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Prediction of Strategic Business Process using Robust Variation Physics-Informed Neural Network

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KEYWORDS

Robust Variation Physics-Informed Neural Network, Strategic Business Process, Distributed Fusion Minimum Error Entropy Kalman Filter, Enhanced Walrus Optimization

ABSTRACT

In today's changing business climate, strategic business process optimization is critical for firms to promote innovation, improve operational efficiency, and keep a competitive advantage.

Challenges like complexity of interconnected processes, resistance to change from employees and stakeholders, inadequate data and insights for decision-making. In this manuscript, Robust Variation Physics-Informed Neural Network based prediction of Strategic Business Process (SBP-RVPNN-EWO) is proposed. This study utilizes data from the Reimbursement Process Dataset and employs preprocessing technique. The Prediction task focuses on to recover productivity, decrease budgets and increase buyer gratification using Robust Variation Physics-Informed Neural Networks (RVPNN). The Enhanced Walrus Optimization (EWO) is introduced for optimizing RVPNN for accurate business process. The proposed method is implemented and analyzed performance metrics likes accuracy, precision, recall. The proposed method attains 20.78%, 17.98% and 25.67% high accuracy more than existing methods like Strategic Business Process with Particle Swarm Optimization (SBP-PSO), Strategic Business Process with Artificial Neural Network and Strategic Business Process with Convolutional Neural Network respectively.

1. INTRODUCTION

The study of events generated during a process's execution to determine whether or not its performance goals and compliance criteria are being met is known as business process monitoring [1]. Process performance may be monitored online using dashboards that show the status of active cases, or offline using reports that are generated on a regular basis [3]. Prognostic monitoring of business processes [3] is a family of online process monitoring techniques that aims to forecast a case's conclusion as soon as feasible based on its current (incomplete) execution trail and a collection of traces from cases that have already been finished [4]. An result in this instance may be the achievement of a business objective, a performance target (such the maximum permitted cycle time), a compliance regulation, or any other property of a case that could be ascertained after it is finished [5-7]. In the context of sales, one possible result may be a potential client placing a purchase order, whereas in the context of debt collection, one possible outcome would be the receipt of a debt payback [8-10]. One of the final areas of difference is high-performance business processes [11]. Predictive analytics may increase corporate value when it is integrated into enterprise operations [12]. Process-aware enterprise information systems (EIS) that generate log events while processes are being carried out include workflow management systems (WMS), enterprise resource planning (ERP), customer relationship management (CRM), and incident management (IM) [13]. These data provide visions into possible process behavior using prognostic analytics, which aids in decision-making. [14]. By preventing anticipated failures and deviations from the planned process performance, an efficient design and execution of prognostic techniques guarantee that business operations will proceed as intended [15]. Some use cases for data-driven predictive process analytics include real-time detection of process irregularities, evaluating consumer behavior patterns to develop customized offers, risk management through the prediction of compliance violations, and efficient resource allocation [16-18]. ML methods are used by many predictive process monitoring systems because, unlike rule-based monitoring strategies, they do not require reliance on expert-defined, subjective decision criteria. Additionally, the hurdles to applying ML are lowered by the growing availability of data [19]. While DL has become more popular in predictive process monitoring, most studies still employ traditional ML methods including support vector machines (SVM), random forests (RF), and decision trees. However, a disadvantage of these methods is that, for low-level feature representations, their effectiveness significantly rely on manual feature engineering [20].

The motivation behind strategic business process optimization lies in the pursuit of sustainable competitive advantage and organizational excellence. Organizations seek to increase operational effectiveness, save costs, boost customer happiness, and swiftly adjust to shifting market conditions by carefully examining and improving essential business processes. The ultimate goal is to drive innovation, agility, and continuous improvement, positioning the organization as a market leader. However, notwithstanding the widespread acknowledgement of the importance of business process optimization, nearby remains a research gap in effectively integrating advanced technologies, such as AL and ML, to predict and optimize complex business processes. Closing this gap is critical for businesses hoping to employ new tools and tactics to stay ahead of the competition and win in the long run in today's fast-paced business climate.

