DOI: 10.21917/ijsc.2026.0588

AN EXPLAINABLE HYBRID GENETIC OPTIMIZATION FRAMEWORK FOR INTELLIGENT BUSINESS ANALYTICS AND STRATEGIC DECISION SUPPORT

Maram Ashok[1] and Abhijeet Das[2]
[1]*Department of Computer Science and Engineering, Malla Reddy College of Engineering, India*
[2]*Department of Civil Engineering, Indira Gandhi Institute of Technology, India*

Abstract

Business organizations increasingly rely on the intelligent analysis of large-scale operational, financial, customer, and market datasets to improve strategic decision-making. The rapid growth of enterprise data creates new opportunities for analytical insights; however, the complexity, heterogeneity, and high dimensionality of business information present substantial challenges for conventional analytical approaches. Existing business analytics models often suffer from limited interpretability, suboptimal feature selection, and reduced adaptability when exposed to dynamic business environments. Such limitations affect the reliability of analytical outcomes and reduce stakeholder confidence in automated decision-support systems. To address these concerns, this study proposes an Explainable Genetic Analytics Optimization Network (EGAON), a novel hybrid framework that integrates the strengths of Genetic Algorithms with Explainable Artificial Intelligence (XAI) techniques for intelligent business analytics. The proposed EGAON method employs a genetic optimization mechanism for the identification of informative business attributes, while an explainability module provides transparent interpretations for predictive outcomes. The framework incorporates adaptive chromosome evolution, fitness-driven feature optimization, and explainable decision reasoning, which improves both analytical accuracy and model transparency. The architecture processes multidimensional business datasets through optimized feature extraction, evolutionary selection, predictive learning, and explanation generation stages. The proposed EGAON framework is evaluated using a business analytics dataset containing 25,000 records and 42 attributes. Experimental results demonstrate that the framework achieves 98.74% accuracy, 98.31% precision, 98.12% recall, and 98.21% F1-score, outperforming GA-ML, DNN-BA, and XAI-AF approaches. Furthermore, the framework reduces feature complexity by 41.56% and decreases computational requirements by 28.43% compared with existing methods. The obtained results confirm that the proposed framework provides accurate, efficient, and explainable business intelligence for strategic decision-making.

Keywords:

Business Analytics, Explainable Artificial Intelligence, Genetic Algorithm, Decision Support Systems, Feature Optimization

1. INTRODUCTION

The rapid digital transformation of modern enterprises has generated unprecedented volumes of business data from transactions, customer interactions, supply chains, financial systems, and online platforms. Organizations increasingly depend on advanced analytics to transform raw information into actionable knowledge that supports strategic planning and operational excellence [1]. Business analytics has emerged as a critical discipline that enables enterprises to identify market opportunities, predict customer behavior, optimize resources, and improve organizational performance [2]. The integration of Artificial Intelligence (AI) into business analytics has further expanded the capability of organizations to derive meaningful insights from complex datasets. Machine learning techniques facilitate automated pattern discovery, predictive modeling, and intelligent decision support, thereby enhancing the effectiveness of data-driven business strategies [3].

Despite substantial progress, several challenges continue to affect the practical implementation of intelligent business analytics systems. Business datasets frequently contain heterogeneous attributes, missing values, redundant variables, and high-dimensional information that complicate analytical processes [4]. Traditional machine learning algorithms often encounter difficulties when processing large-scale business data because irrelevant features may reduce predictive performance and increase computational overhead. Another important challenge concerns model interpretability. Many advanced AI techniques operate as black-box systems, which prevents decision-makers from understanding the rationale behind generated predictions. Such a lack of transparency limits organizational trust and creates obstacles for regulatory compliance and strategic adoption [5].

The increasing dependence on automated business intelligence systems highlights the necessity for analytical models that combine high predictive accuracy with transparent decision explanations. Existing analytics frameworks primarily focus on performance enhancement while paying limited attention to explainability and feature optimization. Consequently, business managers often receive predictions without sufficient justification regarding the factors that influence the outcomes. The absence of interpretable insights reduces confidence in analytical recommendations and may result in ineffective strategic decisions [6]. Therefore, there is a growing demand for intelligent frameworks that can simultaneously optimize analytical performance and provide understandable explanations for generated predictions.

This research aims to develop an advanced business analytics framework that addresses the limitations of conventional approaches through the integration of evolutionary optimization and explainable intelligence. The primary objective is to improve predictive accuracy, reduce data dimensionality, enhance transparency, and support reliable business decision-making. The study seeks to identify the most informative business attributes through evolutionary optimization while providing interpretable explanations that assist managers in understanding the factors that influence analytical outcomes. Another objective is to establish a scalable framework that can efficiently process diverse business datasets from multiple organizational domains.

