Intelligent System for Body Fat Percentage Prediction

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Abstract

Excessive fats in human body results in obesity, which is generally linked to various illness like heart diseases, diabetes, etc. Therefore, determining the quantity of body fat becomes essential to save the human health. Though numerous approaches are available in determining body fat percentage (BFP), intelligent and accurate models can be designed using artificial intelligence (AI) techniques. Conventional single stage methods utilized particular readings from the body or explanatory parameters in predicting BFP. In this view, this study develops a new Gravitational Search Optimization with Neutrosophic rule-based Body Fat Percentage Prediction model. The presented model intends to appropriately determine the level of BFP in an effective and automated way. To accomplish this, the proposed model follows a two-stage process namely prediction and parameter optimization. At the initial stage, the model derives a new neutrosophic set based rule classifier to determine the BFP. Secondly, the membership function in the rule based model is optimally chosen by the use of GSO algorithm and thereby results in enhanced predictive outcomes of the classification model. A wide ranging simulation analysis is performed and the results are inspected under several dimensions.

Keywords: Intelligent Systems; Body fat percentage; Obesity; Body mass index; Neutrosophic set, Rule based classifier.

1. Introduction

Obesity is a general medical issue around the world. Analysts anticipate that corpulence causes a few significant medical problems, for example, disposition issues, cardiovascular illnesses, respiratory infirmities, and stomach related issues. In the clinical, medical services, and wellness areas, a not set in stone as corpulent by ascertaining the individual's body mass index (BMI), which considers the individual's body weight separated by body stature square [1, 2]. BMI is a useful estimation, especially for populace based screening. Be that as it may, subgroups of stout people with ordinary metabolic wellbeing however a higher BMI or large people with poor metabolic wellbeing yet a normal BMI exist [3]. In this way, BMI probably won't catch individuals at a higher gamble of cardio-metabolic issues, like sort 2 diabetes and cardiovascular illness.

The absence of successful data from BMI changed analysts' concentration to body fat rate (BFP), which estimates fat in the body and gives a more precise appraisal [4]. In any case, to scrutinize how much corpulence and forestall it, it is basic to exactly survey BFP.In clinical practice, general wellbeing and the more extensive wellbeing and wellness industry, weight is traditionally characterized utilizing the BMI standard, with a worth of ≥ 30 kg/m2 sorting all kinds of people as large [5]. Despite the fact that there are many advantages to utilizing BMI, especially for populace based screening, proof shows the presence of stoutness sub-gatherings, for example, metabolically sound yet large, or metabolically unfortunate yet ordinary weight [6, 7]. In this manner, utilization of BMI just, is possibly missing the

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mark concerning distinguishing those at an expanded gamble of related conditions, specifically cardio-metabolic infections. Fig. 1 shows the different BFP of men.

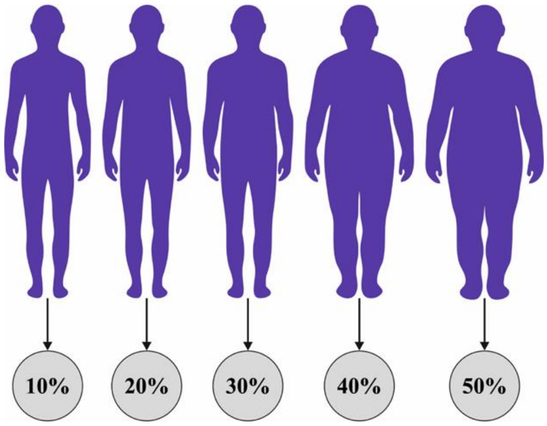

Figure 1: Illustration of different BFP of men

Keeping a decent BFP is an absolute necessity for human wellbeing. In any case, precise and advantageous ways of estimating body fat are not clear [8]. For instance, the hydrostatic weighing was accounted for to be a dependable technique for the estimation of body fat substance, yet it isn't advantageous [9]. Another innovation, DEXA, is exceptionally exact and exact to quantify the body fat. Notwithstanding, DEXA might experience the ill effects of normalization issues; that is, results might differ with the particular gear producer, information assortment strategies, or potentially programming investigation. Thusly, it is attractive to have a few helpful strategies to foresee the BFP. While a few normal examinations have utilized information mining methods to group the presence of specific infections [10], the current review centers around the improvement of smart determining strategies to really anticipate the BFP. The body fat datasets utilized in this study were genuine information. A few examinations have utilized numerous relapse procedures to construct a guaging model to gauge the BFP. Be that as it may, the MR models are censured for its solid presumptions like variety homogeneity.

