Optimized Deep Learning Framework for Intelligent Data Analytics in Information Systems

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ABSTRACT

The exponential expansion of data in contemporary information systems poses a significant barrier to the efficient, accurate, and scalable extraction of useful insights. High-dimensional and heterogeneous data are frequently difficult for conventional machine learning models to handle, which results in poor analytical performance and more computing overhead. The present investigation proposes an Optimized Deep Learning Framework for Intelligent Data Analytics in Information Systems in order to overcome these constraints. The model developed in this study achieved a success rate exceeding 98% across two test sets, indicating a clear advantage in processing accounting information. In the response time evaluation of the financial module, conducted over 60 trials, the system demonstrated an average response time of 0.5 seconds and maintained a 100% success rate, highlighting both its efficiency and reliability. The system can function normally if it can achieve 0.8 seconds and maintain a success rate above 98%. There are 70 test cases created specifically for the finance module in the system operational stability test, 70 of which are executed, with an execution rate of up to 100%. This indicates that the system can function effectively and won't malfunction while in use.

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1. INTRODUCTION

The corporate community's need for efficient administration and use of large amounts of data is continuously growing due to the quick development of information technology and the emergence of the digital era [1]. Deep learning optimizations and big data analysis are now major drivers behind the creation of artificial intelligence in modern businesses, giving them the chance to grow and develop more effectively. In this regard, big data analysis software has emerged as a crucial instrument for deriving knowledge and insights from data. Businesses can better formulate strategies and make decisions by delving deeper into data that reveals important elements like competition behavior, market developments, and consumer preferences. China, a significant exporter of steel, is facing difficulty on two fronts. To progress strategically, conventional steel companies must first modernize and restructure [2]. Second, long-term growth is what new steel firms need to aim for. Reducing energy use, enhancing product quality, and boosting competitiveness are the most realistic ways to do this. The industrial sector has been greatly impacted by the emergence of big data. To begin with, a number of widely used information and communication technologies (ICTs) have completely changed the way production is done. In the era of Industry 4.0, enterprise data systems are essential for achieving smart production systems.

The importance of creating an intelligent accounting information system for enterprise accounting administration is thoroughly explained in this article. This study examined how Libyan SMEs' behavioral intentions to use accounting information systems were influenced by both intrinsic and extrinsic motivation [3]. The article's goal is to clarify how financial environmental factors affect the connection between AIS and Iraqi SMEs that use intelligent accounting information systems, as seen in Figure 1.

