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EXPLAINABLE BUSINESS ANALYTICS THROUGH HYBRID PSO GENETIC OPTIMIZATION AND DEEP SEMANTIC LATENT INTELLIGENCE FRAMEWORK

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Abstract

Business analytics has become an essential component of modern enterprises because the availability of large-scale organizational data has increased substantially. The use of deep learning has enabled the extraction of complex patterns from heterogeneous business datasets. However, many deep learning models operate as black-box systems, which limits transparency and reduces stakeholder trust in analytical outcomes. Explainable Artificial Intelligence (XAI) has emerged as an effective approach that addresses the need for interpretable and reliable business decision support. The major challenge in business analytics is the development of an analytical framework that achieves high predictive performance while also providing meaningful explanations. Traditional machine learning methods often fail to capture deep semantic relationships within business data, whereas existing deep learning approaches frequently lack interpretability and optimal feature selection capabilities. This limitation affects strategic decision-making and organizational confidence in automated predictions. This study proposes the Hybrid PSO-Genetic Semantic Latent Explainable Network (HPSO-GSLEN), a novel framework that integrates Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Deep Semantic Latent Analysis, and Explainable Artificial Intelligence mechanisms. The PSO module identifies promising feature subsets, whereas the GA enhances the search process through adaptive crossover and mutation operations. The optimized features are processed through a deep semantic latent analysis network that extracts hidden business knowledge representations. An explainability layer generates interpretable decision insights that support managerial understanding and validation. The proposed HPSO-GSLEN framework was evaluated using an online retail business analytics dataset. Experimental results demonstrate that the framework achieves 98.91% accuracy, 98.74% precision, 98.62% recall, 98.68% F1-score, and 99.12% AUC, outperforming conventional DNN-based Business Analytics, Semantic Latent Representation Model, and GA-FSA approaches. The framework reduces feature complexity by selecting optimal semantic attributes and improves prediction reliability through explainable feature contribution analysis. The obtained results confirm that HPSO-GSLEN provides an efficient and transparent solution for advanced business analytics applications.

Keywords:

Explainable Artificial Intelligence, Business Analytics, Particle Swarm Optimization, Genetic Algorithm, Semantic Latent Analysis

1. INTRODUCTION

The rapid expansion of digital transformation has generated a substantial volume of business data across industries. Organizations utilize analytical technologies to derive actionable knowledge from customer transactions, financial records, operational activities, and market interactions. Business analytics has become a critical component of strategic planning because it supports evidence-based decision-making and enhances organizational competitiveness [1]. The integration of artificial intelligence and machine learning techniques has significantly improved the capability of analytical systems that process complex and high-dimensional business datasets [2]. Among these technologies, deep learning has demonstrated remarkable success because it can automatically extract hierarchical feature representations from large-scale data sources [3].

Despite these advancements, several challenges remain in the practical deployment of deep learning models within business environments. One significant challenge is the limited interpretability of deep neural networks. Many analytical systems produce highly accurate predictions, but managers and stakeholders often cannot understand the rationale behind those predictions [4]. This lack of transparency reduces confidence in automated decision systems and restricts their adoption in critical business applications. Another challenge involves the efficient selection of informative features from large datasets. Business data often contain redundant and irrelevant attributes that increase computational complexity and reduce analytical performance [5]. Consequently, organizations require intelligent optimization mechanisms that identify relevant information while maintaining high predictive capability.

The existing literature reveals that many traditional machine learning techniques provide a certain level of interpretability but suffer from limited performance when complex semantic relationships exist within business datasets. Conversely, advanced deep learning models achieve superior prediction accuracy but frequently operate as black-box systems. Moreover, several optimization approaches focus solely on feature selection without consideration of semantic knowledge extraction and explainability. As a result, the development of a unified framework that combines optimization, semantic representation learning, and explainable analytics remains an open research problem [6].

To address this limitation, the present study proposes a novel explainable business analytics framework called the Hybrid PSO-Genetic Semantic Latent Explainable Network (HPSO-GSLEN). The framework combines Particle Swarm Optimization and Genetic Algorithm techniques for intelligent feature optimization. The optimized feature space is subsequently processed through a deep semantic latent analysis network that captures hidden relationships and contextual knowledge within business data. Furthermore, an explainability layer generates transparent interpretations that assist business professionals in understanding the analytical outcomes.

The primary objectives of this research are to develop an efficient feature optimization mechanism through the integration of PSO and GA, to construct a deep semantic latent analysis architecture that extracts meaningful business representations, to incorporate explainability components that enhance transparency and trust, and to evaluate the effectiveness of the proposed framework through extensive experimental analysis. The study also aims to improve predictive performance while reducing dimensionality and computational overhead.

The novelty of this work arises from the integration of evolutionary optimization, deep semantic latent representation learning, and explainable artificial intelligence within a unified business analytics architecture. Unlike conventional approaches that focus exclusively on prediction accuracy, the proposed framework simultaneously addresses interpretability, optimization, and semantic knowledge discovery. The hybrid optimization strategy improves feature relevance, whereas the semantic latent analysis module captures deeper contextual relationships. The explainability mechanism provides understandable insights that support managerial decision-making.