Below is a summary of this suggested method's primary contributions:

- ❖ In thi paper, Robust Variation Physics-Informed Neural Network based prediction of Strategic Business Process (SBP-RVPNN-EWO) is proposed.
- ❖ Reimbursement Process Dataset and employs preprocessing technique DFMEKF used to data cleaning, encoding and dimensionality reduction from the collected data.
- ❖ Accurate and precise classification of Strategic Business Process is achieved through Robust Variation Physics-Informed Neural Networks.
- ❖ The weight parameters of RVPNN are enhanced with Enhanced Walrus Optimization Algorithm.

The remaining paper prearranged as: Segment 2 presents literature survey, Segment 3 defines proposed procedure, Segment 4 demonstrates results, Segment 5 ends research.

2. LITERATURE REVIEW

Various study was earlier submitted for the prediction of Strategic Business process by means of deep learning: a few works were studied now,

The main concern facing small and medium-sized businesses (SMEs) worldwide is sustainability. SMEs have a detrimental environmental impact in addition to contributing to the GDP of any nation. The three main topics of previous study on the sustainability of SMEs were the association among maintainable amount hawser performance and economic presentation, the empirical studies on sustainability practices, and the conservational and social practices link. Abdelaziz *et.el* [21] have presented the best possible balance between performance (outputs) and sustainability practices (inputs) to create SMEs' sustainable structure. Due to this, the primary purpose of this study is to create the best possible structure for sustainable SMEs through the use of a multi-objective framework and a neural network and particle swarm algorithm (PSA). The study makes use of data from 30 SMEs in the Midland region of the UK and 54 SMEs in Normandy, France. A questionnaire survey was used to collect the data. Since our target functions are not explicitly specified, we use our databases to train a neural network to offer the values of the various objectives for each profile. We create and apply a multi-objective variant of particle swarm optimization, or MPSO, to produce effective organizational structures. J.P.Bharadiya *et.el.* [22] have presented analytical tools to provide BI systems for business planners and decision makers through the combination of competitive information with historical and operational data. Managers may find it easier to understand their organization's environment of competition with the aid of business intelligence (BI), which strives to improve both the availability and quality of data. By using BI tools and technologies, it can be achieved to assess changes in market share, client tastes, spending habits and behavior, company capabilities, and market dynamics. By using BI, analysts and managers may also assess which modifications are most likely to adapt to evolving patterns. Technological approaches include data a summary, change analysis, anomaly detection, dependent network identification, grouping, and categorization algorithm learning. An enhanced business intelligence setting has resulted from the development of web architecture, the creation of data warehouses as repositories, advances in data purification, and higher hardware and software abilities.

Real-time prediction of business process behavior, performance, and outcomes is the aim of predictive process monitoring. It helps in problem-solving and resource reallocation to reduce waste. Although there have been advancements in deep learning (DL), the majority of current methodologies particularly in outcome-oriented predictive process monitoring—are depend on conventional machine learning (ML) methods. Kratsch *et.el* [23] have presented the effectiveness of ML and DL methods using five publicly accessible event logs, specifically looking at basic feedforward DNN and long short-term memory networks. One might note that DL typically performs better than traditional ML methods.

3. PROPOSED METHODOLOGY

In this Part describe the suggested methodology SBP-RVPNN-EWO. This study leverages the Reimbursement Process Dataset and implements advanced techniques to improve business process. Preprocessing involves Distributed Fusion Minimum Error Entropy Kalman Filter (DFMEKF) for data enhancement. Using RVPNN for prediction can increase customer happiness, lower expenses, and boost productivity. The Enhanced Walrus Optimization is introduced to optimize RVPNN for accurate business prediction. The block diagram is present in figure 1.