1.1 The Accounting Information System's Importance

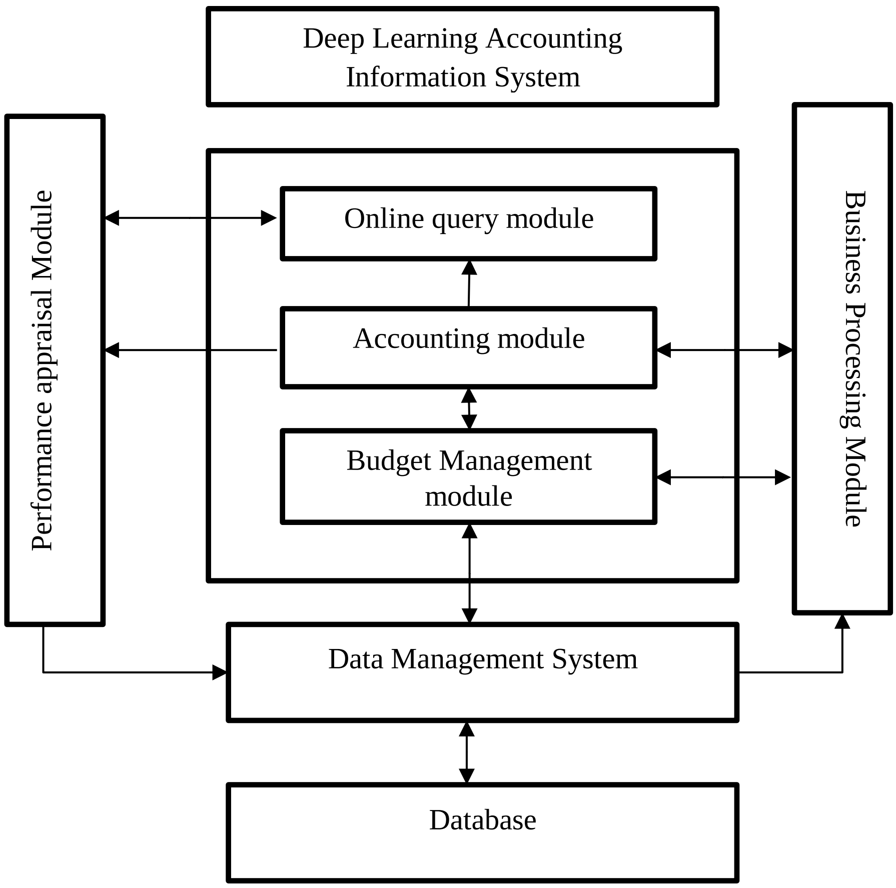

Figure 1. Module for system function

Big data is transitioning from a conceptual stage to large-scale practical applications. One emerging tool for businesses is a versatile, global financial system underpinned by big data, which can enable more efficient process optimization through advanced data-driven workflows [4]. To accelerate the development of smart enterprises, it is essential to design a more dynamic organizational framework, drive innovations in financial accounting, implement sophisticated business logic for informed decision-making in uncertain markets, and establish an integrated ecosystem that balances both internal and external operational dynamics. Many businesses have experienced profound shifts in their management idea and operations, and the accounting management activity has also given rise to an intelligent accounting information management framework.

1.2 Problem Statement and Assumptions

Such large and varied datasets are frequently difficult for traditional analytical models and machine learning methods to interpret effectively, which lead to decreased prediction accuracy, high processing costs, and delayed decision-making. Furthermore, these approaches' scalability and dependability are constrained by their inability to adjust to ongoing data evolution and shifting business needs. Effective data use and real-time insight production are hampered by the lack of an efficient framework that can combine sophisticated deep learning algorithms with intelligent data analytics. Therefore, it is imperative to create an Optimized Deep Learning Framework that improves information systems' analytical capabilities by automating data preprocessing, maximizing feature selection, and facilitating precise, flexible, and intelligent choices for better organizational performance.

The present research is predicated on the availability, dependability, and organized or semi-structured digital form of the enterprise data employed for analysis. Additionally, it is anticipated that the datasets may be successfully pre-processed using common standardization and transformation methods to deal with missing, erratic, or noisy values. The suggested deep learning framework is predicated on the availability of sufficient computational hardware, such as GPUs or cloud-based assets, to facilitate deploying models and retraining.

1.3 Major Contributions

The contributions of this research are summarized as follows:

- A novel hybrid feature selection approach, combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), was developed to identify the most relevant and non-redundant features, thereby improving both model interpretability and computational efficiency.
- Accurate modeling of intricate, dynamic information system datasets is made possible by an integrated CNN–LSTM hybrid deep learning architecture that captures both temporal and spatial information patterns.
- Extensive experimental validation is carried out across several modules, including financial, sales, and management analysis. The results show excellent performance, surpassing conventional SVM and Decision Tree models with over 98% accuracy and responses as low as 0.5 seconds.
- To verify the framework's dependability in enterprise-level information systems, a completely functional system prototype is created and tested for execute rate, reliability, and adaptability.

2. LITERATURE REVIEW

The growing demand to derive actionable insights from large and diverse corporate datasets has accelerated the integration of DL with business intelligence (BI) in recent years. Compared to traditional machine learning methods [5], DL architectures substantially enhance predictive performance for tasks such as fraud detection, credit scoring, and operational forecasting, particularly when integrated within BI pipelines. Multiple studies and application reviews indicate that DL is particularly well-suited to the volume and complexity of modern financial and corporate data streams, owing to its ability to automatically learn hierarchical features from raw, unprocessed data.

