land area of India and approximately 4.5 million USD worth economic damage [8]. Taking advantage of the evolution of computer technology, both in software and hardware assets, and also data availability, numerous methods have been developed for the prediction of landslide susceptibility maps [5].

The decision tree-based hybrid machine learning system is presented to correctly predict the landslide susceptible areas. The landslides may not be stopped or controlled; however, the losses can be reduced by establishing a decision support system to predict possible landslides or identifying landslide prone areas for management. Therefore, prediction of possible landslides at the local and regional levels is required for pro-active landslide mitigation policy creation and management. Although domain-knowledge-driven qualitative approach is advantageous in predicting landslides, data-driven quantitative methods are widely used because collecting field data from landslide areas are challenging and hard to acquire [3].

Machine learning techniques have recently gained good attention among the environmental modelling research community as they are advantageous incipiently capturing the complex relationship between the environmental predictors and the response, such as flood [10], wildfire [11], sinkhole [12], drought [13], gully erosion [14,15], groundwater [16] land/ground subsidence [17], and landslide in this case [3]. Machine learning-based landslide susceptibility models are more cost efficient and rapid than conventional models and can be extended to large area analysis [18].

Literature Review

Lee et al. (2001) [19] discuss the periodicity of land sliding on cliffed coasts where episodic cliff failure events are associated with cliff response to predisposing factors, such as profile steepening bywave action, and triggering factors, such as storms and heavy rainfall. The relationship between these factors is complex: triggering events of the same magnitude may not necessarily lead to land sliding, because preparatory factors may also be required. Such process synergies suggest that successive cliff land sliding events are not independent, because they are influenced by previous events (in other words there are reciprocal feedbacks between pattern and process). Hence, in addition to the scale-limitations on deterministic mechanistic models, traditional statistical models are also not well suited to coastal cliff land sliding. Limitations in traditional models for coastal cliff erosion are slowly being offset by advances in our ability to collect and interrogate remotely sensed data.

Dickson et al., 2007[20] Unfortunately, historical records are often not available for rock coasts composed of more consolidated materials (e.g. sandstones), where erosion may be imperceptibly slow for long periods, interrupted by sudden land sliding failures that can remove several metres of cliff top in a single event. As yet process-models representing the many factors that affect the dynamics and stability of harder-rock cliffs are not available at the spatio-temporal scales (decades, km's) required for coastal management

James et al., 2013[21] with the extracted positive and negative samples from different landslide inventories, the samples are combined to form three databases; namely, the Relict Landslide Database (RelLD), the Recent Landslide Database (RecLD) and the Joint Landslide Database (JLD). For each established database, the data which is originally extracted from the same data layer needs to be normalized as they may have different orders of magnitude. For example, the elevation may reach nearly thousand-meter level while the slope gradient ranges from 0_ to 90_. The inconsistent magnitude of data layers may cause slow convergence or convergent failure of adopted machine learning algorithms. Hence, normalization is conducted to each dimension of the established databases.

Goodfellow et al., 2016[22] as one of the most popular deep learning algorithms, convolutional neural networks have gained much attention for its remarkable contribution in computer vision. A typical CNN is composed of four key components: convolutional layers, activation layers, pooling layers and fully connected layers. Built with these layers, many well-designed CNN structures have been proposed in many fields of study. In this study, each sample with different data layers is like a special ‘picture’ with multiple channels. The classification of high dimensional data is also the strength of the CNN.

Yu et al. (2017) [23] developed an analogous CNN model for their research along with an improved region growing algorithm (RSG_R) for landslide detection. They trained their CNN model by using a set of landslide images, extracting the area and the boundary of the landslides with the RSG_R algorithm, achieving high detection accuracy concerning identifying landslide characteristics.

Ghorbanzadeh et al. (2019) [24] applied a CNN method for landslide detection using optical satellite imagery derived from the Rapid Eye sensor. The authors compared the results obtained from the CNN method with those from three state-of-the-art machine learning methods (ANN, SVM and RF). By using the spectral information of the Rapid Eye images separately along with topographic factors, they estimated the performance of each method and the impact of the used spectral and topographic factors on the landslide detection process. The areas identified as having landslide occurrences are then validated using common remote sensing and GIS validation metrics and the mean intersection-over-union (mIOU) validation method from computer vision.

Proposed Methodology

The identification of landslide is an essential step in landslide hazard assessment and mitigation of landslide-related losses. The purpose of this research is to develop a DNN based model for identifying the landslides. Since, the DNNs have demonstrated impressive performance in various complex machine learning tasks. Also, the performance of the DNN is better than other machine learning conventional techniques. However, the performance of the DNN relay on weight parameters. Therefore, the research aims to incorporate optimization techniques to identify the optimal weights of DNN for identifying landslides effectively. The input parameters considered such as country name, location, distance, geo location (latitude and longitude) and the output parameters such as types of landslide and size of landslide. The optimization techniques considered in this research are GWO, WOA and the proposed conglomeration of and CGW to identify optimal weights for DNN. Here, CGW involves the both GWO and WOA updating procedure for tuning the updating process effectively. Integrating the optimization techniques for identify the weights parameters certainly enhance the performance and certainly reduces the computational time for identifying the optimal weights parameters.

Deep Neural Network

A deep neural network (DNN) is an ANN with multiple hidden layers between the input and output layers. DNNs can model complex non-linear relationships and the foremost purpose of a neural network is to receive a set of inputs, perform progressively complex calculations on them, and give output to solve real world problems like classification. DNN mimics the network of neurons in a brain. It is a subset of machine learning based on artificial neural networks with representation learning. It is called deep learning because it makes use of deep neural networks. This learning can be supervised, semi-supervised or unsupervised. In this research 80% database use for training and remaining 20% used for validation.