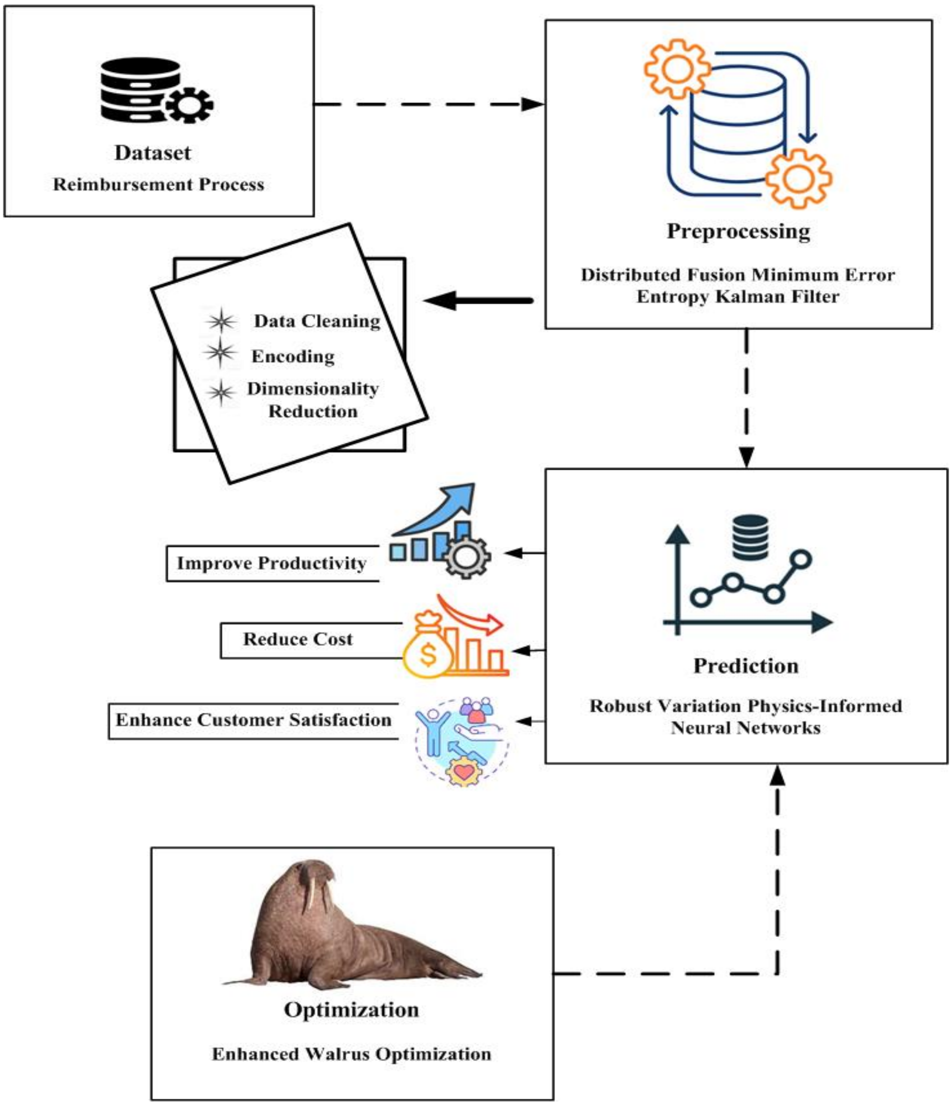

Figure 1: Block diagram of the proposed SBP-RVPNN-EWO

3.1. Data Acquisition

The information gathered via TU/e's reimbursement procedure. Data from 2017 (only two departments) and 2018 (the whole TU/e) are included in the files [26]. The information is divided into travel permits and various request categories, such as domestic and international declarations, prepaid travel expenses, and requests for payment, which are for non-travel-related expenses (e.g., representation fees, hardware purchases for work, etc.). The data does not allow for staff member identification. Instead, the role of the individual who carried out each step is documented. The system, a staff member, UNKNOWN, or occasionally the data is MISSING are the resources listed in the data.