To enhance multi-criteria decision-making frameworks in BI-service applications, recent research has explored independent knowledge analysis approaches based on fuzzy logic, genetic algorithms (GA), and neural or neuro-fuzzy techniques. Specifically, studies have focused on applying fuzzy-based, fuzzy-GA [6], or neuro-fuzzy knowledge analytics to optimize decision-making for developing business security plans in B2C enterprises offering goods and services. Additionally, efforts have been made to synthesize literature on big data alongside emerging research on small-scale (“tiny”) data, examining the connections between the two. Key questions include how large datasets can be distilled into smaller, actionable insights, and whether an inverse relationship exists as small data aggregates into larger datasets.

Extensive data-driven analysis, one of the core artificial intelligence technologies, increases the manufacturing industry's market competitiveness by utilizing the potential and unrealized knowledge value of precise industrial information [7]. It also aids company executives in making informed decisions in a variety of challenging industrial situations. This approach offers fresh approaches to challenging problems and proposes new research directions for this area of study. This page provides a thorough summary of important industrial information. The application of big data-driven innovations to intelligent manufacturing is then discussed. Lastly, we talk about the issues and difficulties this region is currently facing.

The creation of hybrid neural architectures that simultaneously model temporal and spatial patterns is a common theme in clinical studies. Because CNN layers can extract local feature patterns and LSTM layers capture temporal dependencies across sequences, hybrid CNN–LSTM (and related combinations) have been widely used for financial time-series forecasting, energy prediction, and other enterprise tasks [8]. This has resulted in consistent performance gains over single-model baselines in empirical evaluations. This corpus of work demonstrates why it makes sense to combine convolutional and recurring modules when the analytical goal calls for both sequence modeling and local feature abstraction.

When using DL in enterprise environments, where chaotic, redundant, and dimensional features raise training costs and decrease interpretability, choosing features and reducing dimensionality continue to be major issues. Numerous studies have hybridized and improved evolutionary and swarm-intelligence techniques [9], particularly GA and Particle Swarm Optimization (PSO), to enable robust wrapper-style feature selection that strikes a balance between discovery and local refining. Such hybrid optimization is appealing as a feature-optimization step before deep model training because recent hybrid GA–PSO variants and PSO-based networked techniques indicate enhanced convergence and choice stability across various datasets.

Big-data analytics and DL are becoming more and more popular in the accounting and information systems sector. Research has shown that these technologies have useful applications in accounting information systems (AIS) [10], such as timely financial reporting, risk assessment, and routine accounting analytics automation. These AIS studies frequently identify gaps, though, as many solutions concentrate on discrete tasks (like identifying anomalies or disclosure analysis) rather than end-to-end frameworks that incorporate real-time inference, hybrid DL simulation, optimized feature selection, and continuous feedback for enterprise implementation. For AIS contexts, this fragmentation suggests the need for modular, operational frameworks that include optimization, hybrid modeling, and system-level evaluation metrics (precision, latency, and stability).

3. THE PROPOSED METHODOLOGY

3.1 Overview

The Optimized Deep Learning Framework presented in this paper is intended to improve the effectiveness, scalability [11], and intelligence of data analytics in contemporary information systems. Data preparation, feature optimization, intelligent decision analytics, and hybrid deep learning architecture design are all included into the framework.