Uçar et al. [11] intends to decide BFP utilizing hybrid AI strategies with high precision rate and least boundary. Different element bunches were made with highlight choice calculation. In the following stage, 4 distinct models were made by utilizing MLFFNN, SVMs, and DT relapse models. The outcomes show that the created framework can be utilized to assess BFP practically speaking. In addition, the framework can ascertain BFP with only one anthropometric estimation without gadget prerequisite. Alves et al. [12] propose a methodology with some expertise in orientation to appraise body fat rate utilizing AI. One more commitment of this work is a dataset, BodyFat-163 (BF-163), containing the 12 anthropometric measures and the body fat rate from DXA tests gathered by a trained professional. Hussain et al. [13] proposed a crossover AI model in view of SVR-EANNs for exact ongoing BFP forecast utilizing an essential BFP dataset. SVR was applied as a steady quality determination model on seven properties and estimations, utilizing the left-out awareness investigation, and the relapse capacity of the EANN was considered in the forecast stage. Fan et al. [14] proposed a RE-SVM for BFexpectation. We first plan a fuzzy weighted activity, which applies fuzzy loads to the blunder limitations of the RE-SVM, to lighten the impact of commotion information. Then, we additionally apply the fluffy loads to work on the Gaussian portion by thinking about the significance of various examples.

This study develops a new Gravitational Search Optimization with Neutrosophic rule-based Body Fat Percentage Prediction called (GSONR-BFPP) model. The presented GSONR-BFPP model intends to appropriately determine the level of BFP in an effective and automated way. To accomplish this, the GSONR-BFPP model follows a two-stage process namely prediction and parameter optimization. At the initial stage, the GSONR-BFPP model derives a new neutrosophic set based rule classifier to determine the BFP. Secondly, the membership function in the rule based model is optimally chosen by the use of GSO algorithm and thereby results in enhanced predictive outcomes of the classification model. A wide ranging simulation analysis is performed and the results are inspected under several dimensions.

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2. The Proposed GSONR-BFPP model

This study has introduced a novel GSONR-BFPP model to appropriately determine the level of BFP in an effective and automated way. The GSONR-BFPP model follows a two-stage process namely prediction and parameter optimization. At the initial stage, the GSONR-BFPP model derives a new neutrosophic set based rule classifier to determine the BFP. Secondly, the membership function in the rule based model is optimally chosen by the use of GSO algorithm and thereby results in enhanced predictive outcomes of the classification model.

2.1 Process involved in Neutrosophic Set based Rule Classifier

Primarily, the GSONR-BFPP model derives a new neutrosophic set based rule classifier to determine the BFP [15]. The projected Neutrosophic rule based classifier employs Neutrosophic Logic (NL) to generalize the fuzzy rule-based classifier technique. The consequent and antecedent of "IF-THEN" rules in the NRCS are neutrosophic logic statement, rather than fuzzy logic one. The NRCS contains three phases: Deneutrosophication, Neutrosophication, and Inference Engine.

Data extracting stage

Here, significant data are extracted through extracting and reading data records

- the amount of characteristics
- the minimal and the maximal values of characteristic,
- the amount of classes and the names, and
- the decisions or class labels.

Neutrosophication stage

Here, the three functions, i.e., indeterminacy, truth, and falsity are extracted from the fuzzy-Trapezoidal membership function. Next, they are employed on all the values for all the attributes to attain the neutrosophic component < T; I; F > i.e., utilized for representing all the features.

Rules generation stage

The aim is to make rules that is utilized in the following state (classification stage). Consider the information is represented as $X = \{x_1, x_2, \dots, x_n\}$, whereas xi symbolizes the i-th instance and n represent the overall amount of instance. All the samples have one class label that is represented as $c_i \in \{1, 2, \dots, C\}$, whereas C denotes the overall amount of classes. Firstly, the data set is separated into trained information $(X_{training})$ and tested information $(X_{testing})$. Here, neutrosophic rules are created from the trained and tested information. The trained rule is represented as $R_{training} = \{r_{tr}^1, r_{tr}^2, \dots, r_{tr}^{ntr}\}$, whereas r_{tr}^i denotes the rules for the i-th trained instance and n_{tr} indicates the amount of trained instance. Likewise, the tested rule is represented as $R_{testing} = \{r_{ts}^1, r_{ts}^2, \dots, r_{ts}^{ntr}\}$, whereas ri ts indicates the rules for i-th tested instance and nts denotes the amount of tested instances. In NRCS, the characteristic in neutrosophic rules have three mechanisms $< T, I, F >$.