3.2 Pre-processing using Distributed Fusion Minimum Error Entropy Kalman Filter

In this segment, Pre-processing [27] technique is used to data cleaning, encoding and dimensionality reduction from the collected data. This can assist in removing the missing values of the target variable and are used to fill the other features using the mean of the data. The main objectives in pre-processing utilizing DFMEEKF for prediction of business process to create a significant competitive advantage for organizations. It can assist in cleaning the data and reformate the dataset. The fused covariance of measurement is given in the equation (1)

$$D_e^r = diag\left[D_{1,e}, D_{2,e}, \ldots.., D_{m,e}\right] \quad (1)$$

Here, D_e^r represents the filter length; $D_{i,e}$ denotes the values of the target variable; r denotes the time instant; e denotes the group of element. The encoded dataset is defined as the given equation (2)

$$I_e^r = j_e - \hat{j}_e^r \quad (2)$$

Where, I_e^r denotes the newly encoded data; $\hat{j}_e^r$ denotes the initially collected data which is raw and contains wrongly encoded values; $\hat{j}_e^r$ denotes the cleaning data of the target variables. The real state of data is given in equation (3)

$$E_e^r = K_e^r j_e + l_e^r \quad (3)$$

Here, E_e^r denotes the real state of data; K_e^r denotes the mean of the data; l_e^r denotes the features to be included. The Matrix inversion lemma is defined to convert the data and the input data have been enhanced by the following equation (4)

$$(B + CGH)^{-1} = B^{-1} - B^{-1}C\left(G + HB^{-1}C\right)^{-1} HB^{-1} \quad (4)$$

Here G and B are invertible matrices; C and H are conformable matrices; $\left(G + HB^{-1}C\right)^{-1}$ denotes the square matrix by the following equation (5)

$$\overline{M}_e^r = B^{-1}C\left(G + P_e^r B^{-1}C\right)^{-1} \quad (5)$$

Here $\overline{M}_e^r$ denotes the converted dataset; $\left(G + P_e^r B^{-1}C\right)$ denotes the cleaning data. By processing DFMEEKF method have successfully managed the cleaning data and reformatted the dataset. Next, in order to increase output, cut expenses, and boost customer happiness, the pre-processed data are input into the prediction process.

3.3 Prediction of Business Process using Robust Variation

In the section, prediction using Robust Variation Physics-Informed Neural Networks [28] is discussed. To forecast the actions, results, and performance of business processes during runtime, the RVPNN was suggested. Increased customer happiness, cost savings, and productivity are the main objectives. An accurate model cans efficiently outcomes of business processes. By using RVPNN, the model can capture the underlying principles governing the business processes, leading to more robust and interpretable predictions and this is given in equation (6)

$$(\phi, \varphi_n)c = l(k_{\theta,}\varphi_n), \quad for\ n = 1, \ldots\ldots., m \quad (6)$$

Where, ϕ denotes the input dataset; φ_n denotes the runtime variable. The prediction of business processes is given in equation (7)

$$R_s^\phi(k_{\theta,}) := s(k_{\theta,}\phi) + B(k_\theta) \quad (7)$$

Where, $k_{\theta,}$ denotes the runtime of process; R_s^ϕ denotes the outcomes variables. The productivity, decrease price and improve client consummation is predicted by the significant variables. It is given in equation (8)

$$\phi := \sum_{f=1}^{F} \eta_f(\theta)\varphi_f, \quad (8)$$

Where, η_f denotes the additional input data for the prediction of business processes, further relevant environmental variables are calculated using their workflows, resource utilization, and performance metrics. The optimal strategies for enhancing the business processes identified by the following equation (9)

$$V\eta(\theta) = T(\theta) \tag{9}$$

Here, $V\eta(\theta)$ represents the market trends and $T(\theta)$ represents the customer feedback. Thus the final dataset is developed to predict the goal to improve productivity and enhance customer satisfaction. It is given in equation (10)

$$R_s^{\phi}(k_\theta) = T(\theta)^J P^{-1} T(\theta) + U(k_\theta) \tag{10}$$

Where, $R_s^{\phi}(k_\theta)$ represents the productivity; P^{-1} denotes the customer satisfaction and $U(k_\theta)$ represents the probability of business process. Thus RVPINN provides the accurate prediction process enhancements.