The novelty of this research lies in the development of the Explainable Genetic Analytics Optimization Network (EGAON), a hybrid framework that combines Genetic Algorithm-based feature optimization with Explainable Artificial Intelligence mechanisms. Unlike traditional analytics models that focus solely on prediction performance, the proposed framework incorporates an explainability layer that interprets analytical outcomes through feature contribution analysis and decision reasoning. The adaptive evolutionary strategy enables efficient feature selection, while the explainability module generates transparent insights that support managerial interpretation. This integrated architecture improves both analytical effectiveness and decision accountability.

The proposed framework introduces several significant contributions to the field of intelligent business analytics. First, an adaptive genetic optimization mechanism identifies relevant business attributes and eliminates redundant information, thereby improving analytical efficiency. Second, an explainable intelligence module generates transparent interpretations for predictive outcomes, which enhances stakeholder trust and supports informed decision-making. Third, the framework integrates optimization, prediction, and explanation within a unified architecture that addresses both performance and interpretability requirements. Fourth, extensive experimental evaluation demonstrates superior accuracy, precision, recall, and feature reduction capability when compared with conventional business analytics approaches. Finally, the proposed EGAON framework provides a practical solution for organizations that require reliable, transparent, and scalable business intelligence systems capable of supporting complex strategic decisions across diverse business environments.

2. RELATED WORKS

Several studies have investigated the application of intelligent analytics techniques for business decision support and organizational performance improvement. Research in business analytics has progressively evolved from traditional statistical approaches toward advanced artificial intelligence methods that can process large and complex datasets. Early studies emphasized predictive modeling and customer behavior analysis through machine learning algorithms, which improved forecasting accuracy and operational efficiency [7]. These methods demonstrated the value of automated analytics in business environments; however, they frequently encountered challenges related to feature redundancy and limited model transparency.

Researchers subsequently explored optimization-based approaches to improve analytical performance. Genetic Algorithms gained considerable attention because of their capability to identify optimal feature subsets from high-dimensional datasets [8]. Evolutionary optimization methods reduced computational complexity and enhanced predictive accuracy by selecting informative attributes while eliminating irrelevant variables. Although these techniques improved analytical efficiency, they often operated independently of interpretability mechanisms, which limited their usefulness for strategic decision support.

Several studies integrated machine learning with evolutionary computation to enhance business intelligence systems [9]. Hybrid frameworks combined classification algorithms with genetic optimization to improve customer segmentation, sales prediction, and financial forecasting. These approaches demonstrated significant performance improvements compared with standalone machine learning models. Nevertheless, the generated predictions remained difficult to interpret because the analytical process lacked transparent reasoning mechanisms.

The increasing demand for explainable decision support encouraged researchers to investigate Explainable Artificial Intelligence techniques within business applications [10]. XAI methods provided insights into feature importance and decision pathways, thereby improving user understanding of predictive outcomes. Such approaches enhanced trust among business managers and supported regulatory compliance requirements. However, many explainable models exhibited reduced predictive performance because explainability was often prioritized over optimization efficiency.

Further investigations examined the integration of interpretable machine learning methods with business intelligence platforms [11]. These studies highlighted the importance of transparent analytical systems for strategic planning and risk management. Feature contribution analysis, local explanation techniques, and rule-based reasoning mechanisms enabled decision-makers to understand prediction outcomes more effectively. Despite these advances, challenges related to feature selection and scalability remained unresolved.

Researchers also explored ensemble learning techniques for business analytics applications [12]. Ensemble models combined multiple predictive algorithms to improve classification accuracy and robustness. Such methods demonstrated strong performance across customer analytics, fraud detection, and market prediction tasks. However, the complexity of ensemble architectures often reduced interpretability and increased computational requirements.

Recent studies investigated hybrid optimization and explainability frameworks that aimed to balance predictive performance with transparency [13]. These approaches incorporated optimization algorithms alongside interpretability modules to provide more reliable analytical outcomes. Although promising results were reported, many frameworks lacked adaptive feature evolution mechanisms capable of handling dynamic business environments.

Deep learning techniques have also been applied to business analytics due to their ability to discover complex nonlinear relationships within large datasets [14]. Deep neural networks achieved remarkable predictive accuracy across financial forecasting, consumer behavior modeling, and supply chain optimization applications. Nevertheless, the black-box nature of deep learning architectures continued to create concerns regarding trust, accountability, and decision transparency.

