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Women Entrepreneurship Index Prediction Model with Automated Statistical Analysis

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Abstract: Recently, gender equality and women's entrepreneurship have gained considerable attention in global economic development. Prior to the design of any policy interventions to increase women's entrepreneurship, it is significant to comprehend the factors motivating women to become entrepreneurs. The non-understanding of the factors can result in the endurance of low living standards and the design of expensive and ineffectual policies. But female involvement in entrepreneurship becomes higher in developing economies compared to developed economies. Women Entrepreneurship Index (WEI) plays a vital role in determining the factors that enable the flourishment of high potential female entrepreneurs which enhances economic welfare and contributes to the economic and social fabric of society. Therefore, it is needed to design an automated and accurate WEI prediction model to improve women's entrepreneurship. In this view, this article develops an automated statistical analysis enabled WEI predictive (ASA-WEIP) model. The proposed ASA-WEIP technique aims to effectually determine the WEI. The proposed ASA-WEIP technique encompasses a series of sub-processes such as pre-processing, WEI prediction, and parameter optimization. For the prediction of WEI, the ASA-WEIP technique makes use of the Deep Belief Network (DBN) model, and the parameter optimization process takes place using Squirrel Search Algorithm (SSA). The performance validation of the ASA-WEIP technique was executed using the benchmark dataset from the Kaggle repository. The experimental outcomes stated the better outcomes of the ASA-WEIP technique over the other existing techniques.

Keywords: Predictive model; women entrepreneurship; statistical models; gender equality; decision making; work-life balance; learning and development

1 Introduction

Entrepreneur improves the economy and people's lives by creating jobs, exchanging ideas globally, creating technology that improves efficiency, and developing new solutions to problems. Several conditions that help entrepreneurs also help the economy as a whole provide even broader gains from supportive entrepreneurship [1]. Women entrepreneurs might be determined as women or a set of women that operate, initiate, and organize a business enterprise. Women are likely to adopt, innovate, or imitate an economic activity to be named women entrepreneurs. Women entrepreneur plays a significant role in increasing their economy [2]. Once a country doesn't accomplish its maximum potential, the economy suffers. Fewer 'higher potential' female entrepreneurs result in less innovation, fewer jobs created, less export potential, and fewer ideas being realized [3,4]. By using entrepreneurial activity, higher-potential female entrepreneur increases their economic welfare, and also enhance the social fabric and economy of a society with their innovative products, job creation, services, cross-border trade, and processes. Now, the role of women's entrepreneurship was identified in the procedure of economic growth around the world; thus, it should be promoted. Beforehand developing any policy intervention for boosting women's entrepreneurship [5], it is significant to understand the factor driving women to be an entrepreneur. Fig. 1 showcases the statistics of Woman Entrepreneurs.

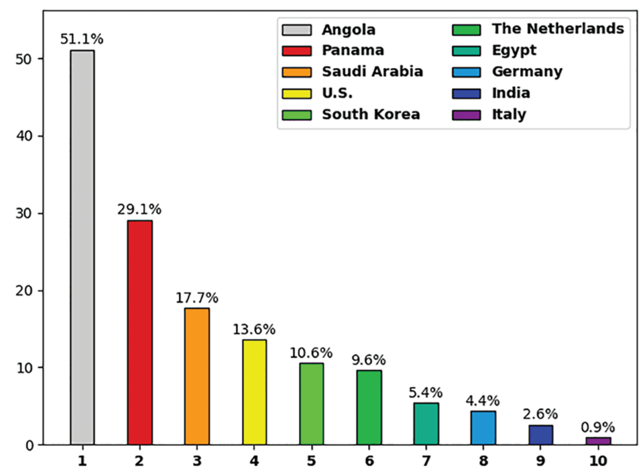

Figure 1: Statistics of Woman Entrepreneurs

The Female Entrepreneurship Index (FEI) searches for identifying the factor that enables the flourishing of higher potential female entrepreneurs—women who operate and own businesses that are export-oriented, innovative, and market expanding. With entrepreneurial activity, high-potential female entrepreneur improves their economic development and contributed to the social fabric and economy of society. A statistical test is utilized to make decisions. To implement analysis using the median, we must utilize a non-parametric test [6]. The non-parametric test is a distribution-independent test whereas the parametric test assumes that the data is a normal distribution. Parametric Test takes the mean into account whereas the Non-Parametric Test considered the median/rank to make a decision [7]. When the information doesn't have the conventional Gaussian distribution, we should resort to the non-parametric version of the significance test. This test operates in the same way; however, they are distribution-free and require that real-valued data be initially converted into rank data beforehand the test is conducted [8]. The study presents well-developed economies, however, studies on female entrepreneurship in developing markets are scarce. Entrepreneurship is important to drive economic development, and also it is important to shedding light on the development of business by the female entrepreneur for highlighting the values that female entrepreneur brings to enhance further growth and global societies [9]. Particularly in developing economies, it is the major contributing factor to the economy and social progress, also it is an important driver for opportunities for employment and industrial competitiveness.