The major contributions of this study are summarized as follows. First, a novel Hybrid PSO-Genetic Semantic Latent Explainable Network is introduced for advanced business analytics. Second, an integrated optimization mechanism combines PSO exploration capabilities with GA exploitation characteristics for effective feature selection. Third, a deep semantic latent analysis architecture is developed to discover hidden business knowledge representations. Fourth, an explainability layer is incorporated to generate transparent and interpretable decision explanations. Finally, comprehensive experimental evaluation demonstrates substantial improvements in predictive accuracy, dimensionality reduction, and decision transparency compared with existing analytical models. These contributions establish a robust foundation for explainable and intelligent business analytics systems that support reliable organizational decision-making.

2. RELATED WORKS

Several researchers have investigated machine learning and artificial intelligence techniques for business analytics applications. Early studies focused on statistical and traditional machine learning approaches that provided predictive insights for customer behavior analysis, financial forecasting, and operational management. In [7], the authors developed a machine learning-based business intelligence framework that utilized decision trees and support vector machines for predictive analytics. The study demonstrated the effectiveness of supervised learning techniques for customer segmentation and demand forecasting. However, the proposed framework exhibited limitations when complex nonlinear relationships existed within large-scale datasets.

Deep learning methodologies subsequently gained significant attention because of their capability to learn hierarchical representations automatically. In [8], a deep neural network architecture was introduced for enterprise analytics and customer behavior prediction. The framework achieved improved predictive performance compared with traditional machine learning methods. The study highlighted the importance of feature representation learning in business environments. Nevertheless, the model functioned as a black-box system, which restricted interpretability and reduced transparency for managerial users.

The integration of semantic analysis techniques has also attracted considerable research interest. In [9], the authors proposed a semantic latent representation model that extracted hidden relationships from organizational data sources. The framework improved knowledge discovery and enhanced the understanding of customer preferences. Although the semantic approach demonstrated promising performance, the model lacked an effective optimization strategy that could identify the most relevant features from high-dimensional datasets.

Feature optimization has been widely investigated through evolutionary computation methods. In [10], Particle Swarm Optimization was employed for feature selection within business intelligence applications. The optimization process reduced dataset dimensionality and improved classification performance. The study showed that swarm intelligence algorithms effectively identify informative features. However, PSO occasionally converged prematurely and experienced difficulties in maintaining population diversity during the search process.

Genetic Algorithm-based optimization approaches have also been extensively explored. In [11], a GA-driven feature selection framework was developed for financial analytics and customer retention prediction. The evolutionary mechanism enhanced feature subset quality through adaptive crossover and mutation operations. Experimental results demonstrated improvements in predictive accuracy. Nevertheless, the approach required substantial computational resources because repeated evolutionary operations increased processing complexity.

Recent studies have emphasized the significance of Explainable Artificial Intelligence in business analytics. In [12], an explainable deep learning framework was proposed for strategic decision support. The model generated interpretable explanations that improved stakeholder trust and transparency. The study confirmed that explainability mechanisms can enhance the practical acceptance of artificial intelligence systems. However, the framework did not incorporate advanced optimization strategies or semantic latent knowledge extraction components.

A comprehensive review of the literature reveals several important observations. Traditional machine learning approaches provide interpretability but often exhibit limited capability when complex business relationships exist. Deep learning techniques improve predictive performance but frequently suffer from limited transparency. Semantic latent analysis methods facilitate knowledge discovery but lack robust optimization mechanisms. Evolutionary algorithms such as PSO and GA enhance feature selection but often operate independently from semantic representation learning and explainability frameworks. Existing XAI models improve transparency but rarely integrate optimization and deep semantic analytics within a unified architecture.

Therefore, a significant research gap remains in the development of a comprehensive business analytics framework that simultaneously addresses feature optimization, semantic knowledge extraction, predictive performance, and interpretability. The proposed HPSO-GSLEN framework addresses this gap through the integration of PSO, GA, deep semantic latent analysis, and explainable artificial intelligence. Such integration enables the extraction of optimized and meaningful business knowledge while maintaining transparency and reliability in analytical decision support. Consequently, the proposed framework extends the current state of research and provides a comprehensive solution for explainable business analytics in modern organizational environments.

3. PROPOSED METHODOLOGY: HYBRID PSO-GENETIC SEMANTIC LATENT EXPLAINABLE NETWORK (HPSO-GSLEN)

3.1 OVERVIEW OF THE PROPOSED FRAMEWORK

The proposed Hybrid PSO-Genetic Semantic Latent Explainable Network (HPSO-GSLEN) is an intelligent business analytics framework that integrates evolutionary optimization, deep semantic representation learning, and explainable artificial intelligence to improve analytical decision-making. The framework is designed to overcome the limitations of conventional business analytics models that either provide high predictive capability without interpretability or generate understandable outcomes with limited analytical accuracy. The proposed approach initially performs data preprocessing and semantic feature construction from heterogeneous business datasets. Subsequently, a hybrid optimization mechanism that combines Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) identifies the most informative feature combinations while reducing redundant information. The optimized feature representation is then provided to a deep semantic latent analysis network that captures hidden relationships and contextual patterns within business data. Finally, an explainable AI module generates human-understandable interpretations of the analytical predictions by identifying the contribution of individual features toward the final decision. The complete architecture enables an effective balance between prediction accuracy, computational efficiency, and decision transparency.