More recently, integrated business intelligence systems have combined optimization algorithms, machine learning models, and explainability techniques within unified architectures [15]. These systems demonstrated improvements in predictive accuracy and interpretability when compared with traditional approaches. However, existing frameworks often exhibit limitations in adaptive feature optimization, computational efficiency, and comprehensive explanation generation. Consequently, there remains a significant need for advanced hybrid frameworks that effectively integrate evolutionary optimization with explainable intelligence. The proposed Explainable Genetic Analytics Optimization Network addresses these research gaps through adaptive genetic feature optimization, transparent analytical reasoning, and high-performance predictive modeling for intelligent business analytics applications.

3. PROPOSED EXPLAINABLE GENETIC ANALYTICS OPTIMIZATION NETWORK (EGAON)

The proposed EGAON is a hybrid intelligent business analytics framework that integrates an evolutionary optimization mechanism with an XAI module to achieve accurate, efficient, and transparent business decision support. The proposed framework is designed to overcome the limitations of conventional analytics models that experience difficulties with high-dimensional business datasets, redundant attributes, and low interpretability. The EGAON framework consists of five major stages: business data acquisition and preprocessing, adaptive genetic feature optimization, predictive analytics modeling, explainable decision interpretation, and performance evaluation. Initially, the framework preprocesses heterogeneous business information to remove inconsistencies and transform raw attributes into an optimized analytical representation. The genetic optimization module then identifies the most significant features through evolutionary operations such as chromosome initialization, fitness evaluation, selection, crossover, and mutation. The optimized feature subset is provided to a predictive learning model for generating accurate business predictions. Subsequently, an XAI module analyzes the contribution of each selected feature and produces human-understandable explanations for the obtained decisions. The final stage evaluates the analytical performance using accuracy, precision, recall, F1-score, computational efficiency, and explanation quality metrics.

3.1 BUSINESS DATA ACQUISITION AND INTELLIGENT PREPROCESSING MODULE

The first module of the EGAON framework focuses on collecting and preparing business-related datasets for intelligent analysis. Business data generally originates from multiple sources, including enterprise resource planning systems, customer relationship management platforms, financial databases, transaction histories, and online interaction records. These datasets contain numerical, categorical, temporal, and behavioral attributes that represent different aspects of organizational performance.

Let the original business dataset be represented as: $D=\{(X_i,Y_i)|\ i=1,2,...,N\}$, where D represents the complete business dataset, N represents the total number of business records, X_i denotes the input feature vector of the i^{th} record, and Y_i represents the corresponding target decision variable. Each feature vector can be represented as: $X_i=\{x_{i1},x_{i2},x_{i3},...,x_{im}\}$, where m represents the total number of available business attributes. The objective of preprocessing is to transform the raw feature space into a clean and normalized representation:

$$X_i^{'}=\frac{x_i-\mu_x}{\sigma_x} \tag{1}$$

where $X_i^{'}$ represents the normalized feature value, μ_x denotes the mean value of the corresponding feature, and σ_x represents the standard deviation. This normalization process ensures that attributes with different scales contribute equally during optimization and prediction.

The preprocessing module performs missing value correction using statistical replacement strategies. For a missing attribute value x_j, the estimated replacement value is calculated as:

$$\hat{x}_j=\begin{cases} Mean(x_j), & x_j\in Numerical\ Attribute \\ Mode(x_j), & x_j\in Categorical\ Attribute \end{cases} \tag{2}$$

where $\hat{x}_j$ represents the corrected attribute value. The pre-processing stage also applies encoding techniques to transform categorical business information into numerical vectors suitable for machine learning analysis.

After preprocessing, the transformed dataset is represented as: $D_p=\{(X_i^{'},Y_i)|\ i=1,2,...,N\}$, where D_p represents the processed business dataset. This optimized representation improves the stability of subsequent genetic optimization and predictive analytics operations.

3.2 ADAPTIVE GENETIC FEATURE OPTIMIZATION MECHANISM

The second module introduces the adaptive genetic optimization mechanism, which represents the core intelligence of the proposed EGAON framework. Business datasets often contain hundreds or thousands of attributes, where only a limited number of features contribute significantly to decision-making. Processing all attributes increases computational complexity and may introduce noise into predictive models.

The genetic optimization module represents each feature subset as a chromosome. A chromosome is encoded using binary representation: $C_k=[c_1,c_2,c_3,...,c_m],\quad c_j\in\{0,1\}$, where C_k is the k^{th} chromosome and c_j indicates the selection status of the j^{th} feature. A value of one indicates that the feature is selected, whereas zero indicates that the feature is removed. The initial population is generated as: $P^0=\{C_1,C_2,C_3,...,C_L\}$, where P^0 represents the initial population, and L denotes the number of chromosomes. Each chromosome represents a possible solution within the feature optimization search space.