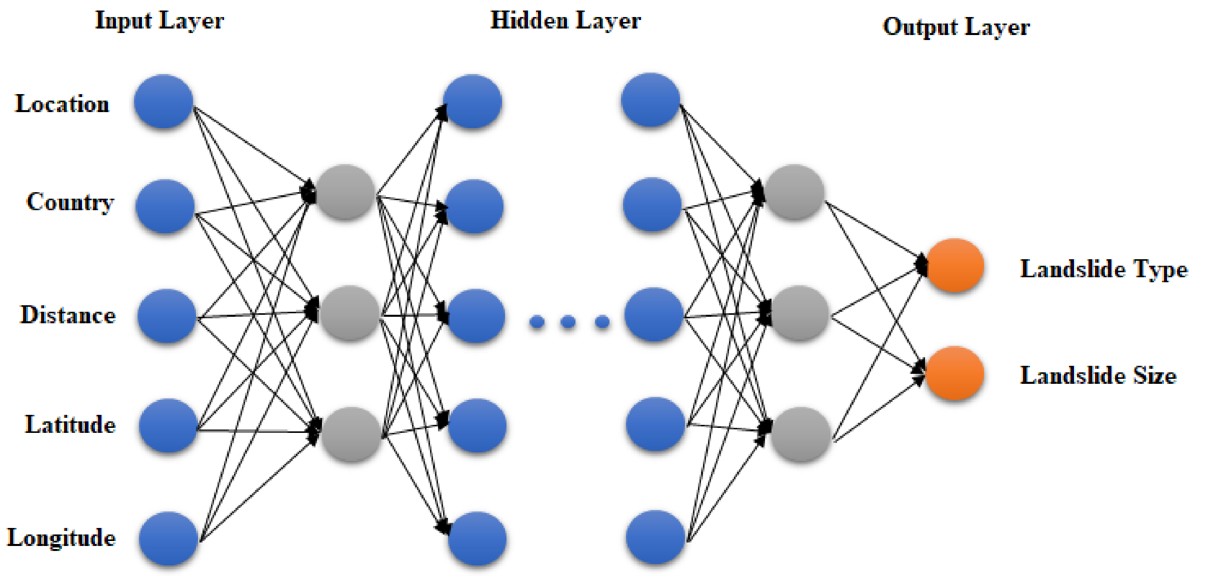

Figure: 1 Architecture of Deep Neural Network

The research includes five inputs and couple of output, DNN majorly relay on weights between inputs and outputs. Rather considering randomly generated weights optimal weights selection place a vital role in reducing computational time and complexity. The investigation involves conglomeration of GWO and WOA to form CGW, where both updating process consider for solution updating.

Conglomerate GWO - WOA

Initial solution

The process of generating random solution in the range of -10 to 10 with respect to number of input attributes for finding appropriate weights. Iteration holds 10-solutions for computation process and the both mathematical expression detailed below.

$$I_i = I_1, I_2, \ldots. I_n \tag{1}$$

Fitness Computation

This process is used to evaluate the fitness of above generated solutions in order to identify the fittest solution appropriate for the research context.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

The proposed approach utilizes the efficient hunting strategy of both GWO and WOA updating process. The research utilizes both updating strategy for fitness evaluation and selects the best half solution for further process.

Grey Wolf Optimization

The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. In addition, the three main steps of hunting, searching for prey, encircling prey, and attacking prey, are implemented. Grey wolves mostly prefer to live in a pack. The group size is 5–12 on average. The leaders are a male and a female, called alpha. The alpha is mostly responsible for making decisions about hunting, sleeping place, time to wake, and so on. The alpha's decisions are dictated to the pack. However, some kind of democratic behaviour has also been observed, in which an alpha follows the other wolves in the pack.

In order to mathematically model the social hierarchy of wolves when designing GWO, we consider the fittest solution as the alpha (α). Consequently, the second and third best solutions are named beta (β) and delta (δ) respectively. The rest of the candidate solutions are assumed to be omega (ω). In the GWO algorithm the hunting (optimization) is guided by α, β, and δ. The ω wolves follow these three wolves.

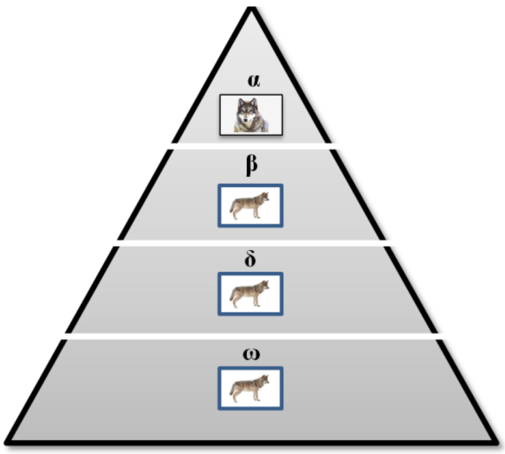

Figure: 2 Grey wolf hierarchies

Encircling prey

As mentioned above, grey wolves encircle prey during the hunt. In order to mathematically model encircling behaviour the following equations are proposed:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)\right| \quad (3)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \quad (4)$$

Where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X_p}$ is the position vector of the prey, and $\vec{X}$ indicates the position vector of a grey wolf.

The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a}. \quad (5)$$

$$\vec{C} = 2.\vec{r_2} \quad (6)$$

Where components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and r_1 , r_2 are random vectors in [0,1].

Hunting

Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behaviour of grey wolves, we suppose that the alpha (best candidate solution) beta and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. The following formulas are proposed as follows.

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right|,\ \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}\overrightarrow{X_\beta} - \vec{X}\right|,\ \overrightarrow{D_\delta} = \left|\overrightarrow{C_3}\overrightarrow{X_\delta} - \vec{X}\right|, \quad (7)$$

$\overrightarrow{X_1} = \overrightarrow{X}_\alpha - \overrightarrow{A_1}.(\overrightarrow{D_\alpha})$, $\overrightarrow{X_2} = \overrightarrow{X}_\beta - \overrightarrow{A_2}.(\overrightarrow{D_\beta})$, $\overrightarrow{X_3} = \overrightarrow{X}_\delta - \overrightarrow{A_3}.(\overrightarrow{D_\delta})$ (8)

$$\overrightarrow{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \quad (9)$$

Here, the final position would be in a random place within a circle which is defined by the positions of alpha, beta, and delta in the search space. In other words alpha, beta, and delta estimate the position of the prey, and other wolves updates their positions randomly around the prey.

Attacking prey

As mentioned above the grey wolves finish the hunt by attacking the prey when it stops moving. In order to mathematically model approaching the prey we decrease the value of $\vec{a}$. Note that the fluctuation range of $\vec{A}$ is also decreased by $\vec{a}$. In other words $\vec{A}$ is a random value in the interval [-2a, 2a] where a is decreased from 2 to 0 over the course of iterations. When random values of $\vec{A}$ are in { 1, 1], the next position of a search agent can be in any position between its current position and the position of the prey.