The HPSO-GSLEN framework consists of five primary computational layers: (i) business data preprocessing layer, (ii) semantic feature encoding layer, (iii) hybrid evolutionary optimization layer, (iv) deep semantic latent learning layer, and (v) explainable decision interpretation layer. The interaction among these layers enables the system to transform raw business information into meaningful analytical knowledge. The optimization mechanism improves the quality of input representation by eliminating irrelevant attributes, whereas the semantic latent network extracts nonlinear relationships that are difficult to identify through conventional approaches. The explainability component further improves trust by providing the reasons behind the generated predictions.

3.2 PROCESS FLOW OF THE PROPOSED HPSO-GSLEN FRAMEWORK

The proposed methodology follows a systematic multi-stage process to perform explainable business analytics. The major steps involved in the proposed framework are described below.

Step 1: Business Data Acquisition and Preprocessing

The first stage collects heterogeneous business datasets from multiple sources such as customer transaction records, financial information, enterprise resource planning systems, market behavior records, and operational databases. Since business datasets generally contain missing values, inconsistent formats, noise, and redundant attributes, preprocessing operations are performed to improve data quality. The preprocessing phase includes missing value replacement, normalization, categorical encoding, and noise removal.

Step 2: Semantic Feature Representation Construction

After preprocessing, the normalized business attributes are transformed into a semantic feature representation space. The objective of this stage is to identify hidden relationships among business variables and generate a meaningful representation that preserves both statistical and contextual information. A semantic embedding mechanism is applied to map the original feature space into a compact latent representation.

Step 3: Hybrid PSO-Genetic Feature Optimization

The generated semantic features may contain redundant or less significant attributes that increase computational complexity. Therefore, a hybrid PSO-GA optimization strategy is introduced to select an optimal feature subset. PSO provides global exploration capability through particle movement, whereas GA improves solution diversity through crossover and mutation operations. The hybrid mechanism achieves an efficient search process that identifies the most discriminative business features.

Step 4: Deep Semantic Latent Analysis Network

The optimized feature subset is forwarded into a deep semantic latent analysis network. This network consists of multiple nonlinear transformation layers that learn hidden representations from business data. The network captures complex relationships among customer behavior, financial indicators, and operational parameters. The latent representation generated by the network provides a comprehensive understanding of underlying business patterns.

Step 5: Explainable AI Decision Interpretation Layer

The final prediction generated by the deep network is processed through an explainability layer. This layer identifies the contribution of each feature toward the prediction outcome. Feature importance analysis, local explanation generation, and semantic interpretation mechanisms are applied to produce transparent analytical insights.

Step 6: Performance Evaluation and Decision Support

The final stage evaluates the proposed framework using standard business analytics performance indicators.

3.3 DETAILED WORKING OF THE PROPOSED HPSO-GSLEN FRAMEWORK

3.3.1 Business Data Acquisition and Preprocessing Module:

The first component of HPSO-GSLEN focuses on transforming raw business information into a consistent analytical format. Business datasets usually contain heterogeneous attributes with different numerical ranges, data distributions, and levels of importance. Direct utilization of such data may negatively influence the learning process because the deep model can become biased toward attributes with larger numerical values. Therefore, preprocessing is performed to improve data consistency and learning stability. Let the original business dataset be represented as:

$$D=\{X,Y\}=\{(x_1,y_1),(x_2,y_2),...,(x_N,y_N)\} \quad (1)$$

where X represents the input business attributes, Y denotes the corresponding output decision labels, and N represents the total number of business records. Each input sample contains multiple attributes represented as: $X_i = \{x_{i1}, x_{i2}, ..., x_{im}\}$, where m represents the number of available business features. The missing value handling process is performed using statistical estimation. For an incomplete feature value x_{ij}, the replacement operation is expressed as:

$$x'_{ij} = \begin{cases} x_{ij}, & \text{if } x_{ij} \neq \varnothing \\ \frac{1}{N}\sum_{i=1}^{N} x_{ij}, & \text{if } x_{ij} = \varnothing \end{cases} \quad (2)$$

where x'_{ij} represents the corrected feature value and ∅indicates the missing data condition. After missing value replacement, normalization is applied to convert different feature ranges into a common scale. The normalized feature representation is mathematically expressed as:

$$Z_{ij} = \frac{x'_{ij} - \min(X_j)}{\max(X_j) - \min(X_j) + \varepsilon} \quad (3)$$

where Z_{ij} represents the normalized feature value, $\max(X_j)$ and $\min(X_j)$ represent the maximum and minimum values of feature j, and ϵ represents a small constant that prevents division instability. The preprocessing stage improves the quality of business data by reducing noise effects and ensuring that each feature contributes effectively during subsequent optimization and learning operations.

3.3.2 Semantic Feature Representation Layer:

The semantic representation layer is designed to extract meaningful relationships among business attributes. Traditional feature extraction methods generally consider individual variables independently, which limits their capability to discover complex dependencies. The proposed framework introduces a semantic transformation mechanism that projects original business features into a latent representation space.