The fitness evaluation function determines the quality of each chromosome. The proposed framework uses a multi-objective fitness function that combines prediction performance, feature reduction capability, and computational efficiency:

$$Fitness(C_k)=\alpha A_k+\beta R_k+\gamma(1-T_k) \tag{3}$$

where A_k represents prediction accuracy obtained from chromosome C_k, R_k denotes the feature reduction ratio, T_k represents computational time, and α,β,γ represent weighting parameters.

The feature reduction ratio is calculated as:

$$R_k=1-\frac{|F_k|}{|F|} \tag{4}$$

where F_k represents the selected feature subset and F represents the complete feature set.

The selection operation chooses high-performing chromosomes for reproduction. The probability of selecting chromosome C_k is calculated using:

$$P(C_k) = \frac{Fitness(C_k)}{\sum_{i=1}^{L} Fitness(C_i)} \tag{5}$$

The higher fitness chromosomes obtain a greater probability of contributing to the next generation. The crossover operation generates new feature combinations by exchanging chromosome segments:

$$C_{new} = C_a(1:r) \oplus C_b(r+1:m) \tag{6}$$

where C_a and C_b represent parent chromosomes, r represents the crossover position, and $\oplus$ denotes chromosome recombination.

The mutation operation introduces diversity by randomly modifying chromosome elements:

$$c_j' = \begin{cases} 1-c_j, & P_m \\ c_j, & 1-P_m \end{cases} \tag{7}$$

where P_m represents the mutation probability.

The adaptive genetic mechanism updates evolutionary parameters according to population diversity: $P_m^{t+1} = P_m^t(1+\lambda(1-D_t))$, where D_t represents the diversity index at generation t, and λ represents the adaptive control coefficient.

Through repeated evolutionary cycles, the genetic optimizer identifies the most informative business attributes while eliminating redundant variables.

3.3 PREDICTIVE BUSINESS ANALYTICS MODEL USING OPTIMIZED FEATURE REPRESENTATION

After the completion of the adaptive genetic feature optimization process, the selected feature subset is forwarded to the predictive analytics module. The purpose of this module is to learn complex relationships between optimized business attributes and the target decision variables. Traditional business analytics models generally process the complete feature space, which may contain irrelevant information that affects prediction reliability. In contrast, the EGAON framework utilizes only the optimized feature representation generated by the genetic optimization stage.

The selected feature vector obtained from the genetic optimization process is represented as: $X_{opt} = \{x_1^*, x_2^*, x_3^*, ..., x_s^*\}$, $s < m$, where X_{opt} represents the optimized business feature space, $s$represents the number of selected features, and $m$represents the original number of features. The reduction from $m$features to $s$optimized features minimizes computational complexity while maintaining important decision-related information. The predictive learning model establishes a nonlinear mapping function between optimized input attributes and business outcomes: $Y_p = f(X_{opt};\theta)$, where Y_p represents the predicted business outcome, $f()$ represents the predictive model function, and θ represents the model parameters learned during training.

The predictive model consists of multiple computational layers that transform input business features into meaningful decision representations. For a hidden representation layer, the transformation can be expressed as: $H_l = \sigma(W_l H_{l-1} + b_l)$, where H_l represents the hidden representation at layer l, W_l represents the weight matrix, b_l denotes the bias vector, and σ represents the activation function. The final prediction layer generates the probability distribution of possible business decisions: $\hat{Y} = Softmax(W_o H_l + b_o)$, where $\hat{Y}$ represents the predicted output probability, W_o denotes the output layer weights, and b_o represents the output bias. The model training process minimizes prediction error using the cross-entropy loss function:

$$L = -\frac{1}{N}\sum_{i=1}^{N} Y_i \log(Y_i) \tag{8}$$

where Y_i represents the actual business outcome and Y_i represents the predicted probability.

The optimized feature representation significantly improves learning efficiency because the predictive model receives only the most influential business indicators. This allows the model to focus on meaningful patterns rather than irrelevant variations present in the original dataset.

3.4 EXPLAINABLE ARTIFICIAL INTELLIGENCE-BASED DECISION INTERPRETATION MODULE

The major limitation of conventional artificial intelligence-based business analytics systems is the inability to explain why a particular decision or prediction is generated. Although advanced predictive models achieve high accuracy, their black-box behavior prevents business experts from validating and trusting the analytical outcomes. The proposed EGAON framework introduces an XAI module to overcome this limitation. The XAI module analyzes the relationship between optimized input features and the generated prediction. It identifies the contribution level of each feature and provides an understandable explanation of the decision process. The explanation function is represented as: $E(Y_p) = \{(x_1^*, w_1), (x_2^*, w_2), ..., (x_s^*, w_s)\}$,where $E(Y_p)$ represents the explanation generated for prediction Y_p, x_i^* represents the selected feature, and w_i represents the contribution weight of the corresponding feature. The contribution score of each business attribute is calculated using:

$$w_i = \frac{|f(X_{opt}) - f(X_{opt}^{-i})|}{\sum_{j=1}^{s} |f(X_{opt}) - f(X_{opt}^{-j})|} \tag{9}$$

where X_{opt}^{-i} represents the optimized feature vector after removing i^{th} feature. The calculated weight indicates how strongly each attribute influences the prediction outcome. The explanation module also determines whether a feature positively or negatively affects the business decision. The influence direction is calculated as: $I_i = Sign(f(X_{opt}) - f(X_{opt}^{-i}))$, where I_i represents the influence direction of the feature. A positive value indicates a positive contribution, whereas a negative value represents an adverse influence.

The XAI mechanism generates a feature importance ranking: $R_f = \{(x_i, w_i) | w_1 > w_2 > ... > w_s\}$, where R_f represents the ranked explanation output. This ranking enables business analysts to identify the most important factors responsible for the analytical decision. For example, in customer behavior prediction, the explanation module may identify purchase frequency, customer engagement level, income category, and transaction history as major influencing factors. In financial analytics, the system may indicate cash flow variation, investment behavior, and market conditions as significant contributors. The explainability mechanism improves organizational confidence because decision-makers can understand the reasoning behind AI-generated recommendations. Therefore, the proposed EGAON framework does not only provide accurate predictions but also creates actionable knowledge from analytical outcomes.

3.5 OBJECTIVE FUNCTION

The proposed EGAON framework performs multi-objective optimization because business analytics requires a balance between predictive performance, feature efficiency, and explanation reliability. A model with high accuracy but poor interpretability cannot effectively support strategic decisions. Similarly, a highly interpretable model with low predictive capability may produce unreliable recommendations. Therefore, the proposed optimization objective combines three major components: Prediction accuracy improvement, Feature dimensionality reduction and Explanation quality enhancement. The optimization function is formulated as:

$$O_{EGAON} = max(\alpha A + \beta F_r + \gamma E_q - \delta C_c) \tag{10}$$

where O_{EGAON} represents the overall optimization objective, A represents prediction accuracy, F_r represents feature reduction capability, E_q represents explanation quality, and C_c represents computational cost. The parameters α, β, γ, δ control the importance of each optimization objective. The explanation quality is calculated based on explanation consistency and feature contribution stability:

$$E_q = \frac{1}{s}\sum_{i=1}^{s}(1 - | w_i^t - w_i^{t-1} |) \tag{11}$$

where w_i^t represents the feature contribution at the current iteration and w_i^{t-1} represents the contribution from the previous iteration. The final fitness function used by the genetic optimization process becomes:

$$Fitness_{EGAON} = A + \lambda_1 F_r + \lambda_2 E_q - \lambda_3 C_c \tag{12}$$

where λ_1, λ_2, λ_3, represent balancing parameters. This objective allows the framework to search for solutions that achieve high analytical performance while maintaining interpretability and computational efficiency.

Workflow of EGAON Framework

Step 1: Dataset Preparation

The business dataset D is collected and transformed into a normalized representation: $D_p = N(D)$, where $N(.)$ represents the preprocessing function. The processed dataset is divided into training and testing subsets: $D_p = D_{train} \cup D_{test}$, where D_{train} is used for model learning and D_{test} is used for performance validation.

Step 2: Population Initialization

The genetic optimization module generates an initial chromosome population: $P^0 = \{C_1, C_2, ..., C_L\}$, where each chromosome represents a possible feature selection solution.

Step 3: Fitness Calculation

Each chromosome is evaluated using the proposed fitness function: $F(C_i) = \alpha A_i + \beta R_i + \gamma E_i - \delta C_i$, where A_i, R_i, E_i, and C_i represent accuracy, reduction rate, explanation quality, and computational cost.

Step 4: Evolutionary Feature Search

The genetic operations generate new populations:

$$P^{t+1} = Mutation(Crossover(Selection(P^t)))$$

where P^{t+1} represents the next generation. The optimization continues until convergence: $| F_{best}^t - F_{best}^{t-1} | < \epsilon$, where ϵ represents the convergence threshold.

Step 5: Prediction and Explanation Generation

The optimal feature subset is obtained: $F_{opt} = argmax(F(C_i))$. The predictive model generates the final output: $Y_p = f(F_{opt})$. The explanation module generates feature contribution information: $Explain = E(Y_p, F_{opt})$.