This article develops an automated statistical analysis-enabled WEI predictive (ASA-WEIP) model. The proposed ASA-WEIP technique mainly intends to determine the WEI. The proposed ASA-WEIP technique includes a sequence of sub-processes like pre-processing, WEI prediction, and parameter optimization. In order to predict WEI, the ASA-WEIP technique utilizes a deep belief network (DBN) model and the parameter optimization process is performed by a squirrel search algorithm (SSA). The performance validation of the ASA-WEIP technique is carried out using the benchmark dataset from the Kaggle repository.

2 Literature Review

In Etim et al. [10], an overall amount of fifty targeted female entrepreneurs in Uyo metropolis, Nigeria, have been purposefully sampled for taking part in our work. Inferential and Descriptive statistics have been adapted for interpreting the essential information. Agarwala et al. [11] highlight the current effort of governments toward presenting new financial systems to help entrepreneurship amongst women that empower them. MUDRA was the novel inventiveness towards offering financial support to women from India without some security.

Ribeiro et al. [12] explore that the entrepreneurship orientation (EO)- nexus is intermediated by the network firm established with resource acquisition, government suppliers, and agencies. Zhu et al. [13] compare women's entrepreneurship in China and Vietnam by exploring the problem, motivation, and success factors associated with women-owned businesses.

Anggadwita et al. [14] analyze the effect of social perceptions, entrepreneurial orientation, and socio-cultural environment on women's entrepreneurial intention. The structural equation modeling method is utilized as an analytical method including 400 women entrepreneurs in micro small and medium-sized enterprises (MSME) in Indonesia. The outcomes show that the social perceptions and socio-cultural environment have significant and positive effects on entrepreneurial orientation. Bouzari et al. [15] purposes for examining the effects of online social media on women's entrepreneurship in comparative research. The statistical population of current research comprises women entrepreneurs active in the domain of online business in Iran and Hungary. ANOVA test has been utilized for examining the parameter of online social networks in distinct environments.

Ingalagi et al. [16] discuss the factors influencing and their impact on satisfaction and firm performance. The presented method and hypothesis were tested by the information collected from beauty parlors, boutiques, retail shops, and carpet manufacturers in Karnataka, India. Data analysis has been performed by bivariate, multivariate, and univariate technologies. In Structural Equation Modelling (SEM), paths have been made to evaluate the cause-and-effect relationships among distinct factors are psychological, social, resource factors, and financial and entrepreneurial satisfaction and performance. Wu et al. [17], proposed a competitive DBN for learning features with more discriminatory data from labeled and unlabeled samples. The presented method comprises four phases: a typical Restricted Boltzmann Machine (RBM) is pre-trained with a massive amount of unlabeled information for initializing its parameter; the hidden unit is grouped based on the category which offers a clustering method for competitive learning; back-propagation and competitive training approaches are utilized for updating the parameter to achieve the clustering task; and apply supervised fine-tuning and layer-wise training, a Deep Neural Networks (DNN) is constructed to attain feature.

3 The Proposed Model

In this study, a new ASA-WEIP approach was developed for the prediction of WEI. The proposed model follows a three-stage process. Initially, the input data is pre-processed for the conversion of original data into a useful format. Secondly, the DBN model is applied for the effectual prediction of WEI. Thirdly, the SSA has been utilized to fine-tune the hyperparameters of the DBN model. The detailed work of each module is offered in the succeeding sections.

3.1 Data Pre-Processing

Primarily, the input data is pre-processed to transform the actual input data into a useful format. The *Z*-score is computed utilizing the standard deviation (SD) and the arithmetic mean of provided WS data has often been utilized as a score normalization approach. It can be predicted that this normalized method is achieving well whether prior data on the average score and score differences of the matcher. The normalizing scores are provided as:

$$s'_k = \frac{s_k - \mu}{\sigma} \tag{1}$$

In which, σ implies the SD and μ stands for the arithmetic mean of the provided information. During this case, the normalized of smoothed data has been completed by *Z*-score normalized.