Whale Optimization Algorithm

In general, the WOA is inspired by the humpback whales' hunting behaviour i.e., a humpbacks's swarm changes their positions (solutions) hunting for preys. It is a swarm-based optimization technique .Whales is very intelligent animals which contain emotion. Humpback whales have a unique hunting pattern among most whales. By employing the bubble net feeding behaviour, the humpback whales have hunt prey on the sea surface. In this mode, humpback whales form bubbles around their prey on a 9-shaped or circular path. The Encircling prey, Bubble net hunting maneuverer and search for prey are considered for the mathematical model phases of WOA.

Encircling prey

Humpback whales can recognize the location of prey and encircle them. Since the position of the optimal design in the search space is not known a priori, the WOA algorithm assumes that the current best candidate solution is the target prey or is close to the optimum. After the best search agent is defined, the other search agents will hence try to update their positions towards the best search agent. This behaviour is represented by the following equations:

$$\vec{D} = \left| \vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t) \right| \tag{10}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A}.\vec{D} \tag{11}$$

Where t indicates the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, X^* is the position vector of the best solution obtained so far, $\vec{X}$ is the position vector, $|\ |$ is the absolute value, and is an element-by-element multiplication. It is worth mentioning here that X^* should be updated in each iteration if there is a better solution.

The vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\vec{a}..\vec{r} \ \ -\vec{a}. \tag{12}$$

$$\vec{C} = 2.\vec{r} \tag{13}$$

Where $\vec{a}$ is linearly decreased from 2 to 0 over the course of iterations (in both exploration and exploitation phases) and $\vec{r}$ is a random vector in [0.1].

Bubble-net attacking method (exploitation phase)

In order to mathematically model the bubble-net behaviour of humpback whales, two approaches are designed as follows:

1) *Shrinking encircling mechanism*: This behaviour is achieved by decreasing the value of $\vec{a}$ in the Eq. (3). Note that the fluctuation range of $\vec{A}$ is also decreased by $\vec{a}$. In other words $\vec{A}$ is a random value in the interval [−a, a] where a is decreased from 2 to 0 over the course of iterations. Setting random values for $\vec{A}$ in [−1,1], the new position of a search agent can be defined anywhere in between the original position of the agent and the position of the current best agent. Figure 1 (a) shows the possible positions from (X ,Y) towards (X*, Y*) that can be achieved by $0 \leq A \leq 1$ in a 2D space.

2) *Spiral updating mechanism*: As can be seen in Figure 3 (b), this approach first calculates the distance between the whale located at (X,Y) and prey located at (X*,Y*). A spiral equation is

then created between the position of whale and prey to mimic the helix-shaped movement of humpback whales as follows:

$$\vec{X}(t+1) = \vec{D'}.e^{bl}.\cos(2\pi l) + \vec{X^*}(t) \tag{14}$$

Where $\vec{D'} = \left|\vec{X^*}(t) - \vec{X}(t)\right|$ and indicates the distance of the ith whale to the prey (best solution obtained so far), b is a constant for defining the shape of the logarithmic spiral, l is a random number [-1,1], and . is an element-by-element multiplication.

Note that humpback whales swim around the prey within a shrinking circle and along a spiral-shaped path simultaneously. To model this simultaneous behaviour, we assume that there is a probability of 50% to choose between either the shrinking encircling mechanism or the spiral model to update the position of whales during optimization. The mathematical model is as follows:

$$\vec{X}(t+1) = \begin{cases} \vec{X^*}(t) - \vec{A}.\vec{D} & if \quad p < 0.5 \\ \vec{D'}.e^{bl}.\cos(2\pi l) + \vec{X^*}(t) & if \quad p \geq 0.5 \end{cases} \tag{15}$$

Where p is a random number in [0,1].

In addition to the bubble-net method, the humpback whales search for prey randomly. The mathematical model of the search is as follows.

Search for prey (exploration phase)

The same approach based on the variation of the $\vec{A}$ vector can be utilized to search for prey (exploration). In fact, humpback whales search randomly according to the position of each other. Therefore, we use $\vec{A}$ with the random values greater than 1 or less than −1 to force search agent to move far away from a reference whale. In contrast to the exploitation phase, we update the position of a search agent in the exploration phase according to a randomly chosen search agent instead of the best search agent found so far. This mechanism and $|\vec{A}| > 1$ emphasize exploration and allow the WOA algorithm to perform a global search. The mathematical model is as follows:

$$\vec{D} = \left|\vec{C}\,\vec{X_{rand}} - \vec{X}\right| \tag{16}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \tag{17}$$

where $\overrightarrow{X_{rand}}$ is a random position vector (a random whale) chosen from the current population.

Some of the possible positions around a particular solution with $\vec{A}$ > 1 are depicted in Figure 3.

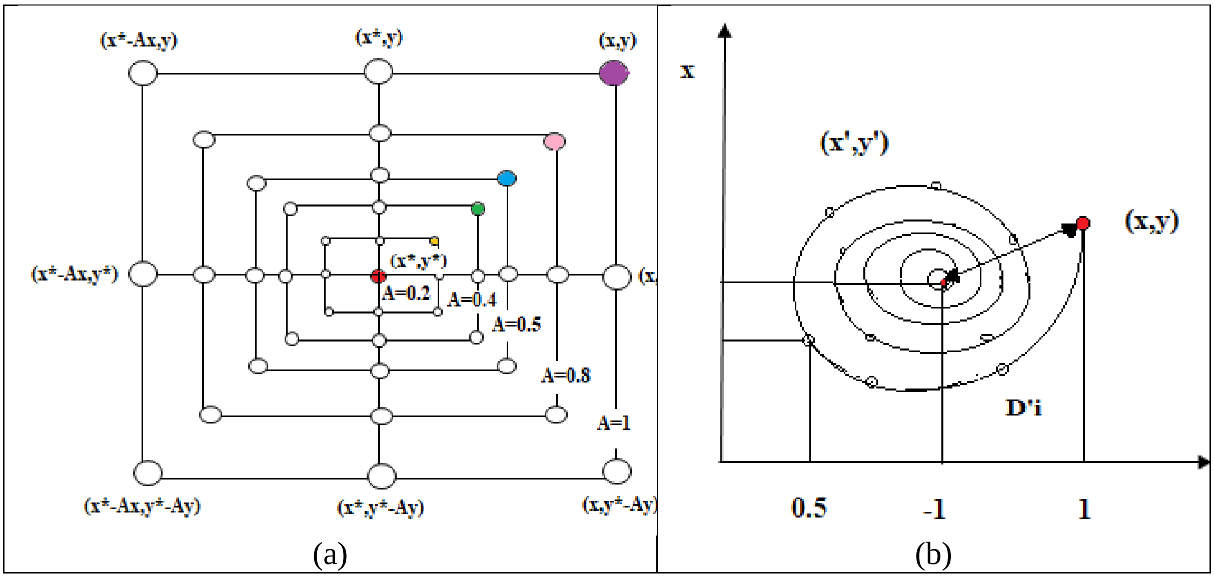

Figure 3: Bubble-net attacking method in WOA: (a) Shrinking encircling prey and (b) Spiral updating position