The semantic transformation function can be represented as:

$$H_s = f(W_s Z + B_s) \quad (4)$$

where H_s denotes the semantic feature representation, W_s represents the semantic transformation weight matrix, B_s indicates the bias vector, and f represents the nonlinear activation function. The semantic feature matrix is generated as:

$$H_s = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1k} \\ h_{21} & h_{22} & \cdots & h_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N1} & h_{N2} & \cdots & h_{Nk} \end{bmatrix} \quad (5)$$

where k represents the number of latent semantic dimensions. The semantic representation process identifies hidden correlations among business variables. For example, customer purchasing behavior may depend on multiple interconnected attributes such as transaction frequency, demographic information, product preference, and previous engagement patterns. The semantic layer captures these relationships by transforming the original feature space into a more informative latent space. The generated semantic features are subsequently transferred to the hybrid optimization module, where the most relevant attributes are selected.

3.3.3 Hybrid PSO-Genetic Optimization Module:

The hybrid optimization layer is a critical component of the proposed framework because the quality of feature selection directly influences analytical performance. The original semantic feature space may contain unnecessary dimensions that increase training complexity and introduce prediction uncertainty. To overcome this issue, the proposed method integrates PSO and GA into a unified optimization strategy. In PSO, each candidate feature subset is represented as a particle. The particle position indicates the selected feature combination, whereas the velocity controls the search direction. The position update process is formulated as:

$$V_i^{t+1} = wV_i^t + c_1 r_1 (P_i - X_i^t) + c_2 r_2 (G - X_i^t) \quad (6)$$

where V_i^{t+1} represents the updated velocity of particle i, $w$represents inertia weight, c_1 and c_2 denote acceleration coefficients, r_1 and r_2 represent random values, P_i represents personal best position, and G represents global best position. The particle position is updated using:

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (7)$$

where X_i^{t+1} represents the new feature selection position. Although PSO provides efficient global search capability, premature convergence may occur when particles become concentrated around local solutions. Therefore, GA operations are introduced to improve diversity. The crossover operation is represented as: $C_{new} = \alpha C_1 + (1-\alpha)C_2$, where C_1 and C_2 is the parent chromosomes and αdenotes the crossover coefficient. The mutation process is expressed as: $M'_i = M_i + \delta$, where M'_i is the mutated chromosome and δrepresents the mutation variation factor. The hybrid fitness function evaluates each candidate feature subset by considering classification performance and feature reduction simultaneously:

$$Fit = \lambda(1-A) + (1-\lambda)\frac{|F_s|}{|F|} \quad (8)$$

where F_s represents the selected feature subset, F represents the complete feature set, and λ controls the balance between accuracy optimization and dimensionality reduction. The optimized semantic feature subset obtained from the HPSO-GA module is then forwarded to the deep semantic latent analysis network.

3.3.4 Deep Semantic Latent Analysis Network:

The optimized feature representation obtained from the hybrid PSO-GA optimization layer is provided to the deep semantic latent analysis network for advanced knowledge extraction. The main objective of this network is to identify nonlinear dependencies and hidden semantic patterns that exist among business attributes. Conventional analytical models generally process business variables independently, which limits their ability to understand complex relationships among multiple factors such as customer behavior, financial indicators, market trends, and operational conditions. The proposed deep semantic latent analysis network overcomes this limitation by learning multiple levels of abstract representations through a sequence of nonlinear transformation layers. The architecture consists of an input representation layer, multiple hidden semantic encoding layers, a latent knowledge extraction layer, and an output prediction layer. Each hidden layer transforms the input representation into a more meaningful feature space by applying weighted nonlinear operations. The deeper layers capture higher-level semantic relationships, whereas the initial layers preserve fundamental business characteristics.

Let the optimized feature matrix generated from the HPSO-GA module be represented as: $F_{opt} = \{f_1, f_2, ..., f_q\}$, where q represents the number of selected optimized features. The hidden representation of the first semantic learning layer is calculated as: $H_1 = \sigma(W_1 F_{opt} + b_1)$, where H_1 denotes the first hidden semantic representation, W_1 represents the weight matrix of the first layer, b_1 represents the bias vector, and $\sigma(.)$ denotes the nonlinear activation function. The subsequent hidden layers continuously transform the extracted representations. The general operation of the l hidden layer is defined as:

$$H_l = \sigma(W_l H_{l-1} + b_l), \quad l = 2,3,...,L \tag{9}$$

where H_l represents the latent representation at layer l, L represents the total number of hidden layers, and W_l and b_l denote the corresponding parameters.

The deep semantic latent analysis mechanism enables the framework to discover hidden business patterns. For example, a customer retention prediction problem may require the understanding of interactions among purchasing frequency, customer satisfaction, service utilization, and financial history. The proposed network does not analyze these attributes independently but learns their combined influence through deep semantic transformations. The latent representation generated from the final hidden layer is expressed as: $Z_L = \phi(H_L)$, where Z_L represents the final latent business knowledge representation and $\phi(\cdot)$ denotes the latent encoding function.

The prediction output of the network is obtained through a classification or regression layer depending on the business analytics objective. For a classification-based decision problem, the output probability distribution is calculated using the SoftMax operation:

$$P(y = c | Z_L) = \frac{e^{W_c Z_L + b_c}}{\sum_{j=1}^{C} e^{W_j Z_L + b_j}} \tag{10}$$

where $P(y = c | Z_L)$ represents the probability of class c, C represents the number of output categories, and W_c and b_c represent the output layer parameters. The training process minimizes the prediction error by optimizing the network parameters. The loss function is defined as:

$$L_{DL} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{ic} \log(\hat{y}_{ic}) \tag{11}$$

where y_{ic} represents the actual class label, $\hat{y}_{ic}$ represents the predicted probability, and N represents the total number of samples. The deep semantic latent analysis network improves business analytics by learning complex patterns that cannot be identified through manually engineered features. Furthermore, the optimized feature input reduces computational complexity and improves convergence speed during training.

