ISSN: 2182-2069 / E-ISSN: 2182-2077

Enriched Deep Neural Network Improved by Chaotic Harris Hawk Optimizer for Prediction of Behavioural Traits of Individuals

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Received: July 23, 2024; Revised: September 3, 2024; Accepted: October 2, 2024; Published: November 30, 2024

Abstract

The enduring patterns of thoughts, feelings, and behaviors that set one person apart from another are referred to as personality traits. A personality identification system could help a corporation find and hire suitable employees, enhance their business by understanding the preferences and personalities of their clients, and more. It necessitates the prediction of an individual's personality classification to determine their behavioural traits using machine learning models. The distribution of class labels significantly affects the training phase of the conventional classification and ensemble algorithms resulting in an overfitting problem and affecting the accuracy rate of personality classification. Hence, in this proposed work deep neural network with its dense layer understands the pattern of the personalities of individuals based on their behavioural traits using the questionnaire prepared based on the demographics, education, and employment attributes. However, the parameters used in the deep neural network are assigned using the gradient descent method that assigns random values. These values are adjusted on a trial-and-error basis using the backpropagation method. This issue is solved in this proposed work by improving the performance of the deep neural network by adopting the chaotic Harris hawk optimizer to fine-tune the hyperparameter of DNN such as weight, bias, and learning rate in dense layers of DNN. The prey searching behavior with the chaotic mapping balances both local and global searching overcomes the early convergence and achieves the highest accuracy rate compared with other algorithms like ensemble models and machine learning models. The simulation results conducted on 725 samples, 20 attributes for prediction of personality trait based on the behavioural characteristics by the proposed model Enriched Deep Neural Network improved by Chaotic Harris Hawk Optimizer Algorithm (EDNN-CHHOA) achieves a better accuracy rate of 0.98% compared with other algorithms.

Keywords: Deep Neural Network, Behavioral Traits, Chaotic Harris Hawk Optimizer.

Journal of Internet Services and Information Security (JISIS), volume: 14, number: 4 (November), pp. 511-523.
DOI: *10.58346/JISIS.2024.I4.032*

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1 Introduction

One crucial aspect of human psychology is personality. A person's personality reflects who they are, what they enjoy, and how they act in particular circumstances (Choi et al., 2019). The amount of information available to individuals at all socioeconomic levels has greatly increased as a result of the rapid advancement of new ICTs and their incorporation into people's daily lives in recent years. Platforms like LinkedIn and job search portals l are frequently used by job searchers (Chhabra et al., 2019). However, a greater number of commercial entities are utilizing their online management platform. The most important factor that reflects an individual's constantly changing personality is their personality (Rout et al., 2019). Typically, candidates send their resumes in the manner of a loosely organized document to online job boards, where an experienced recruiter must review it. In recent years, manual interviews and resumes have become increasingly important in human resources (Alper et al., 2021). Developing a plan that can expedite or shorten the HR department's workload is quite important.

In recent years HR employed the Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (OCEAN) model which are the five personality traits used to measure the potential employers and marketers to understand the customers of their products (Harari, 2020; Rajendran et al., 2021). The prediction of personality based on the behavioral characteristics of the individuals is done using Machine learning methods (Nguyen et al., 2021). As the volume of the dataset keeps on growing, using the conventional algorithms results in overfitting and affects the accuracy rate of the prediction of personality traits (Nguyen et al., 2020).

The Deep learning model plays a vital role in understanding the complexity of the pattern of behavioral characteristics to detect the personality of individuals (Wang et al., 2019; Zhang et al., 2018). In this proposed work, the Deep neural network improved by the Chaotic Harris Hawk Optimization Algorithm is developed to improve the accuracy rate of personality prediction of the individuals in the presence of a high degree of class imbalance in A set of questionnaires was created to determine an individual's behavioural traits (McGough et al., 2015; Dama et al., 2024). A survey with twenty items was used. The database held information on employment, education, and demography. The detailed process of the proposed work Enriched Deep Neural Network improved by Chaotic Harris Hawk Optimizer is discussed in the following sections.