3.4 Optimization

In this section, Enhanced Walrus Optimization Algorithm (EWOA) [29] is described. It is possible to define and initialize for every individual in the system of walrus. . An individual is identified as a binary array during the initialization phase. As a result, during the start-up phase, the population's variety is increased. The walrus possesses two unique qualities in addition to a keen sense of touch. These traits are in handy for a variety of tasks, including food hunting in the sand and mud and self-defense. Combining these features, the EWOA takes into account the connections and social structures among mature, young, and feminine walruses as well as the behavior of walrus populations depending on signals of danger and safety.

Step 1: Initialization

The optimization process is carried out within the lower and higher bounds of the problem variables, using an original set of arbitrarily produced applicant solutions. Iterations are used to update the walrus agents' locations. The safety and danger signs that are essential for interpreting walrus performance are defined by EWOA. The indication of danger is provided in equation (11).

$$R = 2 \times r_1 - 1 \tag{11}$$

Where, R denotes the danger factors. The safety signal is given in equation (12)

$$Safety - signal = r_2 \tag{12}$$

Where, the safety signal is defined as r_2

Step 2: Migration

A walrus's normal behavior is to migrate throughout the summer months as the temperature gets warmer. During this phase, walruses shift dramatically, heading for stony beaches or outcrops. A walrus in the EWO simulation assumes that other walruses' places are their migration destinations. It then chooses one of these spots at random and goes in that direction. By using this approach in the architecture of EWO, worldwide search and discovery capabilities are enhanced. The population update process is prohibited from depending on a specific member, such as the best member of the population, in the foraging process led by the strongest walrus, which is different from the migratory strategy. Early convergence and the algorithm being trapped in local optima are avoided by this update procedure. The walrus's position is updated based on many factors during the migration phase, which in the method symbolizes exploration: a random integer r3 and a migration step control factor β. The formula for updating the walrus location is given by equation (14)

$$Mitigation\_step = \left(X_j^k - X_l^k\right) \times \beta \times r_3^2 \times \theta \tag{13}$$

Here, X_j^k and X_l^k are two arbitrarily nominated locations.