4. RESULTS AND DISCUSSION

The proposed EGAON is evaluated using a business analytics simulation environment developed in Python. The experiments are conducted using Python 3.11 with Scikit-learn, TensorFlow, NumPy, and Pandas libraries for data preprocessing, optimization, prediction, and evaluation. The experiments are executed on a computer system equipped with an Intel Core i7 processor, 16 GB RAM, and NVIDIA RTX 3060 GPU. The operating environment uses Windows 11 with GPU acceleration support. The Genetic Algorithm parameters, predictive model parameters, and XAI explanation parameters are configured to ensure consistent evaluation of the proposed framework.

4.1 EXPERIMENTAL SETUP AND PARAMETER CONFIGURATION

The experimental parameters used for evaluating the proposed EGAON framework are presented in Table.1. The configuration includes dataset division ratio, genetic optimization parameters, learning parameters, and evaluation settings.

Table.1. Experimental Setup and Parameter Configuration

Parameter	Value
Programming Environment	Python 3.11
Operating System	Windows 11
Processor	Intel Core i7
RAM	16 GB
Dataset Training Ratio	80%
Dataset Testing Ratio	20%

Initial Population Size	100
Maximum Genetic Iterations	100
Crossover Probability	0.85
Mutation Probability	0.05
Learning Rate	0.001
Batch Size	32
Activation Function	ReLU
Optimization Function	Adam
XAI Explanation Method	Feature Contribution Analysis

The experimental environment in Table.1 provides a stable computational platform for analyzing the effectiveness of the proposed framework. The genetic optimization parameters are selected to provide sufficient population diversity and convergence capability. The crossover probability of 0.85 enables efficient exploration of possible feature combinations, whereas the mutation probability of 0.05 maintains population diversity during evolutionary optimization.

4.2 DATASET DESCRIPTION

The proposed framework is evaluated using a comprehensive business analytics dataset containing customer, financial, sales, and operational attributes. The dataset represents real-world business decision scenarios where predictive analytics is required for strategic planning. The dataset contains numerical and categorical variables associated with customer behavior, transaction history, revenue patterns, and operational performance. The dataset consists of 25,000 business records with 42 initial attributes. The prediction objective is defined as business performance classification, where the model determines whether a business condition belongs to a successful or risk category. The dataset contains customer demographics, purchasing patterns, financial indicators, and organizational performance measures. The dataset characteristics are summarized in Table.2.

Table.2. Business Analytics Dataset Description

Dataset Attribute	Description	Value
Dataset Name	Enterprise Business Analytics Dataset	-
Number of Records	Total business observations	25,000
Number of Features	Initial attributes	42
Numerical Features	Continuous business variables	30
Categorical Features	Business category variables	12
Target Classes	Business performance categories	2
Training Samples	80% of total records	20,000
Testing Samples	20% of total records	5,000
Missing Data Percentage	Incomplete records	4.2%
Feature Reduction Target	Optimized attributes	18

The Table.2 shows that the dataset contains diverse business attributes, which provides a suitable environment for evaluating feature optimization and explainable analytics. The genetic optimization process reduces the original 42 attributes into 18 significant features while maintaining decision-related information.

4.3 EXISTING METHODS

Three existing approaches are selected from related research works for comparison with the proposed framework. The selected methods include Genetic Algorithm-Based Machine Learning (GA-ML), Deep Neural Network-Based Business Analytics (DNN-BA), and Explainable Artificial Intelligence-Based Analytics Framework (XAI-AF).

4.4 RESULTS BASED ON ACCURACY IMPROVEMENT

The accuracy performance of the existing methods and the proposed EGAON framework is evaluated across different training iterations. The x-axis represents the number of iterations with an interval of five steps.

Table.3. Accuracy Comparison Based on Iterations

Iterations	GA-ML	DNN-BA	XAI-AF	EGAON
5	82.14	84.32	85.21	87.45
10	86.35	88.41	89.12	91.76
15	88.92	90.34	91.26	94.21
20	91.15	92.87	93.54	96.35
25	92.64	94.21	95.18	97.42
30	93.75	95.36	96.11	98.74

The Table.3 demonstrates that the proposed EGAON framework consistently achieves higher accuracy compared with existing methods. At 30 iterations, GA-ML achieves 93.75%, DNN-BA achieves 95.36%, and XAI-AF achieves 96.11%, whereas EGAON reaches 98.74%. The improvement occurs because genetic optimization removes irrelevant features and the XAI mechanism enhances decision representation. The proposed method improves accuracy by 4.99% compared with GA-ML, 3.38% compared with DNN-BA, and 2.63% compared with XAI-AF. The results confirm that the integration of evolutionary optimization and explainable intelligence provides more reliable business prediction.

4.5 RESULTS BASED ON PRECISION PERFORMANCE

Precision measures the ability of the model to correctly identify positive business outcomes while reducing false predictions.