The paper is arranged in the following manner: Section II covers the background study, and Section III analyses the preliminary studies conducted. Section IV presents the proposed framework and methodology. Section V explores the results and discussions and the paper concludes with Section VI.

2 Background Study

A. Related Study

In the medical industry, a humongous amount of data is generated, but this data is not properly used. We can use this data for the better delivery of healthcare services in a systematic way (Harari, 2020). The study aims to identify individuals with behavioural disorders and categorize them based on their traits.

Sai, (2023) used NLTK library to evaluate and pre-process the data using four machine learning models to predict the personality traits. The outputs of the machine learning models to identify the best one using evaluation measures (Vaishnavi et al., 2022). Moreover, this can be applied to the customization of online advertising campaigns and advertisements. Social media businesses can also use it to draw people to follow their interests and personality features (Van der Laan et al., 2020).

Murari and Bharathi (Kamalesh & Bharathi, 2022) put their effort into estimating user personality using the big five personality traits (Alizadeh et al., 2018). To find correlations between feature sets and qualities from datasets, a novel Binary-Partitioning Convertor with Term Frequency and Inverse Gravity Instant is developed. This approach performs better than the baseline set's all-feature extraction average.

Chincholkar et al., (2023) carried out a thorough study in which they classified people's personalities using the regression technique. Moreover, NLP is used by computers to comprehend and speak human languages. Many previous studies have tried to determine a person's personality type automatically. The classification of people according to their personality types is one of the most significant uses of machine learning algorithms (Srividya et al., 2018). These forecasts can be used by anyone to choose a job or other interest.

According to (Yung & Sze, 2024) findings, distinct behavioural patterns may anticipate the major five personality traits in different ways. They might enable inexpensive, questionnaire-free research on personality-related subjects at a never-before-seen scale. The behavioural data is collected through smartphone sensing techniques and machine learning models.

Xu et al., (2021) demonstrates statistically that significant predictions regarding a broader variety of personality qualities for men and women can be made using real-life static facial contour photos. To assess the possible association between static face contour photos and personality traits, we have developed a multi-viewpoint hybrid personality-computing model, which helps us achieve the goal of a thorough understanding of an individual's personality traits. Their findings demonstrate that utilizing static facial contour photos, a deep neural network built by huge labeled datasets can accurately predict people's multidimensional personality traits.

The study conducted (Tadesse et al., 2018) uses a variety of Big 5 model components and metrics to investigate the predictability of personality traits among Facebook users. The authors examine the frequency of language components and social network structures in connection to personality interactions using the Personality Analysis Project data set. They compared and analyzed four machine learning models to ascertain the relationship between each feature set and personality attributes. Even when tested with an identical data set, the prediction accuracy results show that the XGBoost algorithm for the personality prediction system surpasses the average foundation for all the sets of features with the highest prediction accuracy.

The efficacy of college students is predicted using a method based on IQ quotient, personality traits, and personal data. El-Keiey et al., (2022) suggested five machine learning approaches were applied. Several performance metrics were calculated using a dataset of actual students to assess the suggested method's effectiveness (Sun, 2024). To determine how different aspects affected the students' performance, several tests were conducted (Das & Rajini, 2024). When evaluated on the dataset, the suggested method produced encouraging results.

Christian et al., (2021) devised a model to extract characteristics from social media data sources. They developed a novel prediction that combines numerous pre-trained language models, with a multi-model deep learning architecture (Su et al., 2020). To create a prediction, the system finally decides to use model averaging. The suggested work uses numerous social networking data sources and produces a model of prediction for every characteristic using bidirectional terms feature incorporated with extraction method, in contrast to the prior research which utilizes one source of behavioural media data with open- and shut-off phrases obtaining approach.

3 Preliminaries

A. Motivation

A Deep Neural Network (DNN) (Kenton & Toutanova, 2019) is a form of Artificial Neural Network that consists of several layers that serve as a bridge between the layers of input and output (Chincholkar et al., 2023; Nguyen et al., 2020). Neural networks, which are primarily inspired by how the human brain functions, are made up of neurons acting as nodes and parameters like weights and biases sending information to the connections that connect layers one and two. A sophisticated non-linear relationship is built with DNN. Using this design, items are generated in a compositional manner that depicts them as layers (Ibrahim et al., 2020).