The WOA algorithm starts with a set of random solutions. At each iteration, search agents update their positions with respect to either a randomly chosen search agent or the best solution obtained so far. The parameter is decreased from 2 to 0 in order to provide exploration and exploitation, respectively. A random search agent is chosen when | $\vec{A}$ | > 1, while the best solution is selected when | $\vec{A}$ | < 1 for updating the position of the search agents. Depending on the value of p, WOA is able to switch between either a spiral or circular movement. Finally, the WOA algorithm is terminated by the satisfaction of a termination criterion.

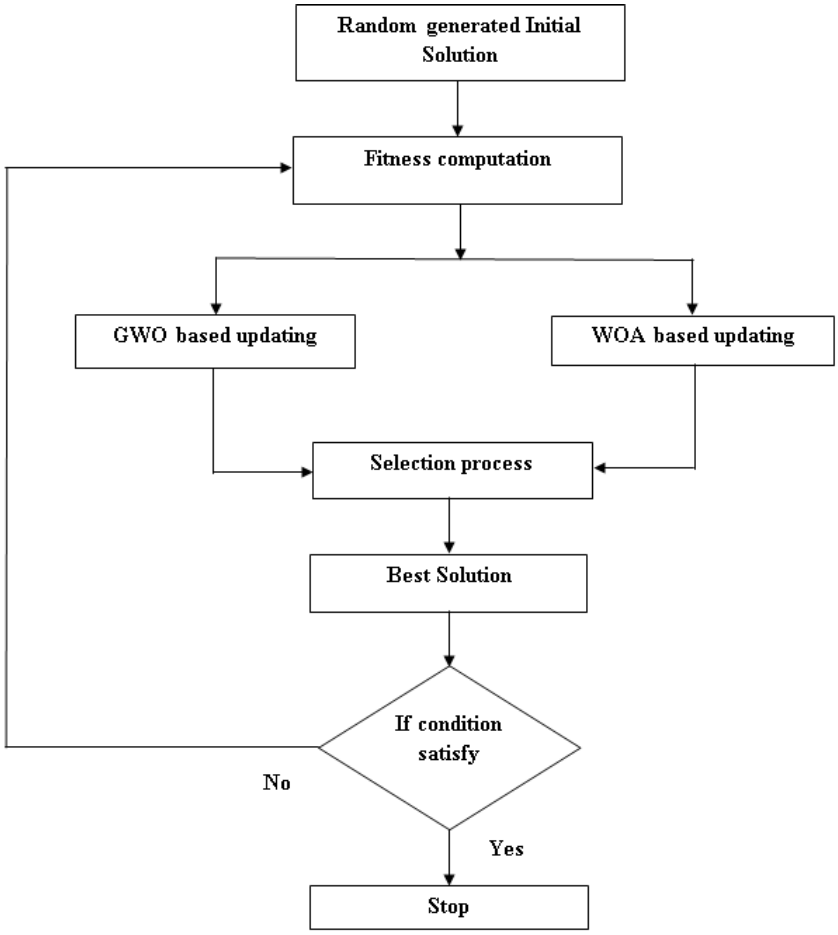

Figure: 4 Flow chart of Conglomerate GWO – WOA

Results and Discussion

The performance of proposed technique evaluate through various measures and evident the superiority over comparative techniques to predict the landslide types and size. It is apparent from the results that incorporating optimization techniques drastically elevates the prediction performance over traditional approach. The measures consider to evaluates the performance of employed techniques are sensitivity, specificity, accuracy, Positive Predictive Value (PPV), Negative Predictive Value (NPV), False Positive Rate (FPR), False Negative Rate (FNR), False Discovery Rate (FDR). Figure 5 to figure 12 shows the performance of employed techniques, where DNN associates CGW achieves the sensitivity 94.94% that is 7.87% better than DNN associates WOA, 5.62% greater than DNN associates GWO and 17.42% a huge marginal difference over traditional DNN. Similarly, in other measures also DNN in associates with CGW achieves better performance over other techniques.