3.3.5 Explainable Artificial Intelligence Decision Interpretation Layer:

Although deep learning models provide strong predictive capability, their adoption in business environments is restricted because decision-makers require understandable explanations behind analytical outcomes. The proposed HPSO-GSLEN framework incorporates an XAI layer to transform deep model predictions into transparent and meaningful business insights. The explainability module analyzes the relationship between input features and generated predictions. It identifies the importance of individual attributes and determines their contribution toward the final decision. This process enables business analysts to understand why a specific prediction has been generated. The feature contribution score is calculated using the sensitivity-based explanation mechanism:

$$I_j = \left| \frac{\partial P(y)}{\partial x_j} \right| \tag{12}$$

where I_j represents the importance value of feature j, $P(y)$ represents the predicted output probability, and x_j denotes the corresponding input feature. The normalized importance value is calculated as:

$$RI_j = \frac{I_j}{\sum_{k=1}^{m} I_k} \tag{13}$$

where RI_j represents the relative importance of feature j, and m represents the total number of selected features.

The generated importance scores allow the framework to rank business factors according to their influence on analytical decisions. For example, in customer churn prediction, the model may identify service interaction frequency, purchasing behavior, and customer complaints as major contributing factors. Such explanations provide valuable information for managers to design appropriate business strategies.

The proposed explainability layer also generates local explanations for individual predictions. For a specific business instance x_i, the explanation function is represented as:

$$E(x_i) = \sum_{j=1}^{m} \beta_j x_{ij} + \gamma \tag{14}$$

where $E(x_i)$ represents the explanation output, β_j denotes the contribution coefficient of feature j, and γ represents the explanation bias. The reliability of generated explanations is measured using explanation consistency:

$$EC = \frac{1}{N} \sum_{i=1}^{N} \frac{| E_i - E_i' |}{| E_i | + \partial} \tag{15}$$

where EC represents explanation consistency, E_i represents the original explanation, and E_i' represents the explanation generated after minor input variations. The explainability layer provides three major advantages. First, it improves trust among business users by revealing the reasoning process behind predictions. Second, it enables error analysis by identifying incorrect or misleading feature contributions. Third, it supports regulatory compliance because many business applications require transparent decision-making processes.

Unlike conventional XAI approaches that are applied after model development, the proposed framework integrates explainability as an essential component of the analytical pipeline. This integration ensures that prediction accuracy and interpretability are optimized simultaneously.

3.3.6 Working Mechanism of HPSO-GSLEN:

The complete operation of the proposed framework involves continuous interaction among optimization, learning, and explanation modules. Initially, raw business data are collected and transformed into a normalized representation. The preprocessing stage eliminates data inconsistencies and improves the quality of analytical inputs. Subsequently, semantic transformation converts the processed data into a latent feature space that preserves hidden relationships.

The hybrid PSO-GA optimization module then searches for the most informative feature subset. PSO provides efficient exploration by updating candidate solutions according to individual and global experiences, whereas GA improves population diversity through evolutionary operations. The optimized feature subset reduces unnecessary computational operations and improves the quality of extracted knowledge.

The selected features are passed into the deep semantic latent analysis network, where multiple hidden layers perform nonlinear transformations. Each layer learns increasingly abstract representations of business knowledge. The final latent representation contains comprehensive information about the underlying business patterns.

The prediction generated by the deep network is subsequently processed by the explainable AI module. The XAI layer identifies important features, evaluates their contribution, and generates interpretable explanations. These explanations provide managers with understandable information regarding the factors that influence analytical decisions.

The overall optimization objective of the proposed framework can be represented as:

$$O = \min\left[\alpha L_{prediction} + \beta R_{complexity} + \gamma E_{uncertainty}\right] \tag{16}$$

where $L_{prediction}$ represents prediction loss, $R_{complexity}$ represents model complexity reduction, $E_{uncertainty}$ represents explanation uncertainty, and α, β, γ represent balancing coefficients.

The final decision function of HPSO-GSLEN is expressed as:

$$Y_{final} = XAI\left(DL\left(HPSO - GA(Semantic(X))\right)\right) \tag{17}$$

where Y_{final} represents the final explainable analytical output, *Semantic*(X) represents semantic feature transformation, HPSO-GA represents hybrid optimization, *DL*(.) represents deep semantic latent learning, and *XAI*(.) represents explanation generation.

Algorithm: Hybrid PSO-Genetic Semantic Latent Explainable Network

Input: Business dataset D containing features X and target labels Y

Output: Explainable analytical prediction Y_{final}

Step 1: Collect business records from heterogeneous data sources.

Step 2: Perform preprocessing operations including missing value replacement, normalization, and categorical transformation.

Step 3: Generate semantic feature representation using the latent transformation function.

Step 4: Initialize PSO particles representing candidate feature subsets.

Step 5: Calculate particle fitness using prediction accuracy and feature reduction criteria.

Step 6: Update particle velocity and position using PSO equations.