- **Data Normalization using Min-Max**

The raw dataset is pre-processed to convert them within range of 0 and 1 using min max normalization as formulated in equation (1).

$$MMN(I) = \frac{I_{att} - Min(X)}{MAX(X) - MIN(X)} \quad (1)$$

Where I_{att} refers to Ith instance specific attribute, Min and Max are the minimum and maximum values of the specific attribute.

- **Working on Deep Neural Network**

As illustrated in Figure 1, DNN operates as a feed-forward network, with data traveling straight from the data source layer to the subsequent level and finally to the output layer.

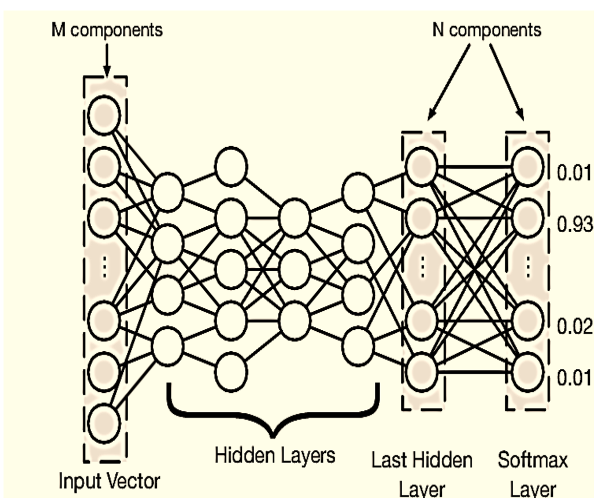

Figure 1: Architecture of Deep Neural Network

The DNN builds a map of virtual neurons and gives links between layers that appear before and after random weighting factors. An output ranging from zero to one is produced by multiplying and adding the weights as well as input values using the activation function. When the expected and observed outputs differ from one another, the difference is referred to as an error. The weight values are changed by a backpropagation technique, which makes the parameters increasingly significant until the approved accuracy rate is found. Figure 2 displays the DNN with an input layer, multiple dense intermediate layers, and an output layer.

4 Methodology

The overall working principle of the newly devised enriched Deep Neural Network is boosted with a chaotic Harris Hawk optimizer Algorithm for the prediction of the behavioural traits of individuals.

A. Proposed Framework of Enriched Deep Neural Network Improved by Harris Hawk Optimizer for Prediction of Behvarioral Traits of Individual

The proposed framework is summarized in Figure 2. The framework illustrates the steps of the presented approach. Initially, the raw dataset collected through the survey comprised 725 samples with five class labels and twenty attributes pre-processed by the min-max normalization to treat all the data values equally (Chen et al., 2021). After pre-processing, the input data is passed to the deep neural network comprised of one input layer, one output layer, and many dense layers (Ali & Zhang, 2022). The Deep neural network, determines the potential features using its filter vectors and those are used for further understanding of the data patterns. The hyperparameters in the dense layers like learning rate, weight, and bias values are assigned using the prey-searching behavior of the Harris hawk instead which balances both local and global searching using the chaotic mapping principle. A detailed explanation of the proposed EDNN-CHHOA is given in the following section.