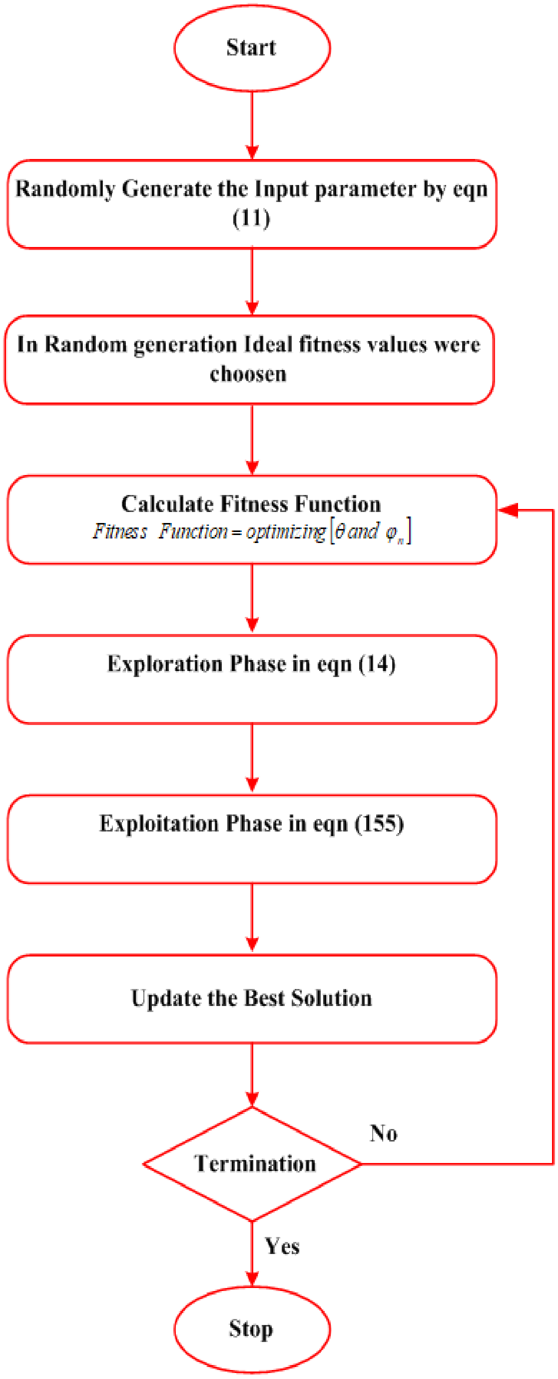

Figure 2: Flowchart of EWO

4. RESULT AND DISCUSSION

The proposed method SBP-RVPNN-EWO is implemented and analyzed the performance metrics likes accuracy, precision, recall. The proposed method SBP-RVPNN-EWO is comparing with existing methods like SPB-PSO [30], SPB-ANN[31] and SPB-CNN[32] respectively.

- TP : A true positive arises once the classification algorithm accurately forecasts a positive class as positive.
- TN : True negatives happen once the classification algorithm forecasts a negative class properly.

4.1 Performance Analysis

Fig 3-8 display the outcomes of the suggested SBP-RVPNN-EWO method's simulation. Next, the current SPB-PSO, SPB-ANN, and SPB-CNN techniques are compared with the new SBP-RVPNN-EWO approach, in that order.

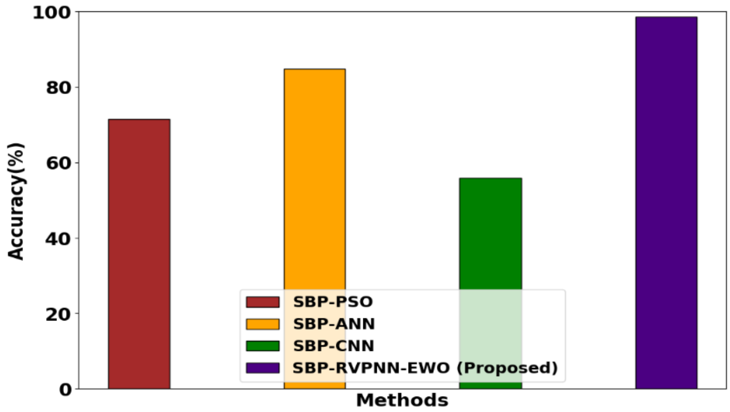

Figure 3: Evaluation of Accuracy Performance

Figure 3 displays the evaluation of accuracy. The proposed SBP-RVPNN-EWO method accuracy is shown compared with the existing methods on the graph. Efficiency gains, cost savings, and increased customer satisfaction are the primary goals. The proposed SBP-RVPNN-EWO method attains 22.3%, 25.5% and 27.7% higher accuracy for predicting the strategic business process estimated to the existing, SPB-PSO, SPB-ANN and SPB-CNN replicas individually.