Classification stage

Here, for all the tested rules $(r_{ts}^i \in R_{testing})$, the Euclidean distances among a tested and trained rules $(R_{training})$ is estimated.

2.2 GSO based Parameter Tuning Process

At the second stage, the membership function in the rule based model is optimally chosen by the use of GSO algorithm and thereby results in enhanced predictive outcomes of the classification model. GSO method is called as a novel approach that depending upon the law of gravity [16, 17]. The agent presents in GSO are presumed as object and mass. Agent is stimulated by each other through a gravity force. When the quality become high, then the gravity become strong. Therefore, location of agent using high mass is called as optimal solution.

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Consider N agent have d-dimension whereas the location of ith agent is shown below,

$$X_{\mathrm{i}} = \left(x_i^1, x_i^2, \ldots, x_i^d\right)\ (\mathrm{i} = 1,2,\ldots,N). \tag{1}$$

During a tth time, the force work on ith agent from jth agent that is expressed by,

$$F_{ij}^d = G(\mathrm{z}) \frac{M_i(\mathrm{z}) M_j(\mathrm{z})}{R_{ij}(\mathrm{z}) + \varepsilon} \left(\mathrm{x}_j^d(\mathrm{z}) - \mathrm{x}_i^d(\mathrm{z})\right), \tag{2}$$

Whereas $M_i(\mathrm{z})$ and $M_j(\mathrm{z})$ represented as masses of ith agent and jth agent, $G(\mathrm{z})$ indicates a gravitation constant at zth time, ε denotes a low constant, and R_{ij} shows the Euclidian distance from ith and jth agents. Fig. 2 shows the flowchart of GSO algorithm.

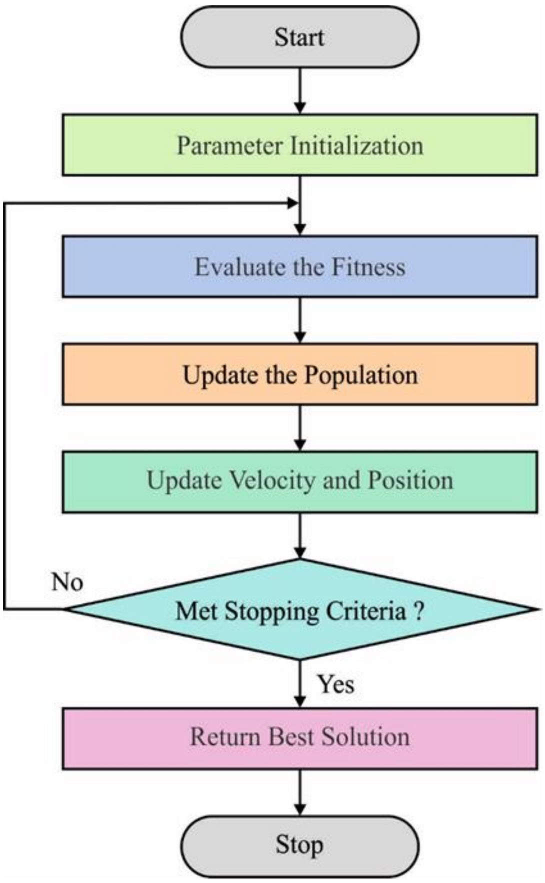

Figure 2: Flowchart of GSO Algorithm

During zth time, complete force is utilized on ith agent as follows:

$$F_{\mathrm{i}}^d(z) = \sum_{j=1, j \neq i}^{N} \mathrm{rand} \cdot F_{\mathrm{ij}}^d(\mathrm{z}), \tag{3}$$

In which $rand$ denotes an arbitrary parameter within [0, 1].