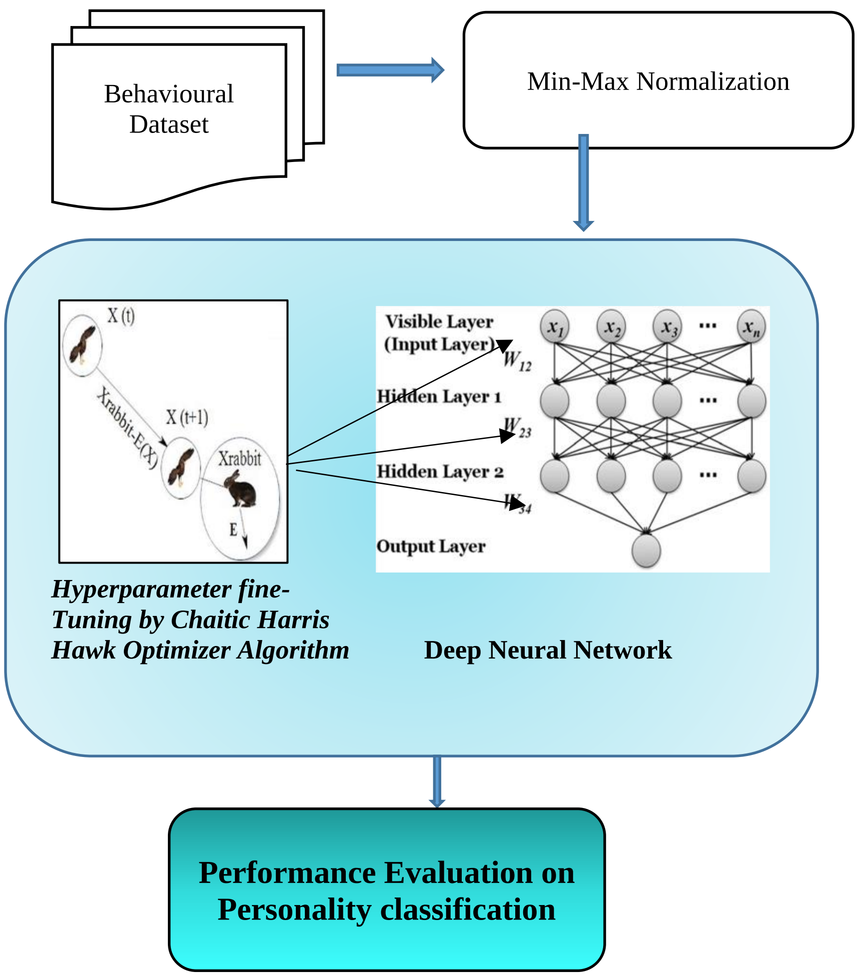

Figure 2: Proposed Framework for EDNN-CHHOA

B. Chaotic Harris Hawk Optimizer Method

The main benefits of the Harris Hawks community approach (Gezici & Livatyalı, 2022; Li et al., 2023), which is inspired by crowd intelligence, are its cooperative behavior and elegant surprise pounce hunting style (Chen et al., 2021). Every search element or hawk works together to pounce on prey at various positions while pursuing the objective, as shown in Figure 3. This process is used to identify the ideal target inside the intricate search space.

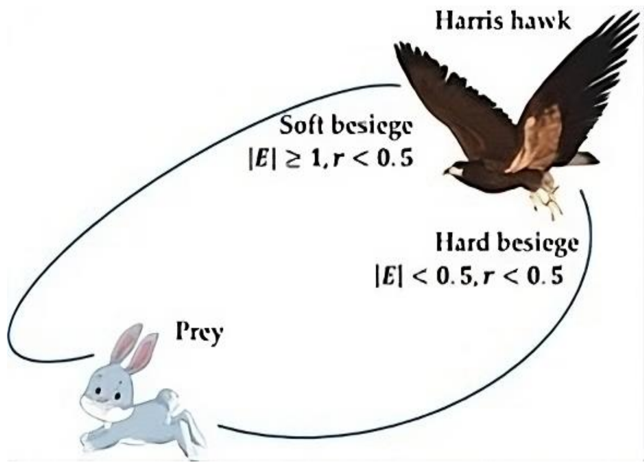

Figure 3: Prey Searching Strategy of Harris Hawk

C. Exploration Stage

Every searcher visits each place at random and seeks to identify an ideal spot based on the following equations (2).

$$Z(t+1) = \begin{cases} Z_\rho(t) - h1|Z_\rho(t) - 2h_2 Z(t)| & R \geq 0.5 \\ (Z_B(t) - Z_m(t)) - h_3(\mathbb{LB} + h_4(\mathbb{UB} - \mathbb{LB})) & R < 0.5 \end{cases} \quad (2)$$