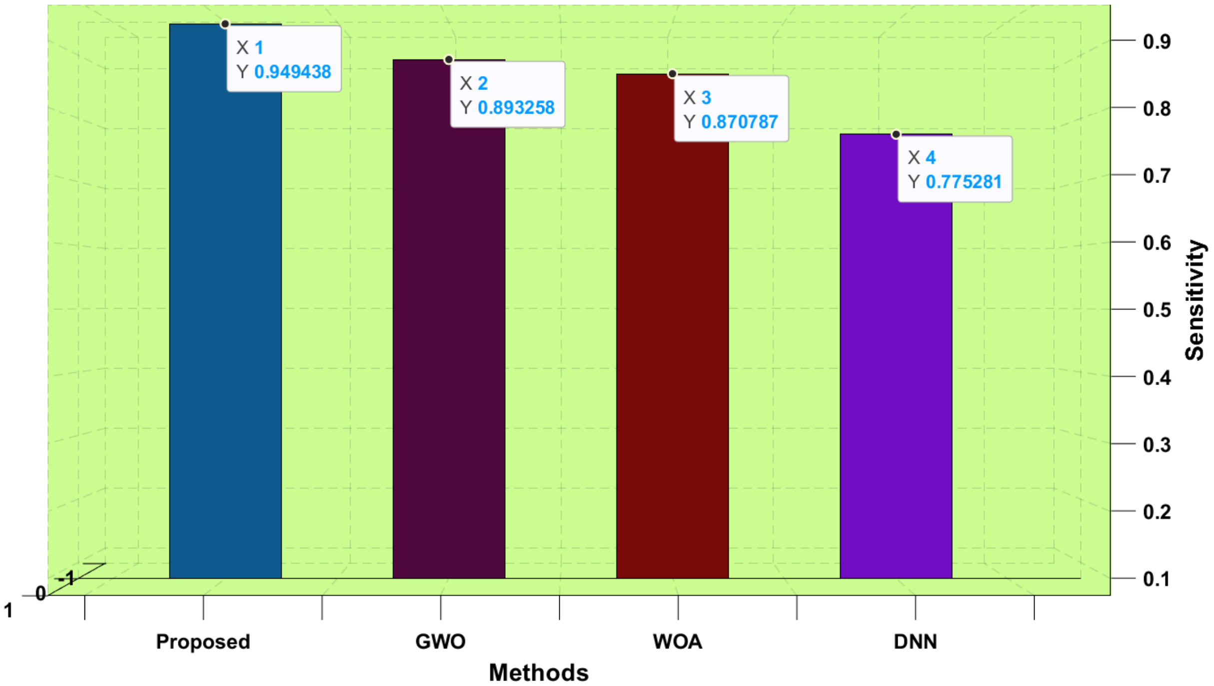

Figure: 5 Average output performance for sensitivity

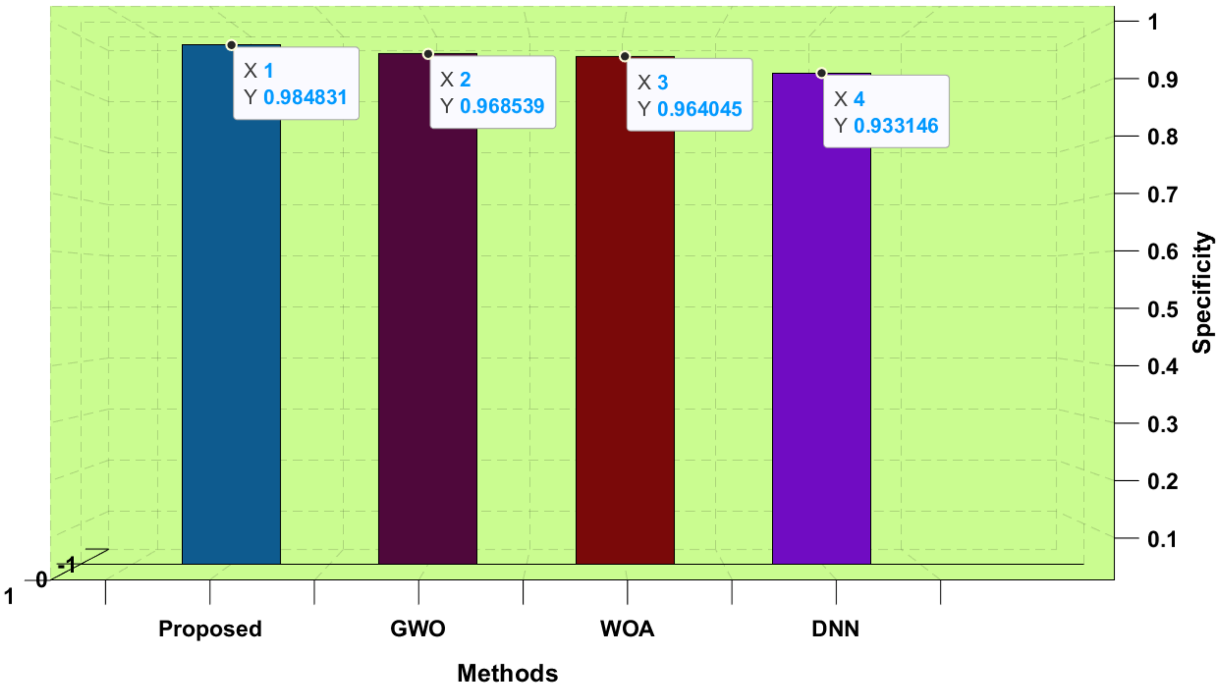

Figure: 6 Average output performance for specificity

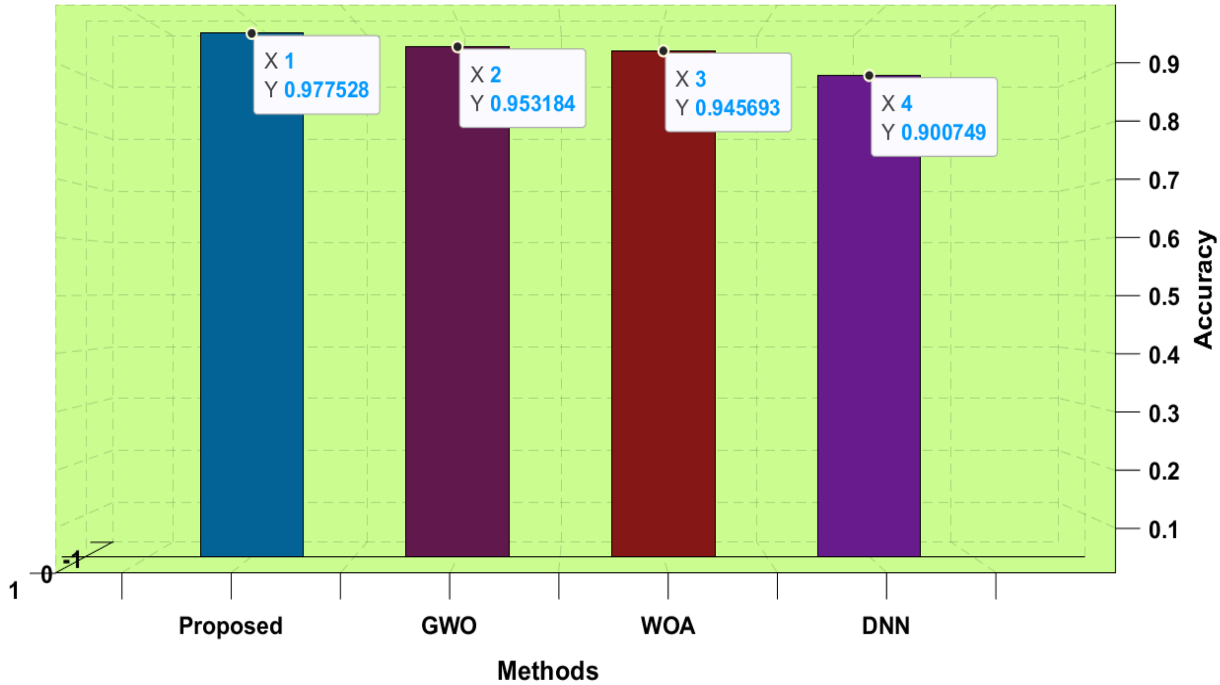

Figure: 7 Average output performance for Accuracy

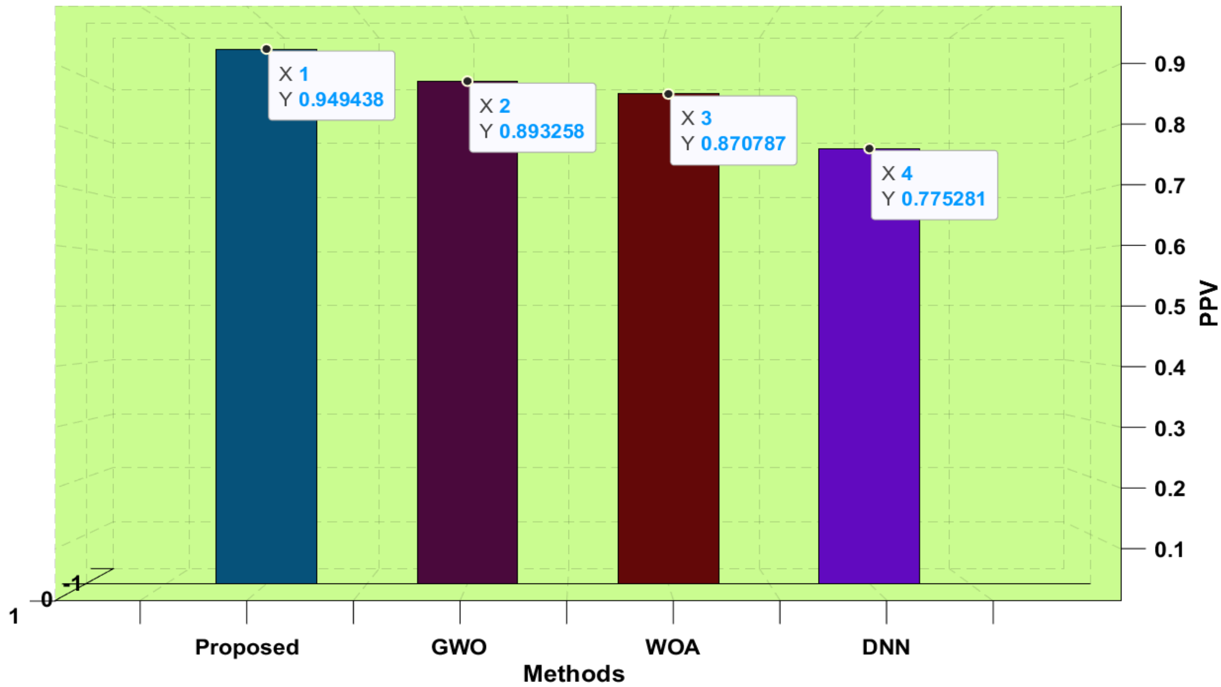

Figure: 8 Average output performance for PPV

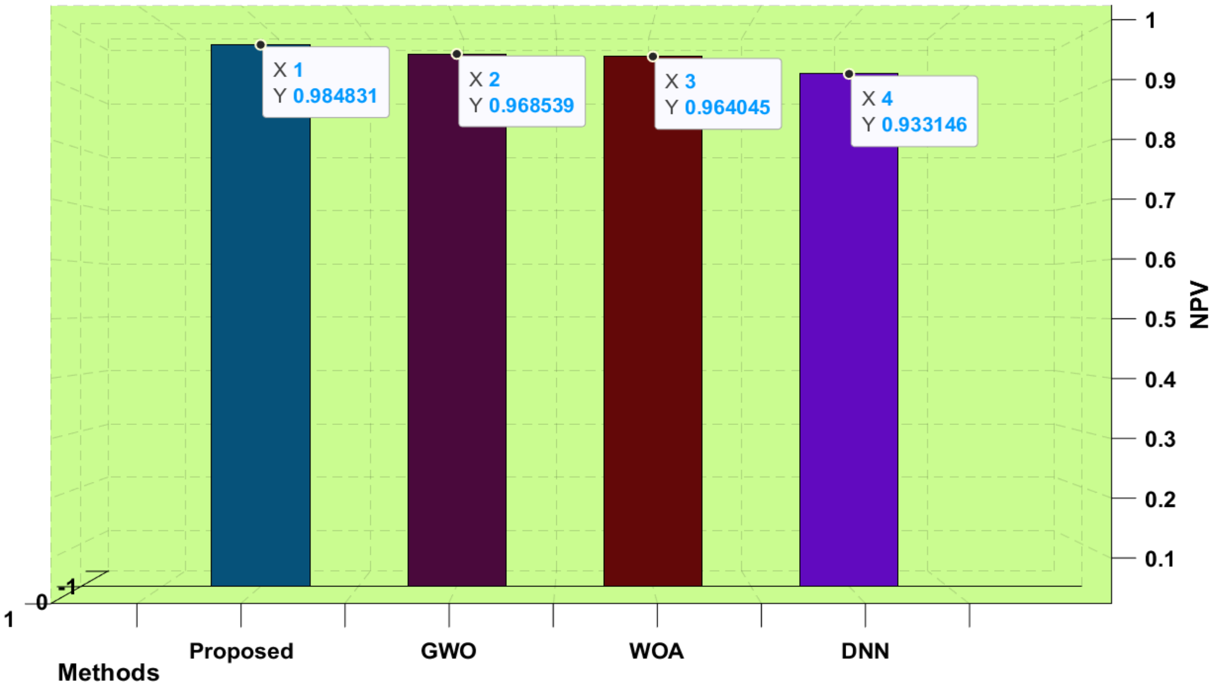

Figure: 9 Average output performance for NPV

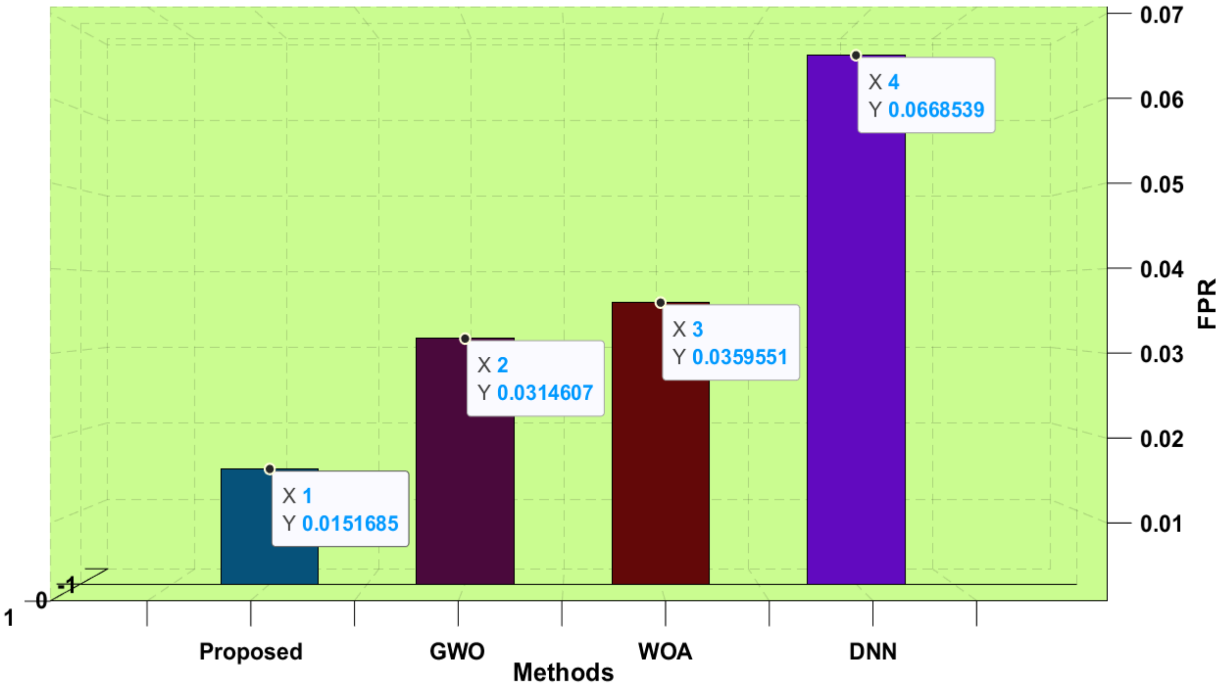

Figure: 10 Average output performance for FPR

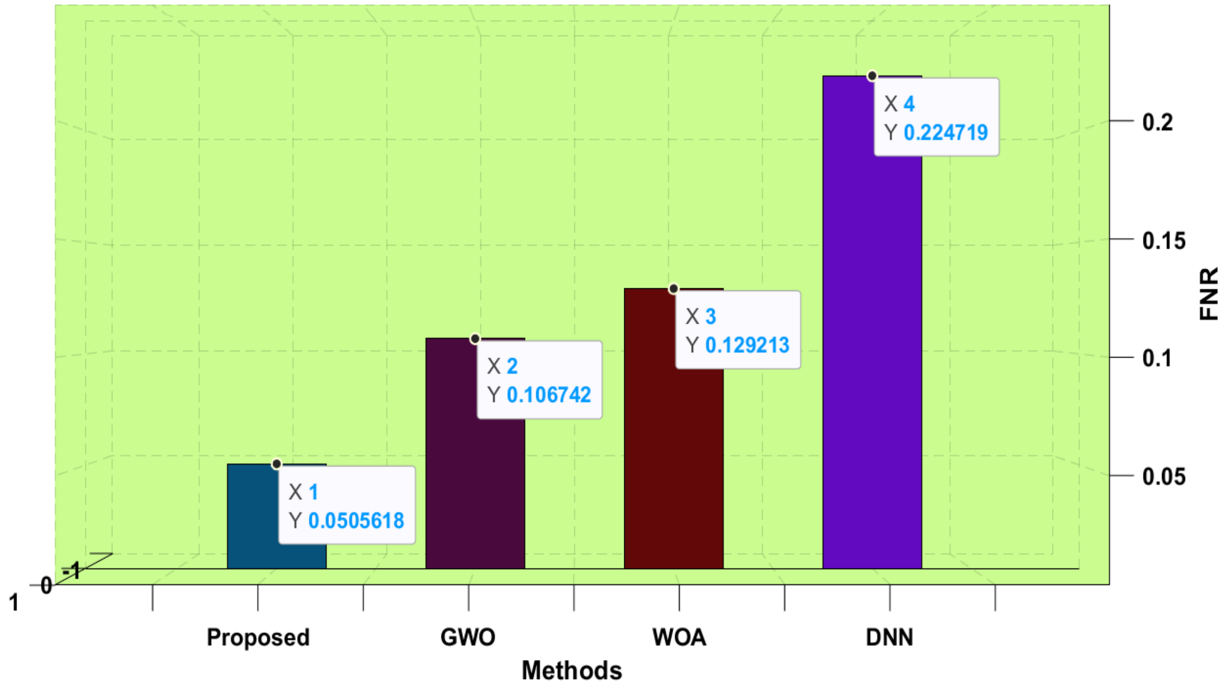

Figure: 11 Average output performance for FNR

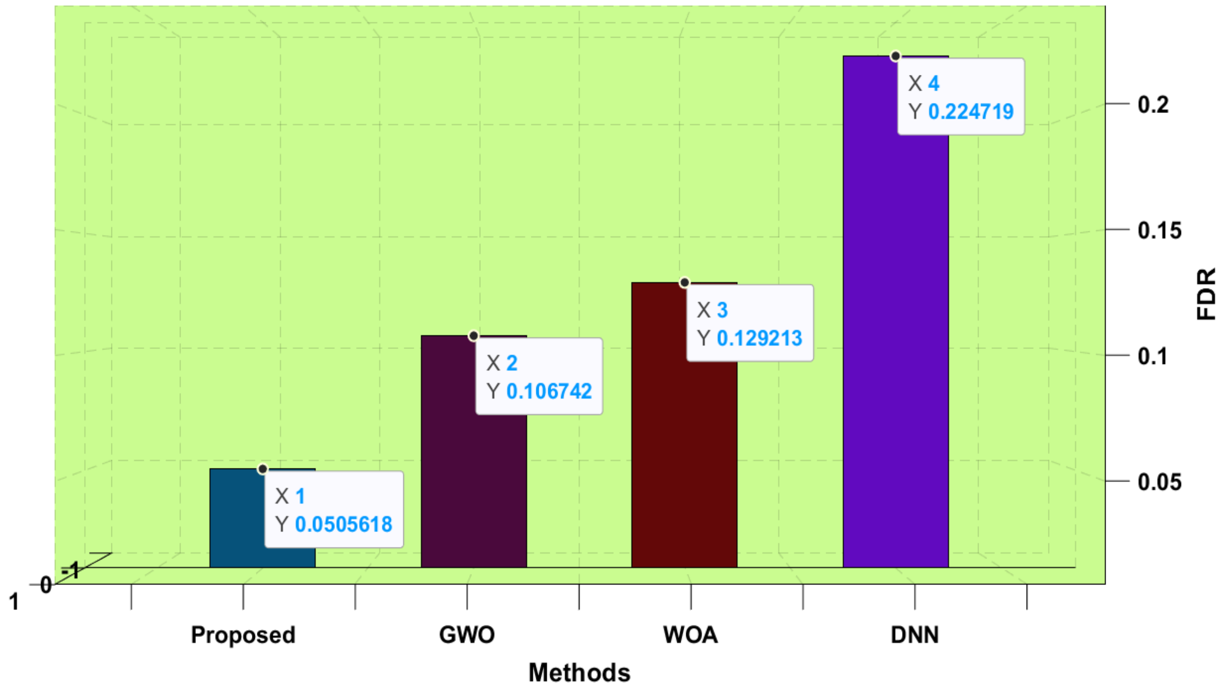

Figure: 12 Average output performance for FDR

True Positive (TP) -	Landslides types/size correctly identified
False Positive (FP) -	Landslides types/size incorrectly identified
True Negative (TN) -	Landslides types/size correctly rejected
False Negative (FN) -	Landslides types/size incorrectly rejected

Table-1 Mathematical expression of performance measures

Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
FDR	$\frac{FP}{FP+TP}$
FNR	$\frac{FN}{FN+TP}$
FPR	$\frac{FP}{FP+TN}$