According to the law of motion, the acceleration of agent in zth time is shown below:

$$a_i^d(\mathrm{z}) = \frac{F_i^d}{M_i(\mathrm{z})}. \tag{4}$$

For all the iteration method, position and velocity of ith agent get upgraded as follows:

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$$v_i^d(z+1) = \text{rand} \times v_i^d(z) + a_i^d(z), \quad (5)$$

$$x_i^d(z+1) = x_i^d + v_i^d(z+1), \quad (6)$$

Whereas $rand$ denotes an arbitrary parameter within [0, 1] and $x_i^d(z)$ and $v_i^d(z)$ denotes the present location and velocity.

3. Experimental Analysis

This section investigates the BFP prediction outcomes of the GSONR-BFPP model using a benchmark dataset [18] from Kaggle repository. The results are assessed under five distinct runs of execution. Fig. 3 showcases the actual and predicted outcomes of the GSONR-BFPP model under run-1. The figure indicated that the GSONR-BFPP model has showcased effectual outcome. It is observed that the GSONR-BFPP model has predicted the BFP values closer to the actual values.

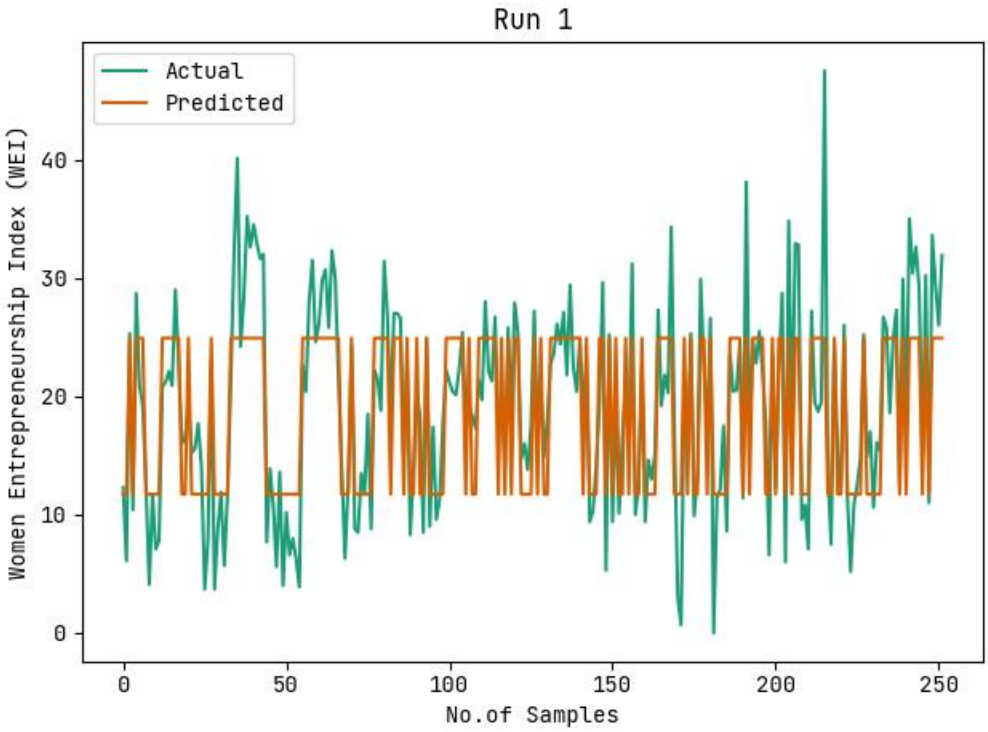

Fig. 3. Actual vs Predicted Outcomes of GSONR-BFPP model on run-1

Fig. 4 illustrates the actual and predicted outcomes of the GSONR-BFPP model under run-2. The figure designated that the GSONR-BFPP model has displayed proficient performance. It is detected that the GSONR-BFPP model has predicted the BFP values closer to the actual values.