The location path of the search agent (Harris hawk) is $Z(t+1)$ at the period t+1, the subsequent group of rabbit is $Z_B(Gong\ et\ al., 2021)$. The current location of exploration agent is Z(t), arbitrary facts are R, h_1, h_2, h_3 and h_4 whose values lies between (0,1) (Ali & Zhang, 2022). These values are updated during each iteration, the lower and the support bound for the search agent is defined by the parameters $\mathbb{UB}$ and $\mathbb{LB}$. $Z_\rho(t)$ is the random search agent chosen and the current crowd's mean position is signified as Z_μ. The average position of the searching agent is formulated as

$$Z_\mu(t) = \frac{1}{M}\sum_{j=1}^{M} Z_j(p) \quad (3)$$

Where $Z_j(p)$ is the present location of each searching hawk, t is the iteration and M is the total number of search agent population show the above equation (3) (Uyulan et al., 2021; Wang et al., 2021).

D. Exploitation phase

During this phase, the prey's energy is determined using the formula (equation (4)).

$$G = 2G_0(1 - \frac{t}{TE}) \quad (4)$$

Where G, TE, and G_0 are the targets escaping energy, total generations, and energy's initial state as shown in Figure 4.

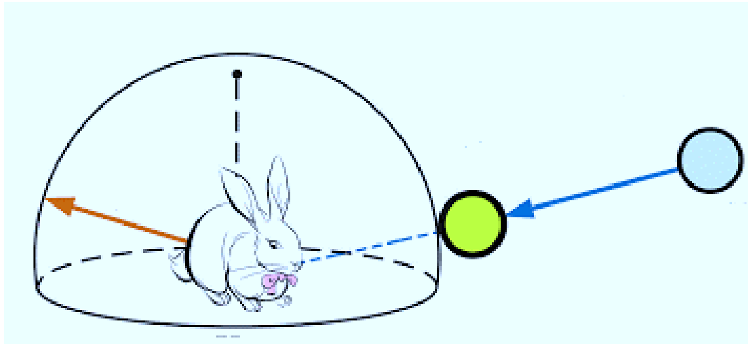

Figure 4: Rabbits as Prey's Position and Energy Computation

During the exploitation phase, two behaviors need to be emulated (Gezici & Livatyalı, 2022). The first behavior, known as mild besiege, allows the rabbit to quickly escape while its energy is still high. Harris hawks attempt to follow it cautiously in this instance and observe it until it grows weary. In this activity, the victim is tired and unable to escape while under heavy siege. Thus, to execute a surprise assault, the Harris hawks create closed circles in this mode (Guo et al., 2020).

This condition indicates that the prey or rabbit has a relatively high escaping energy (G) and a larger than 50% chance of successfully fleeing (TE) when $G \geq 0.5$ and $G_0 \geq 0.5$ (Heidari et al., 2019). Next, the Harris Hawk displays gentle besiege behavior (Agarwal & Karthikeyan, 2022; Chauhan et al., 2019). The search agent achieves these actions by applying the subsequent formula in equation (5) and (6).

$$Z(t+1) = \Delta Z(t) - G|KZ_B(t) - G(t) \quad (5)$$

$$\Delta Z(t) = Z_B(t) - G(t) \quad (6)$$

The following formula represents the rabbit's random leap strength based on its escape strategy in equation (7).

K = 2(1-h5) (7)

$\Delta Z(t)$ stands for variance in the rabbit's location vector, h5 for a random number, and s for the generation's current position. Every iteration, the value of J will be randomly modified to mimic the characteristics of a rabbit (Agarwal & Karthikeyan, 2022; Ibrahim et al., 2020).

When $G \geq 0.5$ and $G_0 < 0.5$, the rabbit is said to be highly energetic. But the chances of escaping successfully are slim because Harris hawks engage in swift dives and progressive soft besiege. The hawks' next move is updated mathematically in equation (8) and (9).

$$V = Z_B(t) - G|Z_B(t) - Z(t)| \quad (8)$$

All agents' current locations in Hard Besiege are updated as,

$$Z(t+1) = Z_B(t) - G|\Delta Z(t)| \quad (9)$$

The Hawks compares the current position to the previous dive and decide which is superior. If the prior dive is exceptional, the Hawks will adopt it. If not, the Hawks will make a new dive using the levy flight (Zhang & Yue, 2024).

