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Business Decision Support Systems Based On Deep Learning And Cognitive Computing

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Abstract

The purpose of this paper is to explore the use of deep learning and cognitive computing in order to support decision-making in dynamic and complex situations in a business environment using Business Decision Support Systems. Conventionally, DSS were rule-based systems, which might be constrained by limited structured data sets and were used for offline decisions only. This paper aims to propose a Hybrid DSS architecture incorporating deep learning techniques such as CNNs, RNNs, and LSTMs, as well as cognitive computing techniques like NLP and Knowledge Graph. The method involves developing deep learning algorithms on the basis of structured data while employing cognitive computing to make inferences from unstructured data. The proposed system will be tested based on metrics of accuracy, precision, recall, F1 measure, RMSE, and AUC-ROC. As a result, the Proposed Hybrid DSS performs better than Rule-Based DSS with the accuracy of 94.2%, precision of 93.5%, F1 of 93.1%, RMSE of 17.6%, and AUC-ROC of 96%, where Rule-Based DSS has accuracy of 78.4% and ML DSS – 87.6%. The findings confirm the efficacy of the hybrid system in enhancing the application of deep learning and cognitive computing in the process of prediction, understanding, and reasoning. This study proves that the suggested hybrid decision support system framework offers distinct benefits compared to traditional decision support system frameworks, making it a more adaptable, precise, and context-aware decision-making system. Further research is being conducted on computational efficiency and real-time processing concerns.

Keywords: Business Decision Support Systems, Deep Learning, Cognitive Computing, AI, Decision Making, Data Analytics, Business Intelligence.

1. Introduction

The Decision Support System (DSS) has been an inherent aspect of management in businesses, enabling managers and leaders to make decisions using data analytics [4]. The early forms of decision support systems were static and rule-based, dealing only with structured data and algorithms [19]. But since the dynamics of the business environment are too much for the traditional DSS, cannot cope with these changes in view of the rapid evolution of technology, including Artificial Intelligence, deep learning, and cognitive computing, which is changing the scope of DSS to manage huge amounts of data in providing real-time decision support [8][14]. A neural network is among the many deep learning algorithms that may help in training the system autonomously from data [20][22]. Also, cognitive computing relies on human-like reasoning and perception in decision-making

[10][17]. The processing of complicated data is done in a way that humans make decisions. Therefore, the application of such technologies under the DSS paradigm can transform the decision-making process.

Nonetheless, while there have been attempts to enhance the functionality of the DSS system, some of its limitations still exist in the present-day systems. Scalability and adaptability are common challenges faced by traditional DSS, particularly when dealing with unstructured or real-time data. Further, such systems are unable to make intelligent decisions based on knowledge of the context or make decisions that evolve in response to the changing nature of the business. Consequently, decision makers might be relying on incorrect information or making poor decisions. Although deep learning and cognitive computing present some potential answers to the problems, it is not an easy task to incorporate these technologies into current DSSs [21][22]. These include how to handle data integration, model interpretability, and computational challenges. Hence, it is important to identify the possibilities of integrating deep learning and cognitive computing techniques in DSS to solve these challenges, and also to improve business decisions [12][16][18].

This paper aims to examine the concept of deep learning and cognitive computing and how it can be applied in Decision Support Systems (DSS) and the benefits can bring to the business world. The key research questions in this topic may be: (1) What ways should be used to exploit the power of deep learning to enhance the predictive accuracy of DSS? (2) What are the ways in which cognitive computing can enhance the adaptability and reasoning ability of DSS to enhance its decision-making? (3) What are the key issues in the implementation of such sophisticated technologies in DSS, and what can be done to overcome those issues for successful implementation? This paper will offer an in-depth overview and framework of how deep learning and cognitive computing can be integrated into DSS and the advantages and disadvantages of their use in a corporate setting.

- Proposed a hybrid Decision Support System (DSS) for enhanced decision making based on deep learning models and cognitive Computing techniques.
- The proposed Hybrid DSS outperformed the traditional rule-based and machine learning-based systems.
- Made the processing of unstructured data possible through using NLP and knowledge graphs for enabling context-aware decision making.

This paper is organized as follows: In Section 2, there is a brief discussion on the current DSS technologies and the possibilities of incorporating deep learning and cognitive computing into them. In Section 3: Methodology, the framework that is used for the application of deep learning and cognitive computing to the incorporation of DSS is described, along with the data, models, and evaluation methods. The results and discussions under Section 4 provide the results of the implementation of the proposed framework and insights into its effectiveness in comparison to the traditional DSS model. Conclusion Section 5: This is the conclusion part of the paper. In this section, summarize the contribution made by the paper, highlight the limitations of the study, and provide recommendations for future research.