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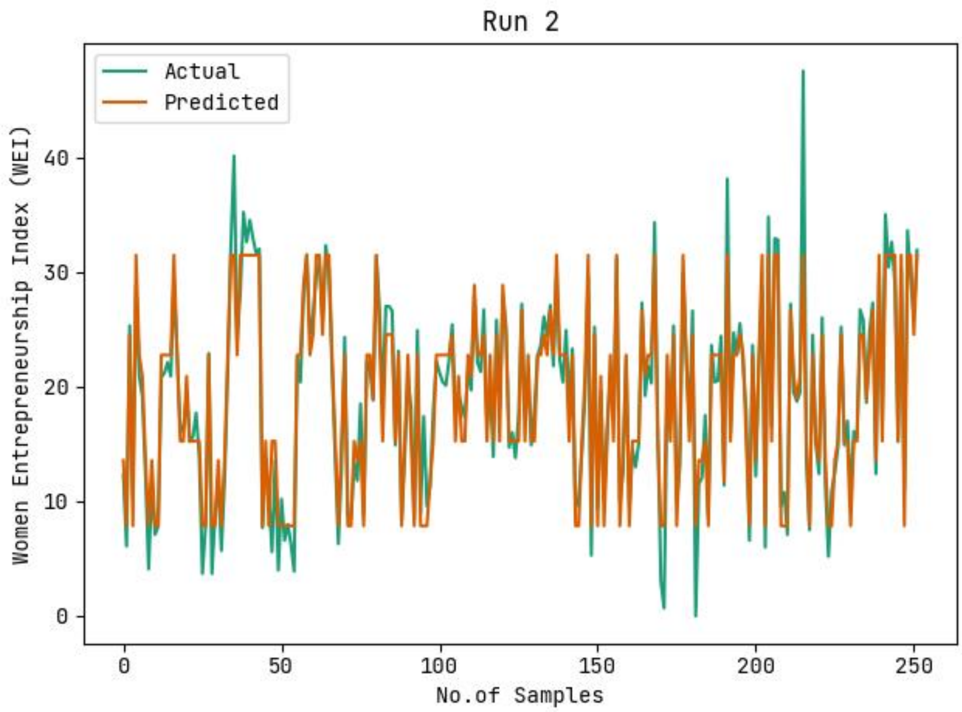

Figure 4: Actual vs Predicted Outcomes of GSONR-BFPP model on run-2

Fig. 5 reports the actual and predicted outcomes of the GSONR-BFPP model under run-1. The figure specified that the GSONR-BFPP model has showcased proficient performance. It is witnessed that the GSONR-BFPP model has predicted the BFP values closer to the actual values.