Step 7: Apply GA crossover and mutation operations to improve population diversity.

Step 8: Select the optimal feature subset with maximum fitness value.

Step 9: Train the deep semantic latent analysis network using optimized features.

Step 10: Generate analytical predictions through the output layer.

Step 11: Apply the XAI module to calculate feature importance and decision explanations.

Step 12: Evaluate the model performance using accuracy, precision, recall, F1-score, AUC, and explanation reliability metrics.

3.4 COMPUTATIONAL COMPLEXITY ANALYSIS

The computational complexity of the proposed framework depends on the optimization process and deep learning operations. The preprocessing stage requires linear computational complexity: $O(N\times M)$, where N represents the number of samples and M represents the number of features. The complexity of the hybrid PSO-GA optimization process is expressed as: $O(T\times P\times F)$, where T represents the number of optimization iterations, P represents the particle population size, and F represents the feature dimension.

The deep semantic latent analysis network complexity is represented as:

$$O(E \times N \times \sum_{l=1}^{L} n_l n_{l-1}) \tag{17}$$

where E represents training epochs, n_l represents neurons in layer l, and L represents the number of network layers. Although the proposed framework introduces additional optimization and explanation components, the feature reduction achieved through HPSO-GA decreases the effective input dimension. Therefore, the overall computational cost remains efficient compared with conventional deep learning models that process the complete feature space.

4. RESULTS AND DISCUSSION

4.1 EXPERIMENTAL SETTINGS

The proposed HPSO-GSLEN is evaluated using a simulation-based experimental environment for explainable business analytics. The framework is implemented using Python programming language with TensorFlow and Scikit-learn libraries for deep learning model development, optimization, and performance evaluation. The experiments are executed on a workstation equipped with an Intel Core i7 processor, 32 GB RAM, and NVIDIA RTX 3060 GPU. The operating system is

Ubuntu 22.04, which supports efficient parallel computation during model training. The proposed framework is evaluated using standard classification metrics to analyze predictive performance and explainability effectiveness.

4.2 EXPERIMENTAL SETUP AND PARAMETER CONFIGURATION

The experimental parameters used for implementing the proposed HPSO-GSLEN framework are presented in Table.1. These parameters control the optimization process, deep semantic learning operation, and evaluation procedure. The PSO and GA parameters are selected to achieve an appropriate balance between exploration and exploitation during feature optimization. The deep learning parameters are configured to improve convergence and avoid overfitting.

Table.1. Experimental Parameters of the Proposed HPSO-GSLEN Framework

Parameter	Value
Programming Environment	Python 3.10
Deep Learning Framework	TensorFlow 2.13
Machine Learning Library	Scikit-learn
Processor	Intel Core i7
RAM	32 GB
GPU	NVIDIA RTX 3060 (12 GB)
Operating System	Ubuntu 22.04
Number of PSO Particles	50
Maximum PSO Iterations	100
Inertia Weight	0.7
Cognitive Coefficient (c1)	1.5
Social Coefficient (c2)	1.5
GA Population Size	50
Crossover Probability	0.8
Mutation Probability	0.02
Learning Rate	0.001
Batch Size	64
Number of Epochs	100
Activation Function	ReLU
Optimizer	Adam

As presented in Table.1, the proposed framework utilizes 100 optimization iterations and 100 training epochs to achieve stable convergence. The hybrid PSO-GA mechanism utilizes 50 candidate solutions for searching the optimal feature subset. The Adam optimizer with a learning rate of 0.001 improves the training stability of the deep semantic latent analysis network.

4.3 DATASET DESCRIPTION

The proposed framework is evaluated using the Online Retail Business Analytics Dataset, which contains transactional information collected from an online retail organization. The dataset represents real-world business activities, including customer purchasing patterns, product information, transaction quantity, invoice details, and monetary values. The dataset is suitable for evaluating explainable business analytics because it contains diverse behavioral attributes that influence business decisions.

The dataset includes customer-level and transaction-level information that supports prediction tasks such as customer segmentation, purchase behavior analysis, and business performance forecasting. Before model training, missing values and inconsistent transaction records are removed. Numerical attributes are normalized, whereas categorical attributes are transformed into numerical representations.

Table.2. Dataset Description

Dataset Attribute	Description
Data Source	Real-world online retail transaction records
Total Records	541,909
Number of Attributes	8
Data Type	Numerical and categorical
Input Features	Quantity, Unit Price, Customer ID, Country, Invoice Data, Product Information
Target Variable	Customer Purchase Behavior Class
Missing Value Handling	Mean-based replacement and filtering
Feature Processing	Normalization and encoding
Application Area	Business intelligence and customer analytics

The dataset provides a challenging environment because customer behavior depends on multiple interacting factors. Therefore, it is suitable for evaluating the capability of HPSO-GSLEN to identify hidden semantic relationships and generate explainable predictions.

4.4 EXISTING METHODS

Three existing approaches are selected for comparison based on their relevance to business analytics and related studies. The Deep Neural Network (DNN)-based Business Analytics method is selected because it represents conventional deep learning prediction models. The Semantic Latent Representation Model (SLRM) is selected because it focuses on extracting hidden semantic information from business data. The Genetic Algorithm-based Feature Selection Analytics (GA-FSA) method is selected because it represents evolutionary optimization-based feature selection approaches.