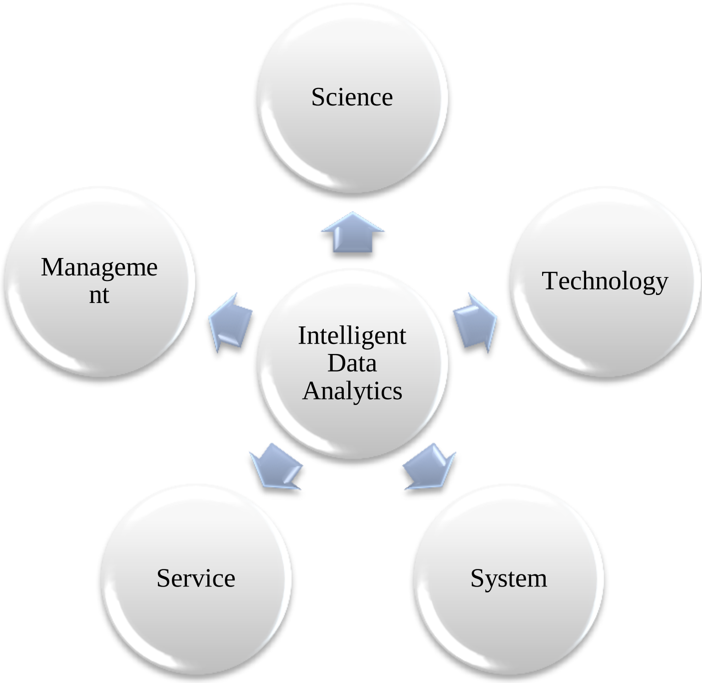

Figure 2. An effective big data analytics management framework

As shown in Figure 2 [12], an intelligent big data analytics management framework encompasses the scientific and technological foundations of intelligent analytics, alongside intelligent systems, services, and managerial processes, all aimed at enhancing business decision-making.

3.2 Sampling and Participants

The study utilized corporate data collected between 2014 and 2018 from multiple organizational divisions, including purchasing, sales [13], finance, and management analysis. The dataset comprised both structured and semi-structured information drawn from medium- and large-scale enterprises in the commercial and industrial sectors' financial information systems. Key features included equity distribution, leverage ratios, return on equity (ROE), company size, location, corporate visibility, and executive structure. To ensure balanced representation across all business domains [14], a stratified sampling approach was employed. This strategy enabled the model to learn from diverse business trends and operational scales while maintaining analytical variety.

3.3 Data Gathering Technique

The data were sourced from operational management systems, financial reporting tools, and intelligence modules integrated with existing enterprise information systems. To ensure confidentiality, all data streams were standardized and anonymized. A unified analytical database was created by merging these heterogeneous datasets [15]. Preprocessing steps—including noise reduction, handling of missing values, and standardization—were applied to mitigate data skewness. Dimensionality reduction using Principal Component Analysis (PCA) was performed to eliminate redundancy, followed by feature encoding techniques to convert categorical variables into numerical representations. Finally, the processed dataset was divided into training and testing subsets using a 70:30 split to facilitate model validation.

3.4 Analyzing Data

The suggested Optimized Deep Learning Structure, which combines a CNN–LSTM deep learning model for forecasting with a hybrid Genetic Algorithm–Particle Swarm Optimization (GA–PSO) for feature selection, was used for data analysis. While the CNN–LSTM architecture collected both geographical and temporal trends within enterprise data, the GA–PSO module maximized information gain and minimized model error to find the most pertinent features. The Adam algorithm with an adaptive learning rate was used to train the model, while regularization strategies including batch normalization and dropout were used to avoid overfitting [16]. Key measures such as accuracy, sensitivity, specificity, and response time were used to analyze the model's performance. Baseline models like Support Vector Machine (SVM) and Decision Tree (DT) were compared. To verify the effectiveness and resilience of the framework, experimental testing was carried out using system performance metrics such reaction time, execution velocity, and stable operation.

3.5 Creation of Deep Learning Model Systems

3.5.1 Model Development

This study uses the following concept to create an enterprise indicator system.

$$XL_{fy} = \sum E + \sum X + \partial_1 + \partial_2 + \partial_2 * Q_{fy} + \partial_2 * N_{fy} + \cdots \quad (1)$$

XL_{fy} Represents the change in the company's strategic value in F sectors and Y years, while F denotes the industry in which the business operates [17] both the overall advantages of the company's strategic adjustments and the changes in the company's several accounting indicators are reflected in this number. $Q_{fy} + \partial_2 * N_{fy}$ is the index coefficient associated with the i-th indicator. Sales expenses are represented by XL_{fy}, management expenses by N_{fy}, fixed asset renewal costs by N_{fy}, capital intensity by XL_{fy}investment by Lfy, corporate financial leverage by Lfy, and mathematical ability value by Cfy.