3.2 WEI Prediction Using DBN Model

At the time of WEI prediction, the DBN model receives the pre-processed data and thereby predicts the values of WEI. DBN is a multilayer probabilistic generation method that is learned for extracting a deep hierarchical depiction of trained data. The DBN is collected from many layers of RBM and classified additional to the topmost layer [18]. The RBM has an energy-based generative method which comprises a layer of visible nodes $\left(v_1,\ v_2,\ \ldots,\ v_j,\ \ldots,\ v_m\right)$ demonstrating the data and layer of hidden node $\left(h_1,\ h_2,\ \ldots,\ h_j,\ \ldots,\ h_n\right)$ learning for representing features, with all $v_i \in \{0,\ 1\}$ and $h_j \in \{0,\ 1\}$. It can be determined that the bias of the visible node is $(b_1,\ \ b_2,\ \ \ldots,\ \ b_i,\ \ \ldots,\ \ b_m)$, and the bias of hidden node is $\left(c_1,\ c_2,\ \ldots,\ c_j,\ \ldots,\ c_n\right)$.

$$E(v,\ h) = -\sum_{i=1}^{m} b_i v_i - \sum_{j=1}^{n} c_j h_j - \sum_{j=1}^{n}\sum_{i=1}^{m} v_i w_{ij} h_j. \tag{2}$$

As stated by the energy function $E(v,\ h)$, the joint likelihood distribution to hidden and visible layers is demonstrated as:

$$P(v,\ h) = \frac{1}{Z}\, exp\,(-E(v,\ h)), \tag{3}$$

In which, Z refers to the partition function that is the sum of entire feasible pairs of hidden and visible layers.

$$Z = \sum_{v}\sum_{h} exp\,(-E(v,\ h)) \tag{4}$$

The probability allocated to visible vector v has been provided by adding feasible binary hidden vector h, in the following:

$$P(v) = \sum_{h} P(v,\ h) = \frac{1}{Z}\sum_{h} exp\,(-E(v,\ h)) \tag{5}$$

When there are no direct links among the similar layers in RBM, this hidden unit is independently offered to the visible unit [19]. Thus, the visible vector v, the conditional likelihood of hidden vector h is represented as follows:

$$P(v) = \prod_{j=1}^{n} P(v). \tag{6}$$

Likewise, in the hidden layer h, the conditional likelihood of visible layer v is represented as follows:

$$P(h) = \prod_{i=1}^{m} P(h). \tag{7}$$

In the visible layer v, the activation state of all the hidden units is conditionally independent. Now, $h_j \in \{0,\ 1\}$, and activation possibility of the jth hidden unit was given by:

$$P(v) = Sigm\left(\sum_{i=1}^{m} w_{ij}v_i + c_j\right), \tag{8}$$

Whereas $Sigm(x) = \dfrac{1}{1+e^{-x}}$ denotes the logistic sigmoid function. Fig. 2 illustrates the DBN structure.

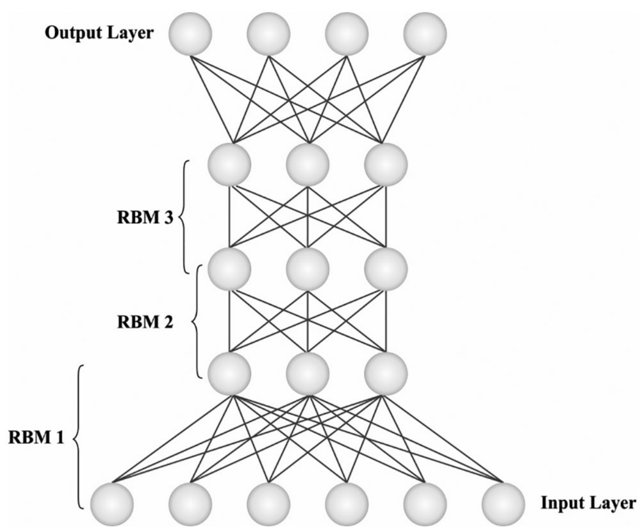

Figure 2: DBN structure

Therefore, the activation possibility of the visible layer is conditionally independent once given a hidden layer h:

$$P(h) = Sigm\left(\sum_{j=1}^{n} w_{ij}h_j + b_i\right). \tag{9}$$

When the RBM was trained, the network energy is reduced, and the possibility in Eq. (5) is maximized. For maximizing the log-the probability of (v), its gradient regarding the network parameter θ is estimated by:

$$\frac{\partial\ log\ P(v)}{\partial\theta} = -E_{P(v)}\left[\frac{\partial E(v,\ h)}{\partial\theta}\right] + E_{P(v',h')}\left[\frac{\partial E(v',\ h')}{\partial\theta}\right] \tag{10}$$

Whereas E represents the expectation operator. CD-k approach approximates the expectancy in Eq. (10) by constraint k (often $k = 1$) iteration of Gibbs sampling to upgrade the network parameter $\theta = (iV,\ \ b,\ c)$. The upgrade method of variable θ is given by:

$$\frac{\partial \log P(v)}{\partial w_{ij}} = P(v) \cdot v_i - \sum_{v'} P(v')P(v') \cdot v'_i, \tag{11}$$

$$\frac{\partial \log P(v)}{\partial b_i} = v_i - \sum_{v'} P(v') \cdot v'_i, \tag{12}$$

$$\frac{\partial \log P(v)}{\partial c_j} = P(v) - \sum_{v'} P(v')P(v'). \tag{13}$$