W= PL + RV * ℘(C) (10)

The variables PL, RV, C, and represent the current location, problem dimension, and levy flight, respectively in equation (10) and (11) (Chauhan et al., 2019; Tian et al., 2023). All personnel must change their positions in both soft and strong besiege scenarios (Mostafa, 2024; Zhang & Yue, 2024).

$$Z(t+1) = \begin{cases} PL, & F(PL) < \wp Z(t) \\ W, & F(W) < \wp Z(t) \end{cases} \quad (11)$$

5 Experiments & Results

This section discusses the performance of the proposed Enriched model of Deep Neural Network boosted by the chaotic Harris howk optimization algorithm (EDNN-CHHOA). The EDNN-CHHOA model is deployed using Python software. The behavior dataset is collected from the survey with 725 samples, 20 attributes comprised of personality traits and demographics, and class labels with 5 different categories. The training-to-testing ratio was established at 90: 10, with ten-fold cross-validation. Following splitting, the testing set consists of 73 samples, while the training set consists of 652 samples. The evaluation metrics used for discovering the reliability of the EDNN-CHHOA are accuracy, precision, recall, and f-measure. The existing algorithms used for comparison are SVM + Bayesian Optimizer, Enhanced Learner, and Deep Neural Network

Table 1: Results of Classification Performance Accuracy

Algorithm	Accuracy	Precision	Recall	F-Measure
SVM + Bayesian Optimization	0.94	0.91	0.92	0.91
Enhanced Learner	0.97	0.96	0.97	0.96
Deep Neural Network	0.96	0.95	0.96	0.95
EDNN-CHHOA	0.98	0.97	0.98	0.97

Table 1 explores the results obtained by four different classification models in the prediction of a person’s behavioral traits. The enriched model of Deep neural network with the knowledge of the chaotic Harris Hawk Optimizer algorithm improves the accuracy rate of predicting personal characteristics. The class imbalance and overfitting problem are well treated in the proposed EDNN-EHHOA while comparing with other existing classification methods.

Figure 5 explores the performance of the accuracy of four different classification models involved in the prediction of behavioral traits of a person.

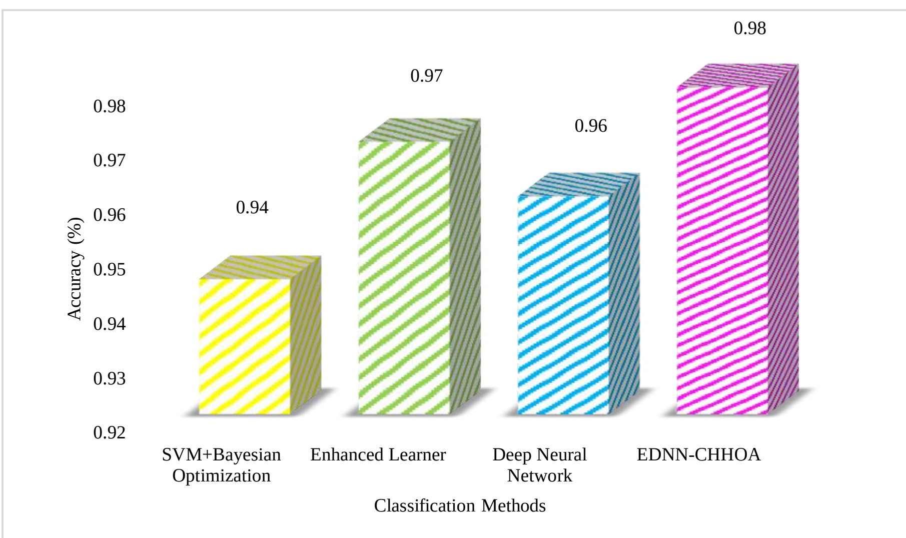

Figure 5: Comparative Analysis based on Accuracy

The enriched model of deep neural network processes the input data with the inbuilt feature extraction process using filters and they are passed to the next level of dense layer. The learning rate and the weight parameters are fine-tuned by applying the Chaotic Harris Hawk optimizer which handles the problem of local optima with the chaotic map and achieves global optimization by optimizing the assignment of values to the hyperparameters. Thus, the EDNN-CHHOA achieves the highest accuracy value of 0.98% in the prediction of individual's behavior.