NPV	$\frac{TN}{TN+FN}$
PPV	$\frac{TP}{TP+FP}$
Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$

Table: 2 Actual output performances from DNN associates CGW

Output	**Sensitivity**	**Specificity**	**Accuracy**	**PPV**	**NPV**	**FPR**	**FNR**	**FDR**
1	0.9325	0.9865	0.9775	0.9325	0.9865	0.0134	0.0674	0.0674
2	0.9662	0.9831	0.9775	0.9662	0.9831	0.0168	0.0337	0.0337

Table: 3 Actual output performances from DNN associates GWO

Output	**Sensitivity**	**Specificity**	**Accuracy**	**PPV**	**NPV**	**FPR**	**FNR**	**FDR**
1	0.8539	0.9707	0.9513	0.8539	0.9707	0.0292	0.1460	0.1460
2	0.9325	0.9662	0.9550	0.9325	0.9662	0.0337	0.0674	0.0674

Table: 4 Actual output performances from DNN associates WOA

Output	**Sensitivity**	**Specificity**	**Accuracy**	**PPV**	**NPV**	**FPR**	**FNR**	**FDR**
1	0.8089	0.9617	0.936	0.8089	0.9617	0.0382	0.1910	0.1910
2	0.9325	0.9662	0.9550	0.9325	0.9662	0.0337	0.0674	0.0674

Table: 5 Actual output performances from DNN

Output	Sensitivity	Specificity	Accuracy	PPV	NPV	FPR	FNR	FDR
1	0.6966	0.9393	0.8988	0.6966	0.9393	0.0606	0.3033	0.3033
2	0.8539	0.9269	0.9026	0.8539	0.9269	0.0730	0.1460	0.1460