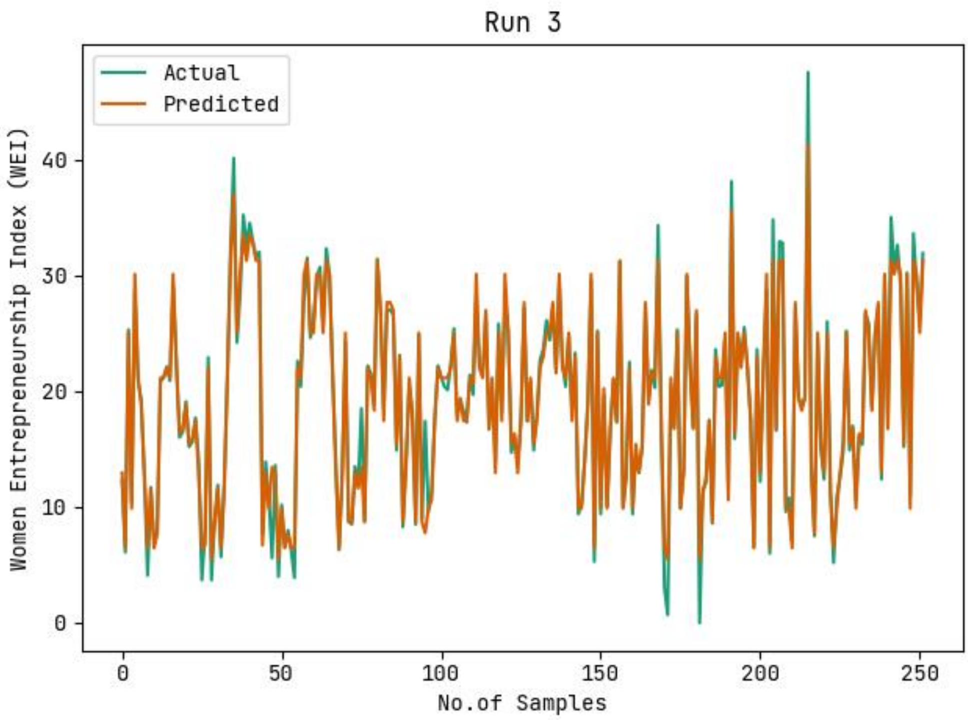

Figure 5: Actual vs Predicted Outcomes of GSONR-BFPP model on run-3

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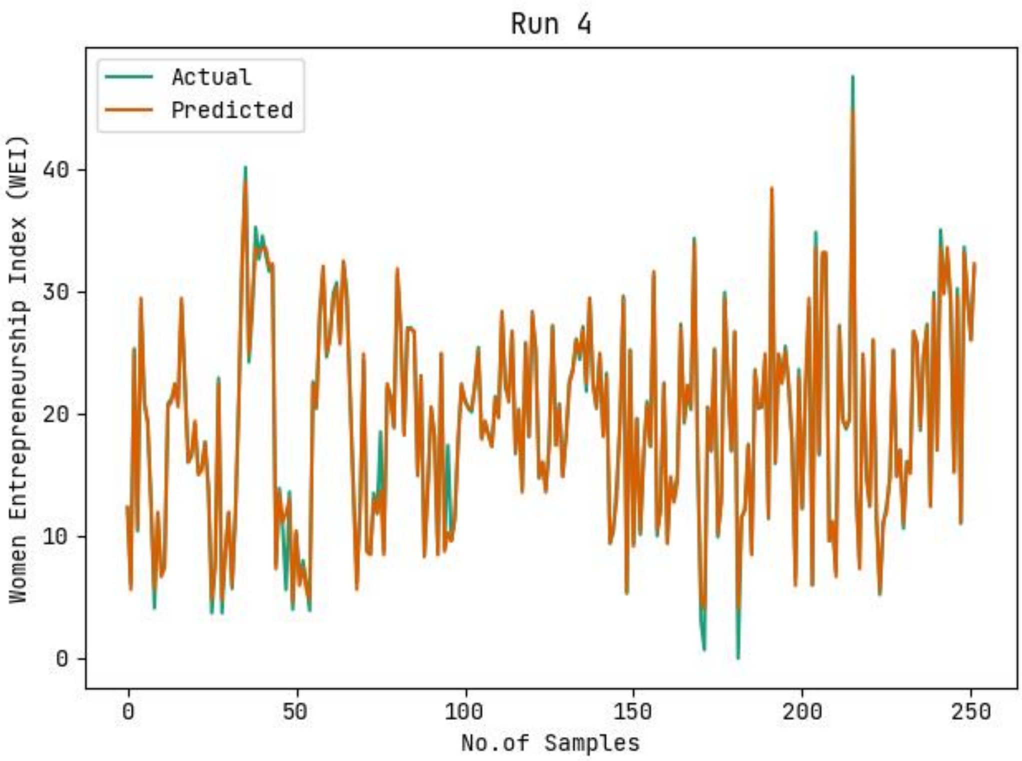

Figure 6: Actual vs Predicted Outcomes of GSONR-BFPP model on run-4

Fig. 6 depicts the actual and predicted outcomes of the GSONR-BFPP model under run-1. The figure showed that the GSONR-BFPP model has resulted to improved performance. It is perceived that the GSONR-BFPP model has predicted the BFP values closer to the actual values.