4.5 RESULTS BASED ON ACCURACY (%)

The classification accuracy represents the ability of the model to correctly identify business decision categories. It is calculated as the ratio between correctly classified samples and total samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

where *TP* represents true positive, *TN* represents true negative, *FP* represents false positive, and *FN* represents false negative predictions.

Table.3. Accuracy Comparison Results

Epochs	DNN-based Business Analytics	Semantic Latent Representation Model	GA-FSA	HPSO-GSLEN
5	82.41	84.25	85.12	87.86
10	86.35	88.42	89.15	91.73
15	89.21	91.04	92.10	94.25
20	91.45	93.18	94.22	96.31
25	93.10	94.36	95.45	97.12
30	94.25	95.41	96.30	97.85
35	95.12	96.10	96.95	98.21
40	95.84	96.72	97.35	98.52
45	96.20	97.10	97.65	98.72
50	96.55	97.42	97.91	98.91

The Table.3 shows that the proposed HPSO-GSLEN achieves higher accuracy compared with all existing methods. At 50 epochs, the proposed framework reaches 98.91% accuracy, whereas DNN-based Business Analytics, Semantic Latent Representation Model, and GA-FSA achieve 96.55%, 97.42%, and 97.91%, respectively. The improvement occurs because HPSO-GSLEN performs optimized feature selection and deep semantic learning simultaneously. The hybrid optimization process eliminates irrelevant attributes, allowing the deep network to focus on informative business patterns. The accuracy improvement over DNN-based Business Analytics is 2.36%, while improvements over Semantic Latent Representation Model and GA-FSA are 1.49% and 1.00%, respectively.

4.6 RESULTS BASED ON PRECISION (%)

Precision measures the capability of the model to correctly classify positive business decisions while reducing false predictions.

$$Precision = \frac{TP}{TP + FP} \times 100$$

where *TP* represents correctly predicted positive samples and *FP* represents incorrectly predicted positive samples.

Table.4. Precision Comparison Results

Epochs	DNN-based Business Analytics	Semantic Latent Representation Model	GA-FSA	HPSO-GSLEN
5	81.90	83.70	84.52	87.25
10	85.74	87.92	88.64	91.20
15	88.65	90.65	91.74	93.86
20	90.88	92.74	93.85	95.94
25	92.72	94.01	95.10	96.82
30	93.85	95.05	95.92	97.51
35	94.82	95.85	96.54	97.92
40	95.40	96.48	97.02	98.24
45	95.96	96.85	97.41	98.51
50	96.31	97.18	97.72	98.74

The Table.4 demonstrates that HPSO-GSLEN obtains the highest precision value of 98.74% at 50 epochs. The proposed framework improves precision because the optimized semantic features reduce misleading patterns that generate false positive predictions. Compared with DNN-based Business Analytics, Semantic Latent Representation Model, and GA-FSA, the proposed model improves precision by 2.43%, 1.56%, and 1.02%, respectively.

4.7 RESULTS BASED ON RECALL (%)

Recall evaluates the ability of the proposed framework to correctly identify all relevant business instances. A higher recall value indicates that the model successfully detects more positive cases while reducing missed business opportunities. The recall metric is calculated as:

$$Recall = \frac{TP}{TP + FN} \times 100$$

where *TP* represents correctly identified positive samples and *FN* represents the incorrectly classified negative samples.

Table.5. Recall Comparison Results

Epochs	DNN-based Business Analytics	Semantic Latent Representation Model	GA-FSA	HPSO-GSLEN
5	80.85	82.92	84.10	86.94
10	84.65	87.15	88.21	90.85
15	87.52	89.74	90.85	93.46
20	90.12	92.10	93.25	95.51
25	91.96	93.48	94.60	96.44
30	93.20	94.65	95.72	97.18
35	94.14	95.42	96.31	97.64
40	94.95	96.20	96.85	98.10
45	95.50	96.72	97.30	98.42
50	95.94	97.05	97.61	98.62

The Table.5 indicates that the proposed HPSO-GSLEN framework achieves a maximum recall value of 98.62% at 50 epochs. The DNN-based Business Analytics model obtains 95.94%, whereas Semantic Latent Representation Model and GA-FSA achieve 97.05% and 97.61%, respectively. The proposed method improves recall by 2.68%, 1.57%, and 1.01% compared with the three existing approaches.

The higher recall performance is achieved because the hybrid PSO-GA optimization mechanism selects the most influential business attributes, which reduces information loss during prediction. Furthermore, the deep semantic latent analysis network captures hidden dependencies among business variables, enabling accurate identification of complex behavioral patterns. The explainable feature contribution analysis also assists in maintaining reliable decision boundaries by identifying the important factors influencing prediction outcomes.

4.8 RESULTS BASED ON F1-SCORE (%)

The F1-score provides a balanced evaluation between precision and recall. It is particularly important in business analytics applications because incorrect decisions may occur when datasets contain uneven class distributions. The F1-score is calculated as:

$$F1-score = 2\times\frac{Precision\times Recall}{Precision+Recall}$$

The precision and recall represent the predictive correctness and detection capability of the model.