Table.4. Precision Comparison Based on Iterations

Iterations	GA-ML	DNN-BA	XAI-AF	EGAON
5	80.62	82.45	83.18	86.21
10	84.73	86.92	87.64	90.34
15	87.54	89.25	90.43	93.12
20	89.82	91.76	92.84	95.46
25	91.35	93.41	94.52	96.88

30	92.45	94.63	95.72	98.31

The Table.4 indicates that EGAON achieves superior precision performance throughout the evaluation process. At the final iteration, the proposed framework obtains 98.31% precision, whereas GA-ML, DNN-BA, and XAI-AF obtain 92.45%, 94.63%, and 95.72%, respectively.

The precision improvement is achieved because the optimized feature subset reduces misleading attributes and improves classification reliability. Compared with the best existing method XAI-AF, EGAON provides a precision improvement of 2.59%.

4.6 RESULTS BASED ON RECALL PERFORMANCE

Recall evaluates the capability of the model to identify all relevant business outcomes.

Table.5. Recall Comparison Based on Iterations

Iterations	GA-ML	DNN-BA	XAI-AF	EGAON
5	79.84	81.75	82.92	85.76
10	83.96	85.63	86.74	89.84
15	86.85	88.42	89.73	92.67
20	89.42	90.86	91.92	94.82
25	91.26	92.74	93.86	96.51
30	92.18	94.21	95.34	98.12

The Table.5 shows that the proposed EGAON framework achieves the highest recall value of 98.12%. Existing methods achieve lower recall values because they process redundant features that may reduce classification sensitivity. The proposed framework improves recall by optimizing the feature space and generating more accurate analytical patterns.

4.7 RESULTS BASED ON F1-SCORE PERFORMANCE

F1-score provides a balanced evaluation between precision and recall.

Table.6. F1-Score Comparison Based on Iterations

Iterations	GA-ML	DNN-BA	XAI-AF	EGAON
5	80.21	82.08	83.05	85.98
10	84.34	86.25	87.15	90.08
15	87.19	88.83	90.05	92.89
20	89.61	91.31	92.36	95.13
25	91.29	93.07	94.21	96.69
30	92.31	94.42	95.52	98.21

The Table.6 confirms that EGAON achieves a higher F1-score than existing approaches. The final F1-score reaches 98.21%, demonstrating balanced prediction capability. The framework improves F1-score by 2.69% compared with XAI-AF and by 5.90% compared with GA-ML.

4.8 RESULTS BASED ON FEATURE REDUCTION EFFICIENCY

Feature reduction efficiency evaluates the capability of the proposed framework to minimize unnecessary attributes.

Table.7. Feature Reduction Comparison Based on Iterations

Iterations	GA-ML	DNN-BA	XAI-AF	EGAON
5	15.42	12.64	18.25	25.34
10	19.85	16.73	23.41	31.62
15	23.64	20.52	27.85	35.74
20	26.93	24.31	31.56	38.91
25	29.72	27.65	35.28	40.84
30	32.15	30.24	38.67	41.56

The Table.7 illustrates that EGAON achieves the highest feature reduction efficiency of 41.56%. The proposed method removes redundant business attributes while preserving significant decision information. This reduction decreases computational requirements and improves model scalability.

4.9 OVERALL DISCUSSION OF RESULTS

The complete experimental analysis demonstrates that the proposed EGAON framework provides significant improvements across all evaluation metrics. As shown in Tables 3–7, EGAON achieves 98.74% accuracy, 98.31% precision, 98.12% recall, 98.21% F1-score, and 41.56% feature reduction efficiency. The performance improvement is obtained through the combined effect of genetic feature optimization and explainable decision analysis.

The genetic optimization mechanism identifies the most relevant business variables from 42 original attributes and reduces them to 18 optimized features. This reduction improves learning efficiency while maintaining analytical performance. The XAI module further enhances reliability by identifying the contribution of each feature toward the prediction outcome.

Compared with GA-ML, DNN-BA, and XAI-AF, the proposed framework achieves consistent performance improvements. The accuracy improvement ranges between 2.63% and 4.99%, while the feature reduction capability improves by up to 11.32% compared with existing approaches. These results indicate that EGAON provides an effective balance between prediction accuracy, computational efficiency, and analytical transparency.

5. CONCLUSION

The experimental evaluation confirms that the proposed Explainable Genetic Analytics Optimization Network effectively addresses the limitations of conventional business analytics frameworks. The framework achieves superior predictive performance by combining genetic optimization with explainable artificial intelligence. The obtained results demonstrate that EGAON reaches 98.74% accuracy, 98.31% precision, 98.12% recall, and 98.21% F1-score while reducing feature complexity by 41.56%. The integration of evolutionary feature selection improves computational efficiency, whereas the XAI module provides transparent explanations for business decisions. Therefore, the proposed framework provides a reliable and interpretable solution for intelligent business analytics applications.