Afterward, an RBM was trained; another RBM is stacked on the topmost one. Hence, various layers of RBM are stacked for extracting distinct features that denote complicated structures in the information. Once the DBN has been trained, the network parameter $\theta = (W, \ b, \ c)$ is utilized for initializing the weight of multilayer FFNN. The backpropagation model is utilized for finetuning the network parameter $\theta = (W, \ b, \ c)$ for improving the detection accuracy of the NN.

3.3 Parameter Optimization Using SSA

For boosting the predictive outcomes of the DBN technique, the SSA is utilized and thereby enhances the overall performance. The hunting process begins if flying squirrels start scavenging. Simultaneously, it can alter its regions and examine several areas of wood. While the climatic states are appropriately hot, it can meet its daily vitality requires further quickly on eating routine of oak seeds tree (OST) available from bounty and therefore, it is devouring OST rapidly afterward determining them. The ability of hickory nuts is for helping from maintaining its vitality prerequisites from harsh climates reduce the costly search excursion and enhance the probability of endurance [20–24]. Concerning the finishing of wintertime, squirrels again developed a dynamic. It can be a monotonous process and infrastructure for the establishment of SSA. Fig. 3 depicts the flowchart of SSA. The purpose of employing SSA in optimizing the parameter is its efficiency in determining solutions for the unimodal, multimodal optimization functions.

Figure 3: Flowchart of SSA

Considering the count of squirrels is N, and the upper as well as lower limits of detection space, are X_U and X_L, the N squirrels are randomly generated as:

$$X_i = X_L + rand(1,\ D) \times (X_U - X_L) \tag{14}$$

In which X_i represents the i^{th} squirrel, $(i = 1{:}\,N)$, $rand()$ signifies the arbitrary number from the range of zero and one, and D stands for the measurement of the problem. Amongst the N trees, have one hickory tree (HT) and N_a OST, but the rests are classical trees taking no food. The HT is an optimum food asset to the squirrels but the OST arises the second. The locate the fitness estimates of the populace from increasing requests, the squirrel is divided into 3 classes:

- Squirrels placed at HT (W_h);
- Squirrels located in ordinary trees (W_n)
- Squirrels located at OST (W_a)

The squirrel refreshes its conditions by skimming to HT or OST as follows:

$$X_i^{t+1} = \{X_i^t + d_g G_c\left(X_{ai}^t - X_i^t\right) \, if \ r_2 \geq P_{dp} \ Random\ location\ otherwise \tag{15}$$

$$X_i^{t+1} = \{x_i^t + d_g G_c\left(X_h^t - X_i^t\right) \, if \ r_3 \geq P_{dp} \ Random\ location, \ \ otherwise \tag{16}$$

P_{dp} is valued at 0.1 and denotes the chaser possibility. During the case that $r > P_{dp}$, no chasers appear, and the squirrel coast from the backwoods for discovering the food and is protecting. When $r < P_{dp}$, the chaser appears, and the squirrel is compelled for limiting the degree of exercise and is imperiled, and its places are transferred arbitrarily. d_g refers to the skimming separation which is expressed as:

$$d_g = \frac{h_g}{tan(\phi)} \tag{17}$$

In which, h_g refers to the constant evaluated by 8, $tan(\phi)$ signifies the coasting point which is represented as:

$$tan(\phi) = \frac{D}{L} \tag{18}$$

The drag power and lift power are evaluated as:

$$D = \frac{1}{2\rho V^2 SC_D} \tag{19}$$

$$L = \frac{1}{2\rho V^2 SC_L} \tag{20}$$

To start all generations, the SSA requires that the whole populace is in winter which represents that the places of every squirrel were upgraded [22–24]. At this point, once the squirrel is refreshed, anyway the season, altered has been decided by a subsequent equation:

$$S_c^t = \sqrt{\sum_{k=1}^{d} \left(X_{ai,\,k}^t - X_{hk}^t\right)^2} i = 1,\ 2,\ \ldots,\ N_a \tag{21}$$

$$S_{min} = \frac{10e^{-6}}{365^{t/(T_{max}/2.5)}} \tag{22}$$

If $S_{tc} < S_{min}$, winter has ended and the season drives to summer, then the season has been unchanged. But the squirrels skimming to W_a and not gathering with chaser move its states as follows:

$$X_{inew}^{t+1} = X_L + Le'vy(x) \times (X_U - X_L) \tag{23}$$

The levy is the arbitrary walk method whose progression observes with Levy appropriation and is demonstrated as:

$$Le'vy(x) = 0.01 \times \frac{\alpha \times r_a}{|r_b|^{\frac{1}{\beta}}} \tag{24}$$

where α is defined as:

$$\alpha = \left[\frac{\Gamma(1+\beta) \times sinsin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2\left(\frac{\beta-1}{2}\right)}\right]^{\frac{1}{\beta}} \tag{25}$$