The following is the input for sales expenses:

$$Q_{fy} = \frac{RE}{S} \quad (2)$$

The following is the input for management fees:

$$N_{fy} = \frac{NE}{S} \quad (3)$$

The following is the input for fixed asset renewal costs:

$$E_{fy} = \frac{ME}{OE} \quad (4)$$

The following is the capital intensity:

$$C_{fy} = \frac{MF}{RN} \quad (5)$$

The R&D expenditure is as follows:

$$J_{fy} = \frac{LF}{S} \quad (6)$$

Corporate financial leverage is as follows:

$$XL_{fy} = \frac{RD+LD+DP}{W} \quad (7)$$

The financial risk prediction formula is

$$DE = \frac{F(v)-E}{F(v)\alpha B} \quad (8)$$

Given that the Wiener technique can be followed by changes in the target business's actual asset prices, there are

$$Du_A = \cup V_A dt + \partial a V_a dz \quad (9)$$

One method for creating the connection between stock value and asset value is as follows:

$$U_E = U_A M(d1) - f^{-rt} * M(d2) \quad (10)$$

$$\partial_F = \frac{U_A}{V_A}\partial \quad (11)$$

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

Real-world accounting and enterprise data gathered between 2014 and 2018 were used to assess the suggested Optimized Deep Learning Framework. The studies sought to evaluate the framework's capacity to effectively handle diverse data, pinpoint important accounting variables, and guarantee system-level responsiveness and stability within the integrated information system.

Eleven secondary indicators had standardized values of 1 in 2014, according to the experimental data in Table 1 [18]. Each factor's standardized values started to shift in 2015. The ownership structure's standardized coefficient in 2015 was 3.75, or 11 items.

Table 1. Every factor's standard information

Index	**2014**	**2015**	**2016**	**2017**	**2018**
EDI	2.00	0.13	0.46	0.17	1.25
LEV	2.00	0.34	0.70	0.61	1.38
ROE	2.00	0.37	0.75	0.57	0.68
INSIZE	2.00	1.05	1.20	1.10	1.29
AREA	2.00	0.50	1.41	1.50	1.33
SCALE	2.00	0.90	1.10	1.48	1.98
CEO	2.00	0.10	0.40	0.60	0.80
HERF5	2.00	3.75	3.38	0.63	0.70
NSH	2.00	0.89	0.53	0.84	1.05
CSR	2.00	0.65	0.82	0.89	0.92
VISIBILITY	2.00	0.15	0.34	1.47	2.38
BIG	2.00	0.44	0.63	1.25	0.56