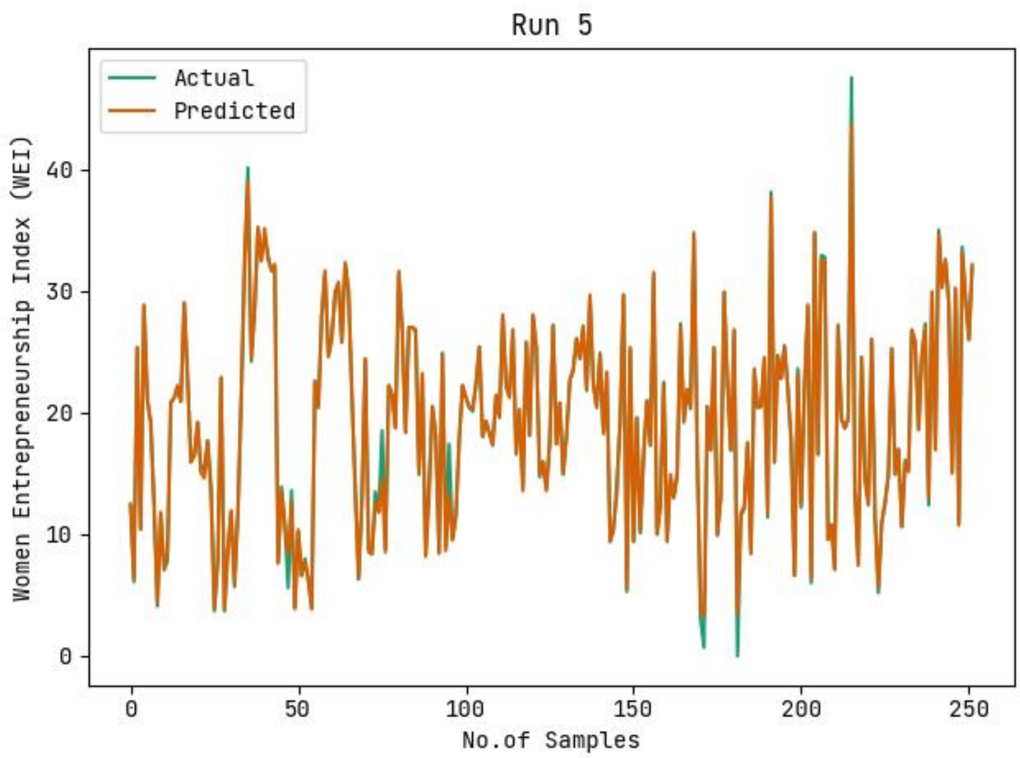

Figure 7: Actual vs Predicted Outcomes of GSONR-BFPP model on run-5

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Fig. 7 exhibits the actual and predicted outcomes of the GSONR-BFPP model under run-1. The figure directed that the GSONR-BFPP model has showcased effectual outcome. It is observed that the GSONR-BFPP model has predicted the BFP values closer to the actual values.

Table 1 and Fig. 8 provides a detailed BFP prediction outcomes of the GSONR-BFPP model in terms of different measures. The experimental values indicated that the GSONR-BFPP model has resulted to effective predictive outcomes. The GSONR-BFPP model has obtained MSE of 0.35. At the same time, the GSONR-BFPP model has obtained RMSE of 0.59. Followed by, the GSONR-BFPP model has resulted to MAE of 0.24. At last, the GSONR-BFPP model has attained R2-score of 0.99.

Table 1: Prediction outcomes of GSONR-BFPP model

Metrics	Values
Mean Squared Error	0.35
Root Mean Squared Error	0.59
Mean Absolute Error	0.24
R2-Score	0.99