4 Performance Validation

The proposed ASA-WEIP model is simulated using the benchmark Women Entrepreneurs Analysis dataset from the Kaggle repository [25]. The dataset holds four numeric variables such as WEI, entrepreneurship index, inflation ratio, and female labor force participation rate. Next, the list of categorical variables is country, level of development, European Union Membership, and Currency. Fig. 4 illustrates the correlation matrix of the ASA-WEIP technique.

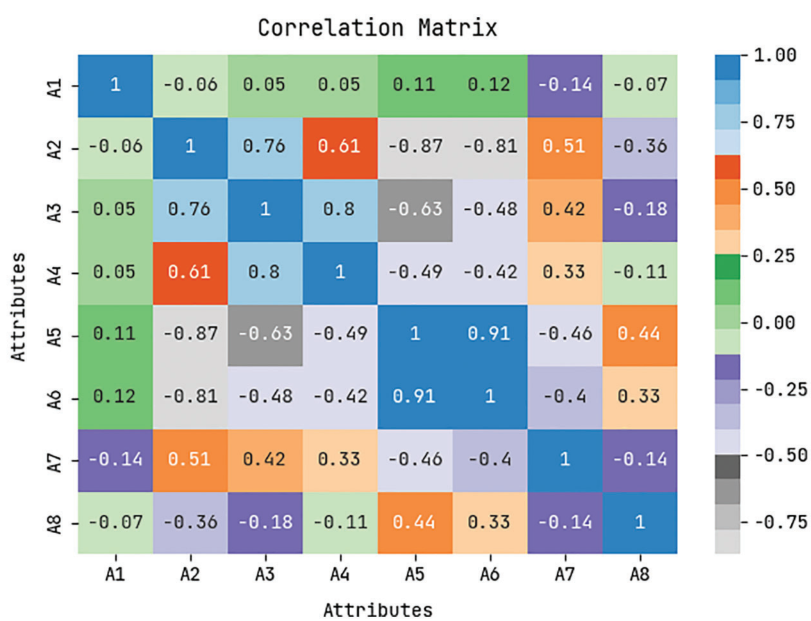

Figure 4: Correlation matrix of ASA-WEIP technique

Fig. 5 shows the actual and predicted WEI values of the ASA-WEIP model under run-1. The figure demonstrated that the ASA-WEIP model has resulted in effective outcomes with closer values of actual and predicted outcomes. Besides, it is noticed that the variance amongst the actual and predicted values is found to be minimal.

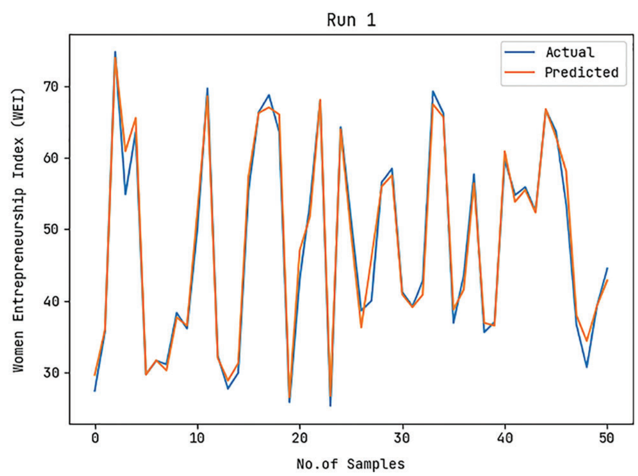

Figure 5: Actual and Prediction WEI analysis of ASA-WEIP model under run-1

Fig. 6 illustrates the actual and predicted WEI values of the ASA-WEIP approach under run-2. The figure demonstrated that the ASA-WEIP model has resulted in effective outcomes with closer values of actual and predicted outcomes. Moreover, it is noticed that the difference among the actual and predicted values is found to be lower.