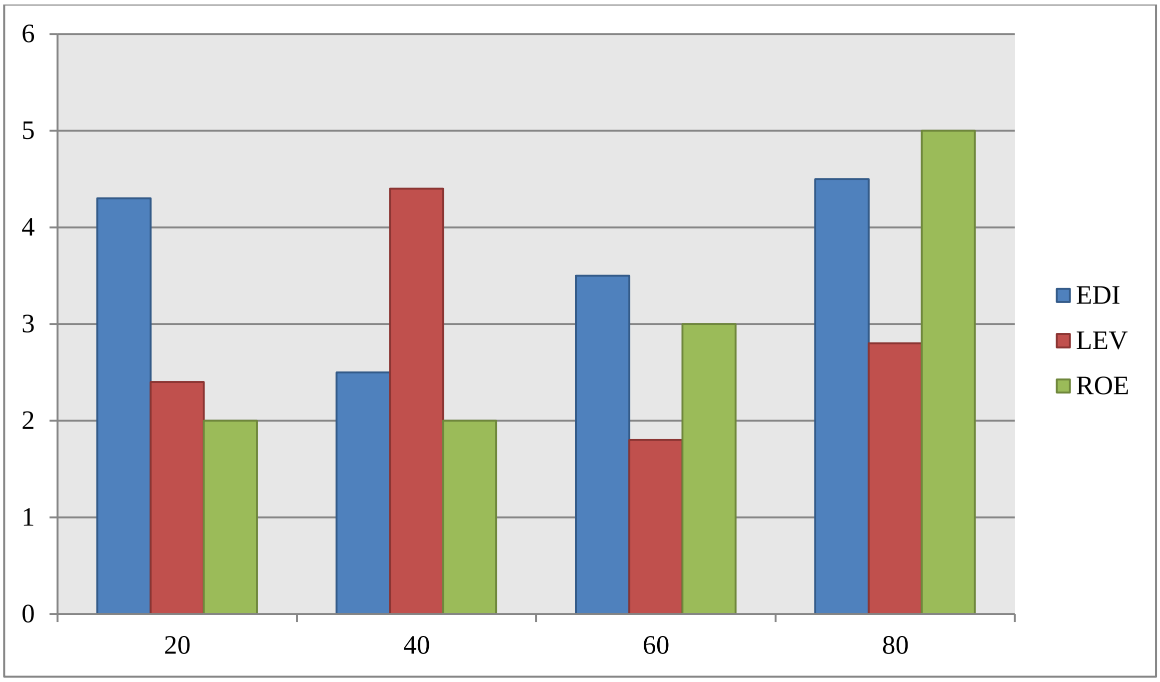

Figure 3. Data on the variables influencing the degree of disclosure of accounting information

Operational management independence exhibited the least impact, with a standardized value of 0.1—the lowest among the tested indicators. In contrast, the standardized coefficients for region and firm size exceeded 1.0 between 2016 and 2018, indicating that these two independent variables exert a relatively strong influence. The effects of the secondary indicators are detailed in Table 2 and illustrated in Figure 3.

Table 2. An explanation of the elements that affect accounting information

Index	**2014**	**2015**	**2016**	**2017**	**2018**
EDI	0.73	0.09	0.33	0.12	0.89
LEV	0.59	0.20	0.41	0.36	0.81
ROE	0.29	0.11	0.22	0.41	0.20
INSIZE	0.89	0.95	1.12	1.30	1.73
AREA	0.20	1.00	0.82	1.25	1.33
SCALE	0.89	0.86	0.92	1.34	1.65
CEO	0.05	0.10	0.02	1.00	0.40
HERF5	0.08	0.30	0.27	0.45	0.56
NSH	0.95	0.85	0.50	0.80	1.00
CSR	0.05	0.25	0.45	0.89	0.50
VISIBILITY	0.69	0.15	0.24	1.53	2.38
BIG	0.80	0.35	0.50	1.00	0.45