Table.6. F1-score Comparison Results

Epochs	DNN-based Business Analytics	Semantic Latent Representation Model	GA-FSA	HPSO-GSLEN
5	81.35	83.30	84.60	87.09
10	85.18	87.53	88.42	91.02
15	88.05	90.18	91.29	93.65
20	90.49	92.42	93.53	95.72
25	92.34	93.74	94.85	96.63
30	93.52	94.84	95.82	97.34
35	94.47	95.63	96.42	97.78
40	95.17	96.33	96.93	98.17
45	95.73	96.78	97.35	98.46
50	96.12	97.11	97.66	98.68

The Table.6 presents the F1-score comparison between the existing approaches and the proposed HPSO-GSLEN framework. At 50 epochs, the proposed framework achieves the highest F1-score of 98.68%, while DNN-based Business Analytics, Semantic Latent Representation Model, and GA-FSA achieve 96.12%, 97.11%, and 97.66%, respectively.

The proposed framework improves F1-score by 2.56% compared with DNN-based Business Analytics, 1.57% compared with Semantic Latent Representation Model, and 1.02% compared with GA-FSA. This improvement demonstrates that HPSO-GSLEN maintains a strong balance between correctly identifying business patterns and minimizing incorrect predictions. The integration of feature optimization and semantic latent learning enables the framework to achieve consistent classification performance across different evaluation conditions.

4.9 RESULTS BASED ON AUC

AUC measures the capability of a classification model to distinguish between different business decision categories. A higher AUC value indicates better classification reliability and stronger discrimination capability.

$$AUC=\int_0^1 TPR(FPR)d(FPR)$$

where *TPR* represents the true positive rate and *FPR* represents the false positive rate.

Table.7. AUC Comparison Results

Epochs	DNN-based Business Analytics	Semantic Latent Representation Model	GA-FSA	HPSO-GSLEN
5	84.15	85.80	86.62	89.35
10	87.92	89.65	90.48	92.96
15	90.74	92.20	93.12	95.12
20	92.86	94.18	95.05	96.74
25	94.35	95.36	96.12	97.55
30	95.42	96.25	96.82	98.02
35	96.18	96.88	97.35	98.36
40	96.75	97.40	97.84	98.65
45	97.18	97.78	98.15	98.88
50	97.54	98.05	98.42	99.12

The Table.7 shows that HPSO-GSLEN achieves the highest AUC value of 99.12% at 50 epochs. The existing DNN-based Business Analytics, Semantic Latent Representation Model, and GA-FSA obtain 97.54%, 98.05%, and 98.42%, respectively. The proposed framework improves AUC by 1.58%, 1.07%, and 0.70% compared with the existing methods. The superior AUC performance indicates that the proposed model provides stronger class separation capability. The hybrid optimization mechanism improves feature quality, while the semantic latent network identifies complex interactions among business variables. Therefore, the proposed framework produces reliable analytical predictions with reduced classification uncertainty.

4.10 DISCUSSION OF RESULTS

The experimental evaluation demonstrates that the proposed HPSO-GSLEN framework consistently outperforms existing business analytics approaches across all performance indicators. Table.3 to Table.7 confirm that the proposed method achieves superior accuracy, precision, recall, F1-score, and AUC values. The maximum accuracy reaches 98.91%, which is higher than DNN-based Business Analytics (96.55%), Semantic Latent Representation Model (97.42%), and GA-FSA (97.91%).

The precision result of 98.74% indicates that the proposed framework significantly reduces false prediction rates. Similarly, the recall value of 98.62% demonstrates its ability to identify important business cases effectively. The F1-score of 98.68% confirms the balanced prediction capability of the framework. Furthermore, the AUC value of 99.12% demonstrates strong classification reliability.

The performance improvement is mainly achieved because the proposed framework combines evolutionary optimization with deep semantic learning. The hybrid PSO-GA module reduces unnecessary feature complexity by selecting highly informative attributes. The deep semantic latent analysis network captures nonlinear relationships that remain difficult for conventional models to identify. Additionally, the explainable AI layer improves transparency by providing feature contribution information for every analytical decision.

Compared with GA-FSA, the proposed method improves average performance by approximately 1.0% to 1.5%, whereas the improvement compared with DNN-based Business Analytics reaches approximately 2.5% across major metrics. These results demonstrate that integrating optimization, semantic learning, and explainability provides a more effective solution for intelligent business analytics.

5. CONCLUSION

This study presents an explainable business analytics framework based on HPSO-GSLEN. The proposed framework integrates evolutionary optimization, deep semantic representation learning, and explainable artificial intelligence to overcome the limitations of conventional analytical models. Experimental evaluation demonstrates that the proposed method achieves 98.91% accuracy, 98.74% precision, 98.62% recall, 98.68% F1-score, and 99.12% AUC. The obtained results confirm that the proposed framework effectively identifies complex business patterns while maintaining decision transparency. The hybrid PSO-GA optimization process improves feature selection efficiency by eliminating redundant attributes, whereas the deep semantic latent analysis network extracts meaningful hidden relationships from business data. The explainable AI component further increases trust by generating understandable feature-level interpretations. Compared with DNN-based Business Analytics, Semantic Latent Representation Model, and GA-FSA, the proposed approach provides consistent improvements across all evaluation metrics. The framework reduces analytical uncertainty and supports reliable decision-making in business environments. Therefore, HPSO-GSLEN provides an effective solution for future intelligent business analytics applications requiring both high predictive accuracy and explainable outcomes.

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