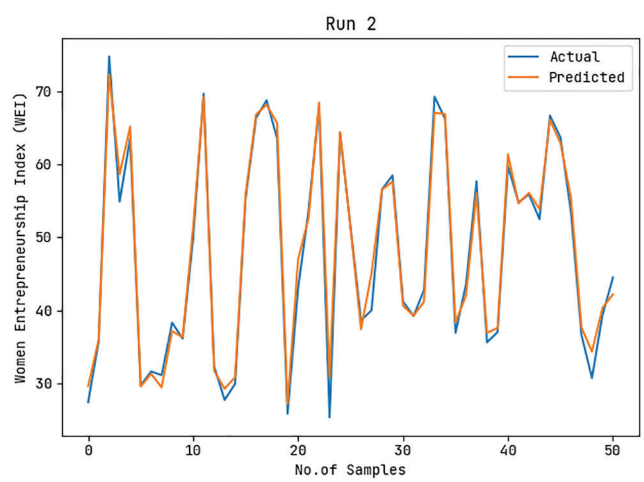

Figure 6: Actual and Prediction WEI analysis of ASA-WEIP model under run-2

Fig. 7 displays the actual and predicted WEI values of the ASA-WEIP method under run-3. The figure r that the ASA-WEIP model has resulted in effective outcomes with closer values of actual and predicted outcomes. In addition, it can be noticed that the difference between the actual and predicted values is found to be minimal.

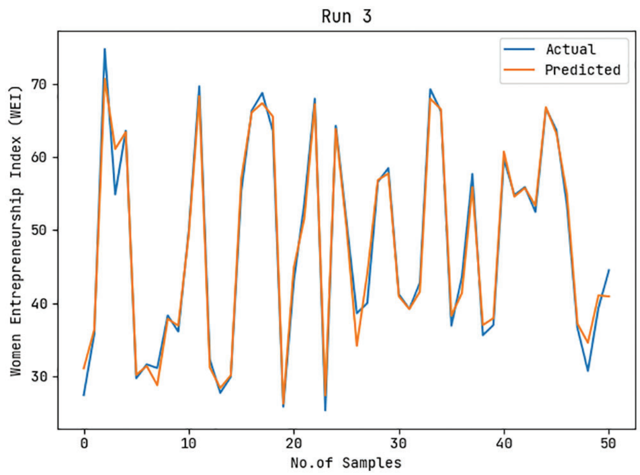

Figure 7: Actual and Prediction WEI analysis of ASA-WEIP model under run-3

Fig. 8 demonstrates the actual and predicted WEI values of the ASA-WEIP approach under run-4. The figure exposed that the ASA-WEIP model has resulted in effective outcomes with closer values of actual and predicted outcomes. Besides, it can be noticed that the difference amongst the actual and predicted values is found to be minimal.

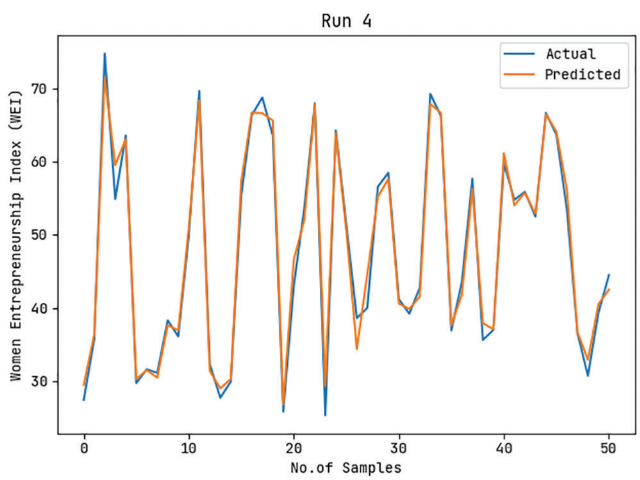

Figure 8: Actual and Prediction WEI analysis of ASA-WEIP model under run-4

Fig. 9 depicts the actual and predicted WEI values of the ASA-WEIP technique under run-5. The figure demonstrated that the ASA-WEIP model has resulted in effective outcomes with closer values of actual and predicted outcomes. Also, it can be noticed that the difference among the actual and predicted values is found that minimal.

Table 1 and Fig. 10 provide a brief comparative result analysis of the ASA-WEIP technique with existing algorithms under distinct runs. The experimental values represented that the ASA-WEIP technique has resulted in effectual results with minimal values of MSE and RMSE. For instance, with run-1, the ASA-WEIP system has provided decreased MSE of 1.09 whereas the LR, RR, SVM, and ELM models have accomplished increased MSE of 2.95, 2.41, 1.97, and 1.53 respectively. Also, with run-2, the ASA-WEIP technique has provided decreased MSE of 0.64 whereas the LR, RR, SVM, and ELM techniques have accomplished increased MSE of 2.58, 2.14, 1.60, and 1.17 correspondingly. Also, with run-3, the ASA-WEIP approach has provided decreased MSE of 0.74 whereas the LR, RR, SVM, and ELM approaches have accomplished increased MSE of 2.76, 2.26, 1.76, and 1.27 correspondingly. Moreover, with run-4, the ASA-WEIP technique has provided decreased MSE of 0.69 whereas the LR, RR, SVM, and ELM models have accomplished higher MSE of 2.75, 2.25, 1.66, and 1.25 respectively. Furthermore, with run-5, the ASA-WEIP technique has provided a reduced MSE of 0.69 whereas the LR, RR, SVM, and ELM methodologies have accomplished improved MSE of 2.86, 2.29, 1.76, and 1.23 correspondingly.