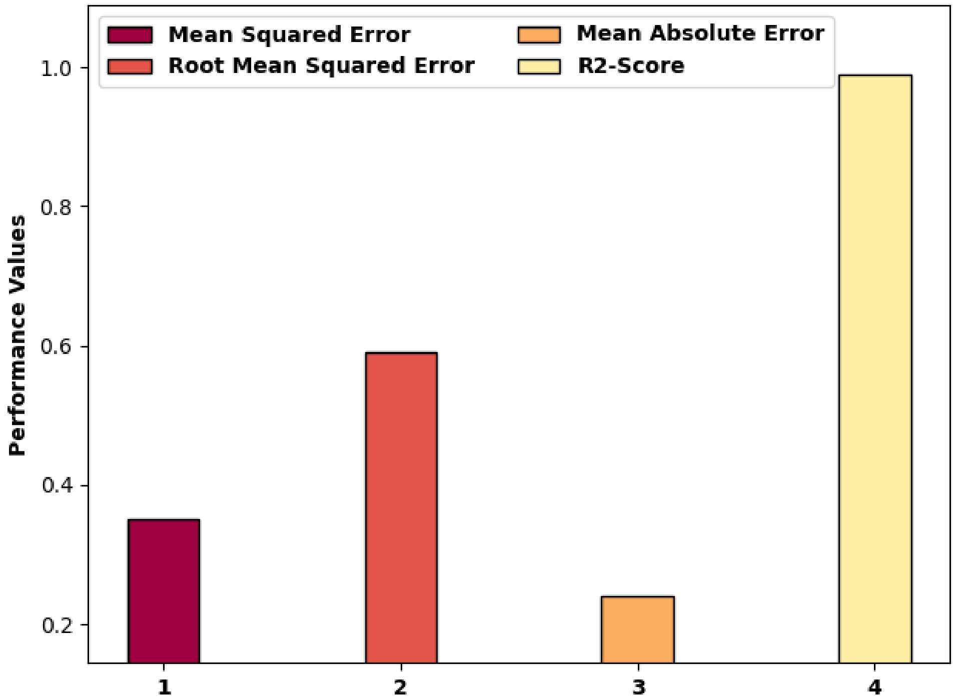

Figure 8: Performance analysis of GSONR-BFPP model

For ensuring the betterment of the GSONR-BFPP model, a wide range of simulations were carried and compared with existing models [19] in Table 2 and Fig. 9. The results indicated that the MR-ANN and MR-SVR models have showcased poor performance with increased RMSE values of 1.660 and 1.500. Followed by, the MR-MARS and MARS-MR models have reached to slightly reduced RMSE values of 1.380 and 1.430 respectively.

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Table 2: Comparative Prediction outcomes of GSONR-BFPP model

Methods	RMSE
MR-ANN	1.660
MR-MARS	1.380
MR-SVR	1.500
MARS-MR	1.430
MARS-ANN	1.110
MARS-SVR	0.970
GSONR-BFPP	0.590

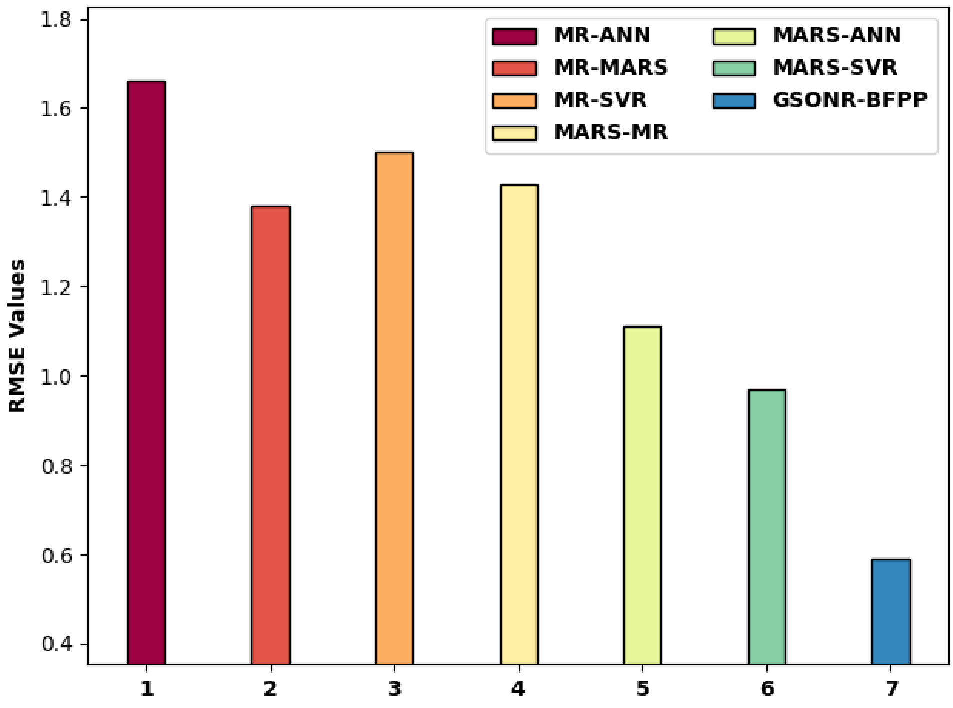

Figure 9: Comparative RMSE analysis of GSONR-BFPP model

Followed by, the MARS-ANN and MARS-SVR models have resulted to reasonably closer RMSE values of 1.110 and 0.970 respectively. However, the GSONR-BFPP model has accomplished better results with minimal RMSE of 0.590. From the above results and discussion, it is evident that the GSONR-BFPP model has resulted to maximum BFP predictive outcomes.

4. Conclusion

This study proposed an intelligent model to appropriately determine the level of BFP in an effective and automated way. The proposed model follows a two-stage process namely prediction and parameter optimization. At the initial stage, the suggested model derives a new neutrosophic set based rule classifier to determine the BFP. Secondly, the membership function in the rule based model is optimally chosen by the use of GSO algorithm and thereby results in enhanced predictive outcomes of the classification model. A wide ranging simulation analysis is performed and the results are inspected under several dimensions. The comparative study highlighted the effectual results of our model over the other models. In future, deep learning models can be introduced to boost the outcomes of the our model.

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