The table-1 shows the mathematical expression of the performance measures utilized in this research. The table 2 to 5 shows the actual output performance of employed techniques for predicting landslide types (1) and size (2). Other than proposed techniques, the accuracy in predicting landslide size is better than predicting landslide types. In general, the performances of proposed is significantly better in all measures over the comparative techniques. Rather than considering individual updating process; Incorporating both updating strategy significantly converge the best solution (i.e) identifying optimal weights parameters.

Convergence graph

The figure 13 shows the converging performance of involved techniques during training process and it is apparent from the graph that proposed technique having upper hand in fitness (accuracy) computation process. The research investigation shows that proposed technique having certain advantages like earlier convergence speed and higher global search accuracy than the existing individual algorithms GWO and WOA. The proposed technique converges in 400th iteration that is earlier settling performance over other comparative techniques.

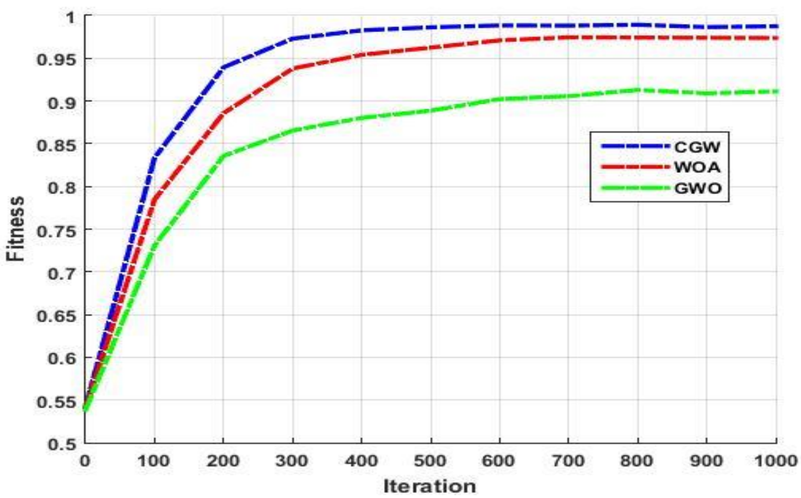

Figure: 13 converging performance of employed techniques

Conclusion

The purpose of predicting landslide successfully accomplished through DNN associates CGW optimization techniques. Identifying the optimal weights certainly reduces computational time and complexity over traditional approach. In average the proposed approach attains 97.75% accuracy that is 3.19% better than DNN-WOA, 2.44% greater than DNN-GWO and 7.75% better than traditional DNN. It is apparent from the performance measures that proposed model attains greater results over comparative techniques. The proposed model assists in identifying the landslide hazard assessment and mitigation of landslide-related losses; also preventing from affecting the population with significant socioeconomic damage and high economic losses. In the future, the research will examine the usability and suitability of other deep neural network architectures, e.g., Convolutional and Recurrent Neural Networks, for landslide prediction and compare their performance with the proposed approach of this study.

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