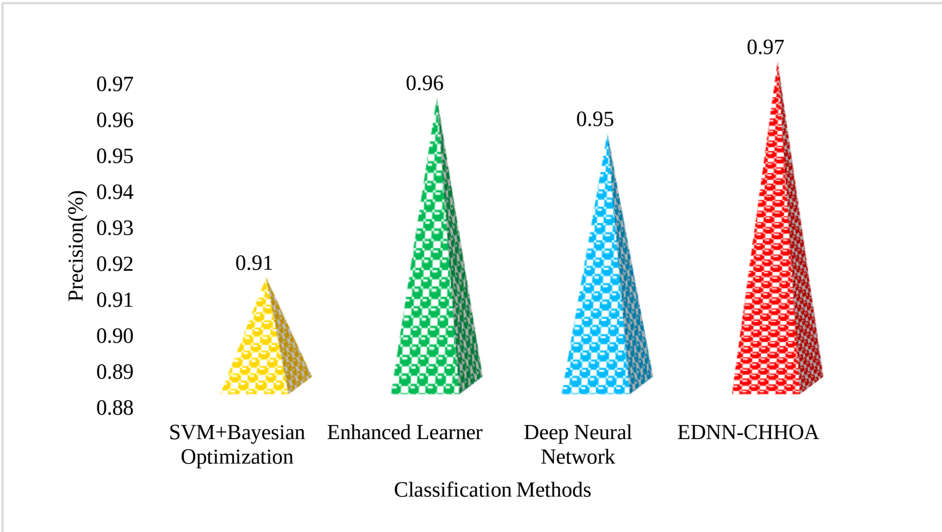

Figure 6: Comparative Analysis based on Precision

The comparative results based on the Precision value of four different prediction models for the behavioural traits of a person are illustrated in Figure 6. Without performing external feature selection, the enriched model of the Deep neural network conducts a sub-sampling process and filters potential features from the input. In the fully connected layer during the training phase hyper-parameter values are optimized by inducing prey-searching behavior of the Harris Hawk optimizer algorithm. Henceforth, the newly devised the EDNN-CHHOA achieves highest precision value of 0.97% in the prediction of an individual's behavior.