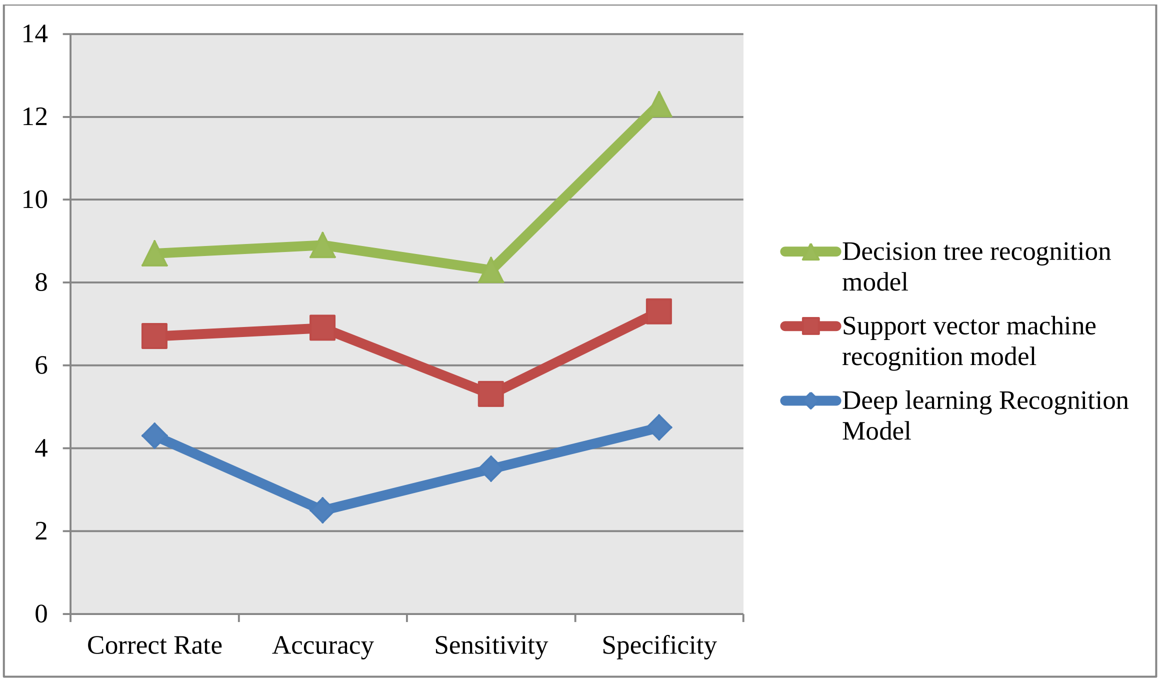

Figure 4. Statistics of model evaluation results

In general, the training set is used to optimize the model's parameters, allowing it to capture underlying patterns in the data, while the test set evaluates the model's predictive performance on unseen information. Figure 4 presents the experimental results obtained from the two distinct test sets.

Table 3. Table of evaluation indexes

Metric	Formula	Definition
Accuracy (PPV)	(\text{TP} / (\text{TP} + \text{FP}))	Indicates the proportion of correctly identified samples among all results predicted as correct by the model.
Sensitivity (TPR)	(\text{TP} / (\text{TP} + \text{FN}))	Indicates the proportion of true positive samples correctly recognized by the model.
Specificity (TNR)	(\text{TN} / (\text{TN} + \text{FP}))	Indicates the proportion of true negative samples correctly recognized by the model.

Table 4. Table of training set model evaluation results

Recognition Model	**Correct Rate (%)**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Deep Learning Recognition Model	94.80	98.23	96.15	76.32
Support Vector Machine Recognition Model	84.95	94.71	87.76	64.71
Decision Tree Recognition Model	88.87	93.75	93.36	60.53

Table 3 summarizes the model evaluation metrics. Based on the data presented in Table 4, the proposed model achieves the highest accuracy among the tested models, with an accuracy rate of 98.23% and a correctness rate of 94.8% following training. In comparison, another model records the lowest performance, with an accuracy of 94.71% and a correctness rate of 84.95%. The decision tree recognition model demonstrates a sensitivity of 93.36% and an overall accuracy of 88.87%.

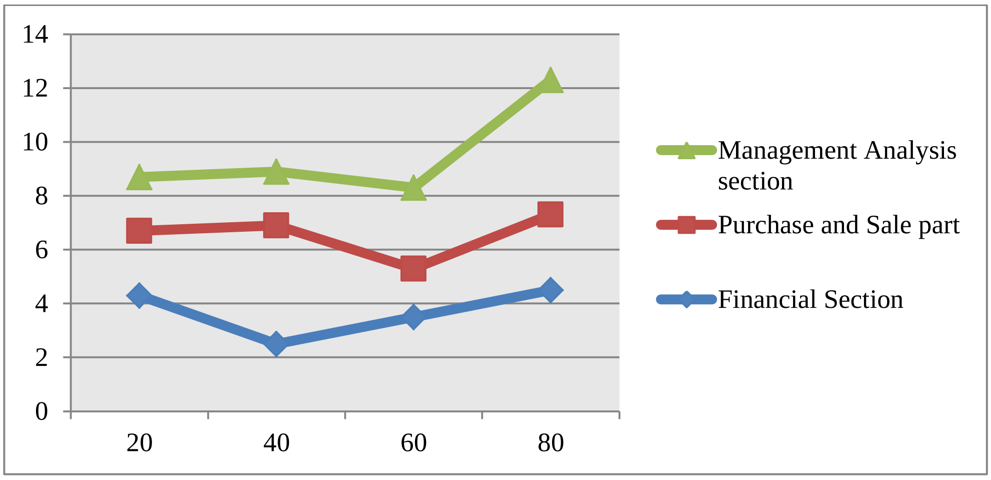

Figure 5. Curve of average response time

4.1 Test of Page Response Time

The experimental results presented in Table 5 and Figure 5 indicates that the mean response time increases with the number of tests conducted. Among all modules, the finance section exhibited the lowest average response time. Specifically, with 130 tests, the finance module averaged 1.2 seconds per response, while the purchasing, sales, and inventory module averaged 1.5 seconds, and the management analysis module averaged 1.8 seconds.