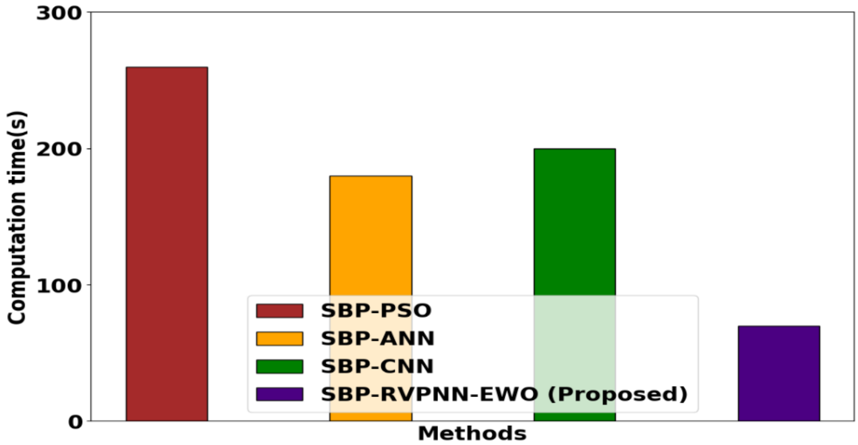

Figure 4: Computation time performance analysis

Figure 4 shows Computation time performance analysis. Here, SBP-RVPNN-EWO reaches 22.12%, 18.77% and 24.87% lower Computation time comparing to the current SPB-PSO, SPB-ANN and SPB-CNN models respectively.

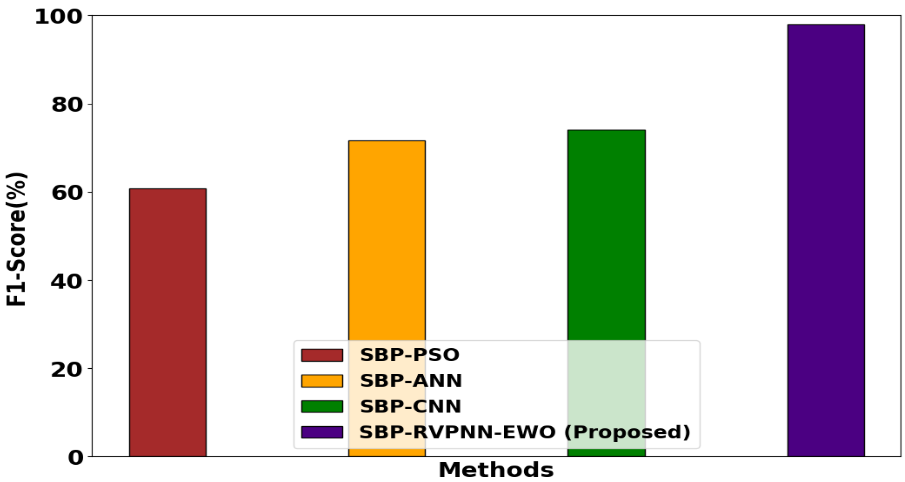

Figure 5: Evaluation of F1-Score Performance

Figure 5 displays: Evaluation of F1-Score Performance. The suggested SBP-RVPNN-EWO method reaches 23.4%, 26.6% and 27.3% higher F1-Score for predicting the strategic business process estimated to the existing SPB-PSO, SPB-ANN and SPB-CNN models respectively.

Table 1: Efficiency and effectiveness as value creation processes

Process	Activity Outcome Efficiency	Activity Outcome Effectiveness
Business Process	Exchange value based on serial, pooled and reciprocal interdependencies	Use value based on exchange value reciprocal interdependencies
Focus	Exchange of resources	Utilization of Resources
Activities	Buying/ selling and producing	Fit between exchanged resources and existing resource adaptation

5. CONCLUSION

In conclusion, the study on "Robust Variation Physics-Informed Neural Network based prediction of Strategic Business Process" highlights the importance of leveraging advanced deep learning techniques for accurate and efficient prediction of Business Process. Through the optimization and utilization of RVPNN significant improvements in prediction performance have been achieved. Embracing strategic business process optimization as a core business strategy empowers organizations to drive sustainable performance improvements, increase customer satisfaction, and position themselves as industry leaders in today's competitive landscape. The performance of the proposed SBP-RVPNN-EWO method approach contains 28.96%, 33.21% and 23.89% higher Sensitivity, and 26.28%, 31.26%, and 19.66% higher Specificity 26.12%, 15.23% and 21.87% higher F1-score, 19.75%, 29.59% and 23.52% higher RoC, and 22.12%, 18.77% and 24.87% lower Computation time when examined to the current methods such as SPB-PSO, SPB-ANN and SPB-CNN respectively. Reducing expenses, raising customer happiness, and accurately predicting productivity are all achieved by the RVPNN.

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