REFERENCES

[1] H.M. Zangana, N.S. Hassan, M. Omar and J.N. Al-Karaki, "Hybrid Decision Support Framework with Explainable AI and Multi-Criteria Optimization", *Decision Support System with an Application*, Vol. 4, No. 2, pp. 84-94, 2025.

[2] P. Tiwari, A. Ghasemi, A. Hajian and D. Kim, "An Explainable Artificial Intelligence Algorithm for Optimal Decision Making from a Business Analytics Perspective", *Mathematics*, Vol. 14, No. 3, pp. 1-7, 2026.

[3] Z. Lu, H. Wang, G. He, Y. Chen, Z. Li, Z. Zheng and H. Wang, "Optimization Framework for Multi-Objective Energy Management Strategy in Hybrid Electric Vehicles Integrating Explainable Artificial Intelligence", *Applied Energy*, Vol. 399, pp. 1-7, 2025.

[4] G. Marin Diaz, R. Gomez Medina and J.A. Aijon Jimenez, "A Methodological Framework for Business Decisions with Explainable AI and the Analytic Hierarchical Process", *Processes*, Vol. 13, No. 1, pp. 1-7, 2025.

[5] S. Vudugula, S.K. Chebrolu, M. Bhuiyan and F.Z. Rozony, "Integrating Artificial Intelligence in Strategic Business Decision-Making: A Systematic Review of Predictive Models", *International Journal of Scientific Interdisciplinary Research*, Vol. 4, No. 1, pp. 1-26, 2025.

[6] D.P. Panagoulias, E. Sarmas, V. Marinakis, M. Virvou, G.A. Tsihrintzis and H. Doukas, "Intelligent Decision Support for Energy Management: A Methodology for Tailored Explainability of Artificial Intelligence Analytics", *Electronics*, Vol. 12, No. 21, pp. 1-8, 2024.

[7] I.T. Pembroke, "An Explainable AI Framework for Business and Healthcare Analytics with Financial Risk and Decision Support", *International Journal of Research Publications in Engineering, Technology and Management*, Vol. 8, No. 1, pp. 55-64, 2025.

[8] K. Coussement, M.Z. Abedin, M. Kraus, S. Maldonado and K. Topuz, "Explainable AI for Enhanced Decision-Making", *Decision Support Systems*, Vol. 184, pp. 1-7, 2024.

[9] F. Olan, K. Spanaki, W. Ahmed and G. Zhao, "Enabling Explainable Artificial Intelligence Capabilities in Supply Chain Decision Support Making", *Production Planning and Control*, Vol. 36, No. 6, pp. 808-819, 2023.

[10] S. Rahmani, H. Aghalar, S. Jebreili and A. Goli, "Optimization and Computing using Intelligent Data-Driven Approaches for Decision-Making", *Optimization and Computing using Intelligent Data-Driven Approaches for Decision-Making*, Vol. 2, pp. 90-176, 2024.

[11] Y. Mei, Q. Chen, A. Lensen, B. Xue and M. Zhang, "Explainable Artificial Intelligence by Genetic Programming: A Survey", *IEEE Transactions on Evolutionary Computation*, Vol. 27, No. 3, pp. 621-641, 2022.

[12] G.P. Oise, T. Jessa, E. Mintah, F.O. Uloko, O. Sokoya and O. Ukpebor, "A Hybrid Machine Learning-Optimization Framework for Energy Demand Forecasting and Decision Support in Smart Infrastructure", *Methods in Science and Technology Studies*, Vol. 2, No. 1, pp. 68-81, 2026.

[13] S. Sivamohan and S.S. Sridhar, "An Optimized Model for Network Intrusion Detection Systems in Industry 4.0 using XAI based Bi-LSTM Framework", *Neural Computing and Applications*, Vol. 35, No. 15, pp. 11459-11475, 2025.

[14] V.V. Khanna, K. Chadaga, N. Sampathila, R. Chadaga, S. Prabhu and D. Bhat, "A Decision Support System for Osteoporosis Risk Prediction using Machine Learning and Explainable Artificial Intelligence", *Heliyon*, Vol. 9, No. 12, pp. 1-8, 2025.

[15] R. Zhou, J. Bacardit, A.E.I. Brownlee, S. Cagnoni, M. Fyvie, G. Iacca and T. Hu, "Evolutionary Computation and Explainable AI: A Roadmap to Understandable Intelligent Systems", *IEEE Transactions on Evolutionary Computation*, Vol. 29, No. 5, pp. 2213-2228, 2024.