Table 5. Results of the page response time test

Testing Frequency	**60**	**70**	**80**	**90**	**100**	**110**	**120**	**130**
Financial Section	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2
Purchase and Sale Part	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5
Management Analysis Section	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8

4.2 Tests for System Operation Stability

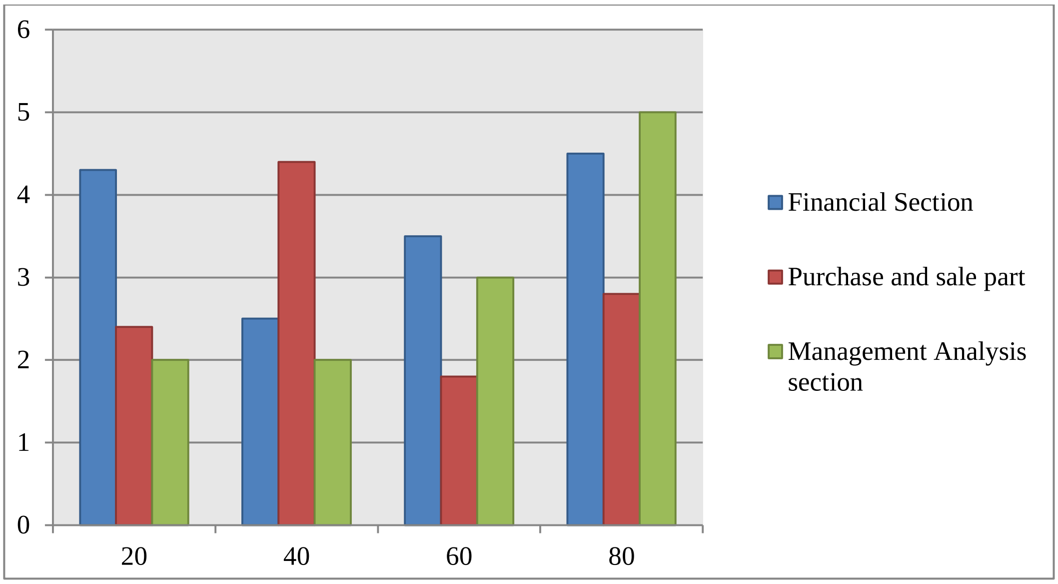

Figure 6. Execution test case statistics

The system's execution rate test in Figure 6 shows that when there are 140 design test cases, the financial module has 140 executed use cases, the purchase, sale, and storage module has 139 executed use cases, and the management analysis section has 138 executed use cases. The system can function normally since the three modules' execution rates are maintained above 98% and almost 100%.

5. CONCLUSION

In order to improve intelligent data analytics in contemporary information systems, this research developed an Optimized Deep Learning Framework. The framework successfully addressed important issues in managing large-scale, heterogeneous enterprise data by combining hybrid CNN–LSTM architecture with GA–PSO. The system was created to increase responsiveness, scalability, and accuracy, guaranteeing trustworthy analytical results for challenging decision-making situations.

The suggested model consistently outperformed conventional machine learning techniques like SVM and Decision Trees (DT), according to experimental assessments utilizing multi-year accounting data (2014–2018). With an astounding accuracy of 98.23% and a correct rate of 94.80%, the deep learning model demonstrated its exceptional prediction power and flexibility in the face of changing data conditions. Additionally, with execution success rates surpassing 98% across all modules, the reaction time and stability tests confirmed that the framework retains operating efficiency and resilience.

Additionally, the study found that regional distribution and organizational size have a greater impact on the quality of accounting information than structural or managerial characteristics. The significance of contextual and spatial elements in enterprise data analysis is highlighted by this realization. Thus, the optimized framework offers both interpretability and analytical precision, allowing stakeholders to extract useful insights from intricate data ecosystems.

To sum up, the suggested solution provides a strong basis for cognitive analytics in real time in business settings. Applications like financial forecasting, smart accounting systems, and strategic resource planning can all benefit from it. Future research will concentrate on integrating blockchain-based data validation and reinforcement learning to further improve data security, transparency, and ongoing model optimization, opening the door to completely autonomous, reliable information systems.

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