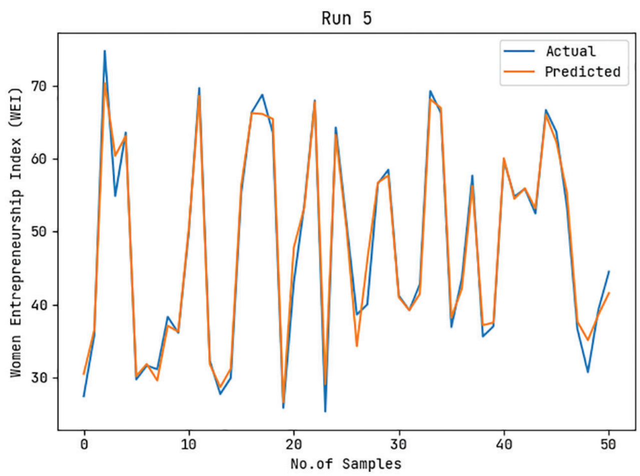

Figure 9: Actual and Prediction WEI analysis of ASA-WEIP model under run-5

Table 1: Comparative analysis of ASA-WEIP technique under distinct runs with existing approaches

Methods	MSE	RMSE	Methods	MSE	RMSE
Run-1			**Run-2**		
Lasso regression	2.95	1.72	Lasso regression	2.58	1.61
Ridge regression	2.41	1.55	Ridge regression	2.14	1.46
Support vector machine	1.97	1.40	Support vector machine	1.60	1.26
Extreme learning machine	1.53	1.24	Extreme learning machine	1.17	1.08
ASA-WEIP	1.09	1.04	ASA-WEIP	0.64	0.80
Run-3			**Run-4**		
Lasso regression	2.76	1.66	Lasso regression	2.75	1.66
Ridge regression	2.26	1.50	Ridge regression	2.25	1.50
Support vector machine	1.76	1.33	Support vector machine	1.66	1.29
Extreme learning machine	1.27	1.13	Extreme learning machine	1.25	1.12
ASA-WEIP	0.74	0.86	ASA-WEIP	0.69	0.83
Run-5			**Average**		
Lasso regression	2.86	1.69	Lasso regression	2.78	1.67
Ridge regression	2.29	1.51	Ridge regression	2.27	1.51
Support vector machine	1.76	1.33	Support vector machine	1.75	1.32
Extreme learning machine	1.23	1.11	Extreme learning machine	1.29	1.13
ASA-WEIP	0.69	0.83	ASA-WEIP	0.77	0.87