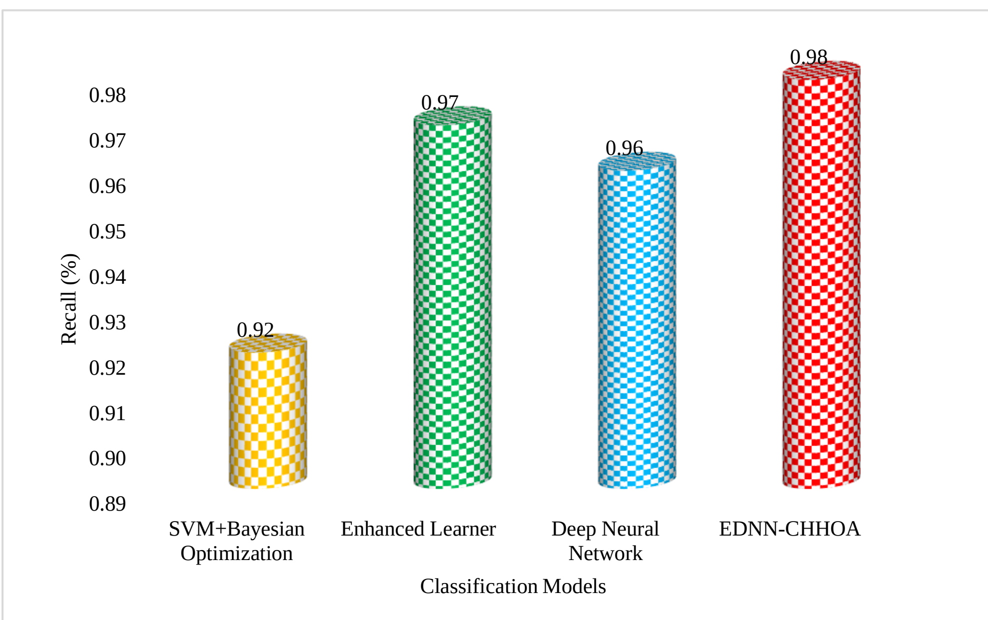

Figure 7: Comparative Analysis based on Recall

Figure 7. reveals the result of four prediction models Recall value for the prediction of a person’s behavior pattern. The problem of backpropagation in assigning the hyperparameters on a trial-and-error basis that affects the accuracy rate of the behavioral prediction is overcome by developing an enriched model of deep neural network that utilizes the prey searching behavior of the Harris Hawk Optimizer to select the best set of values to the hyperparameters to understand the pattern of inputs and classify them more accurately. While compared with other existing models the proposed EDNN-CHHOA achieves the highest recall value of 0.98% in prediction of individual’s behavior.

The performance of the F-Measure of four distinct categorization models that predict a person's behavioural attributes is examined in Figure 8.

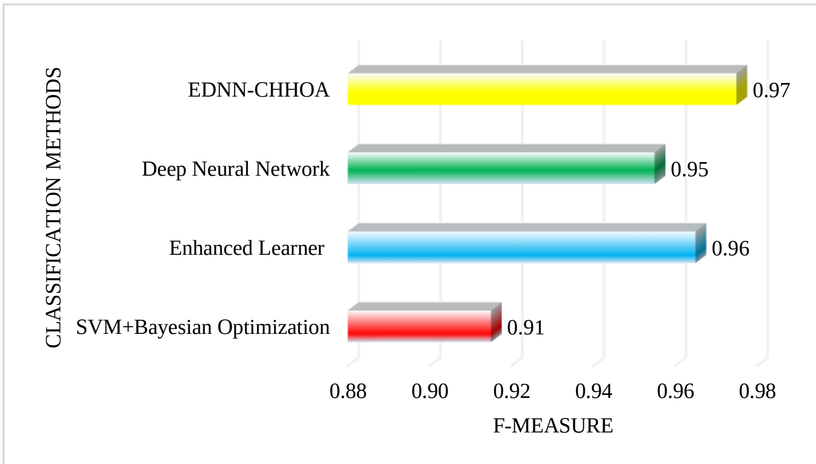

Figure 8: Comparative Analysis based on F-Measure

The input data is processed by the enriched model of a deep neural network employs filters to extract built-in features before being sent to the next dense layer. By using the Chaotic Harris Hawk optimizer, which addresses the issue of local optima with the chaotic map and accomplishes global optimization by optimizing the assignment of values to the hyperparameters, the learning rate and weight parameters are adjusted. The EDNN-CHHOA predicts individual behavior with the greatest F-Measure value of 0.97%.

6 Conclusion

This paper aims to devise an enriched model of deep learning paradigm for predicting the individual’s personality based on their behavior. The major issue in the prediction of personality identification is the class imbalance and insufficient distribution of instances leads to overfitting problems while using the traditional classification models especially deep learning algorithms. Hence, this research work focuses on handling the class imbalance by devising a chaotic Harris hawk optimizer in fine-tuning the learning parameters, weight, and bias parameters of the fully connected layer which are the major components of predicting the outcomes in the prediction of a person's characteristic depending on their behavior traits. The simulation results proved that the preying searching behavior of CHHOA optimizes the accuracy rate of EDNN based on the fitness value computation on the hyperparametric value assignment process instead of using the gradient descent method. Thus, compared to other state-of-the-art models involved in the prediction of individual personality classification, the proposed EDNN-CHHOA accomplishes its objective of improving the detection rate more prominently.

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