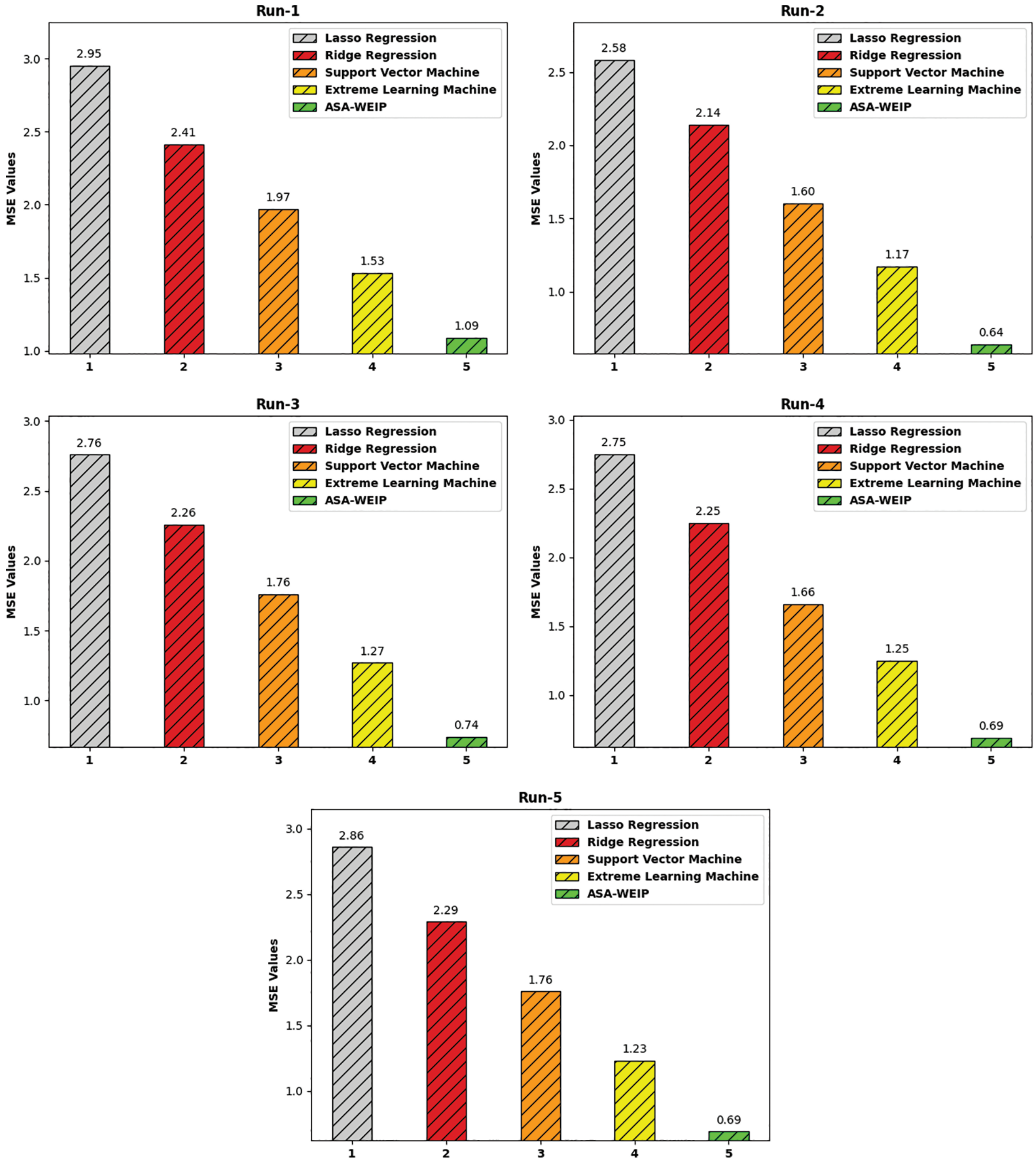

Figure 10: MSE analysis of ASA-WEIP technique with different runs

Fig. 11 demonstrates the average result analysis of the ASA-WEIP system with recent models. The figure shows that the ASA-WEIP technique has resulted in effective outcomes over the other methods. On measuring the results in terms of MSE, the ASA-WEIP technique has resulted in to lower MSE of 0.77 whereas the LR, RR, SVM, and ELM models have reached a higher MSE of 2.78, 2.27, 1.75, and 1.29 respectively.

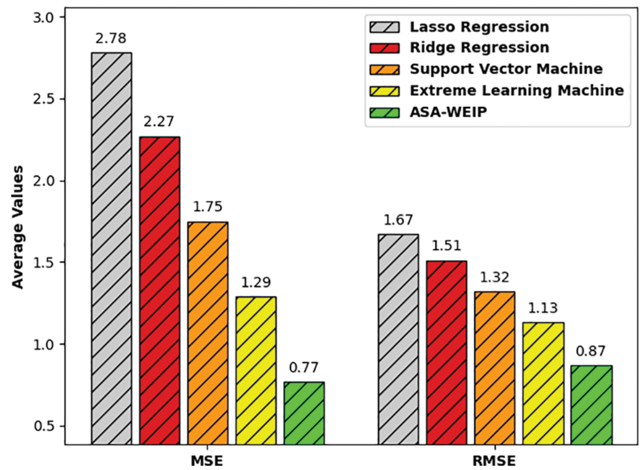

Figure 11: Average MSE and RMSE analysis ASA-WEIP technique with existing approaches

Moreover, in measuring the results with respect to RMSE, the ASA-WEIP technique has resulted in a minimum MSE of 0.87 whereas the LR, RR, SVM, and ELM methods have reached superior RMSE of 1.67, 1.51, 1.32, and 1.13 correspondingly. From the above-mentioned tables and figures, it is apparent that the ASA-WEIP technique has resulted in maximum performance over the other methods.

5 Conclusion

In this study, a novel ASA-WEIP technique was developed for the prediction of WEI. The proposed model follows a three-stage process. Initially, the input data is pre-processed for the conversion of original data into a useful format. The DBN model is applied for the effectual prediction of WEI. Next, the SSA has been utilized to fine-tune the hyperparameters of the DBN model. The performance validation of the ASA-WEIP technique was executed using the benchmark dataset from the Kaggle repository. The experimental outcomes stated the better outcomes of the ASA-WEIP technique over the other existing techniques. Therefore, the ASA-WEIP approach was employed as an effectual tool for managing gender equality and women entrepreneurship management. In the future, the proposed model was extended to the consumption of data from the real-time environment.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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