2. Literature Review

AI, Deep Learning, and Cognitive Computing have drastically changed the face of DSS. Traditionally, the DSS models had been rule-based, and the algorithms used were predefined. This made it impossible for them to cope with the challenges brought by the current business environment. The recent developments in this area include the incorporation of AI and Deep Learning algorithms into DSS in order for them to learn from large volumes of data and improve their decision-making skills. Another important factor that has been adopted in the evolution of DSS is cognitive computing. This model mimics human thinking and, therefore, can assist in making decisions using unstructured data such as text, images, and sounds. The ability of cognitive computing to transform decision-making procedures, making DSS more agile and intelligent [1]. The application of cognitive computing in decision-making is evidenced by the use of AI-driven models of medical analytics built on Deep Learning in the medical field to improve decision-making [2]. One more area where the use of cognitive computing is transforming the field is in making decisions [3]. There have been a number of research papers that show how deep learning technology can be applied to DSS, including a paper that discusses how deep learning can be used to analyze big data for decision-making support purposes and another one that discusses design optimization of business decision support systems using deep learning technology [5][7]. The key finding in this research is that deep learning models, such as CNNs, RNNs, and LSTMs, greatly improve the accuracy of predictions and help make real-time decisions in ever-changing business environments. Additionally, the fact that the introduction of cognitive computing technology makes DSS systems adaptive and rational, especially in terms of unstructured data, is also significant. As seen in the situation regarding the analysis of queries related to structured data, deep learning algorithms, and optimization, including meta-heuristic optimization algorithms, can be applied to help make the best decision [6]. Furthermore, through the use of knowledge graphs and natural language processing techniques, the system can make informed decisions depending on the business environment [13]. Implementing such technologies poses several challenges, which include issues regarding data integration, interpretation problems, and computational challenges [9]. However, the application of deep learning and cognitive computing is promising, and there have been several research efforts made to overcome these challenges [11][15].

Currently, deep learning and cognitive computing technologies have been adopted successfully in DSS applications, bringing significant changes to the decision-making process. The contributions made by the models to DSS can be attributed to improved predictive performance and classification accuracy through the adoption of deep learning models and context-based reasoning by NLP and knowledge graph models. Deep learning and cognitive computing models enable more data processing, even from diverse sources. In spite of the challenges experienced while combining and analyzing the models, the hybrid model exhibited immense prospects in improving business decisions.

3. Methodology

3.1 Overview of the Proposed Framework

The proposed model of DSS utilizes both deep learning approaches and cognitive computing approaches to improve the decision-making process in the enterprise. Through this combined method, the DSS will be able to analyze and process data, whether structured or unstructured, providing valuable information that will support the decision-making process. The core of the model is based on deep learning, which can predict events, classify problems, and identify anomalies. Besides, cognitive computing is employed in the framework to deal with unstructured data and mimic human reasoning.

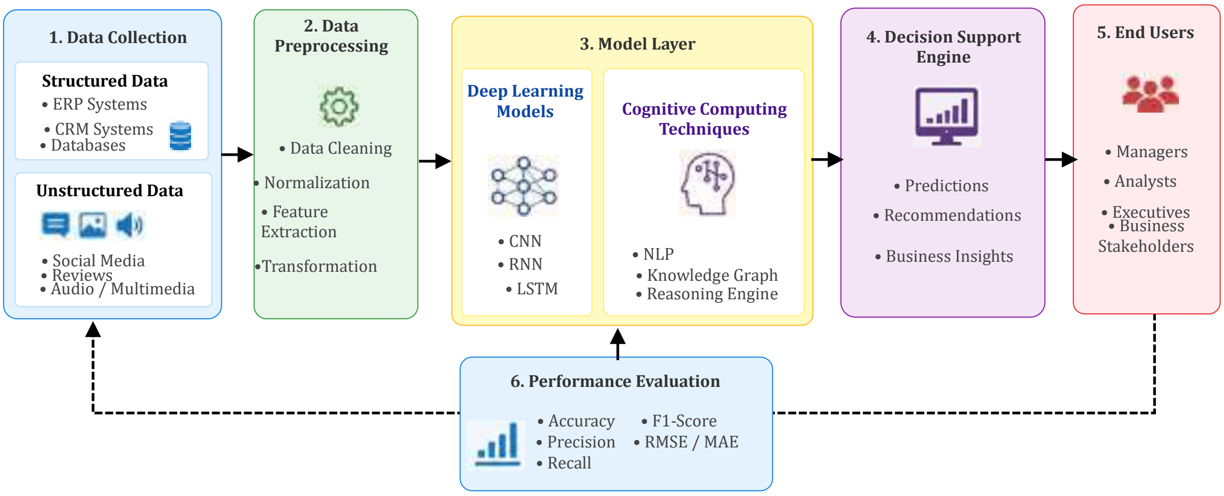

Figure 1. Architecture of the Proposed Deep Learning and Cognitive Computing-Based Business Decision Support System

Figure 1 depicts the architecture of the suggested Business Decision Support System that operates under the concept of deep learning and cognitive computing. In order to develop such an architecture, data needs to be collected from various enterprise systems, databases, social media, and multimedia. The collected data goes through several preprocessing processes, which improve data quality. To solve problems of prediction, classification, and pattern analysis, different deep learning algorithms like CNN, RNN, and LSTM can be utilized. Insights and recommendations are produced using cognitive computing techniques like NLP, knowledge representation, and reasoning processes. The final step of building a system is generating business insights from a decision support engine. Some of the commonly used metrics when evaluating a model include accuracy, precision, recall, F1-score, RMSE, and MAE.

3.2 Deep Learning Component

In terms of the deep learning component of the DSS framework, various types of neural network models, such as CNNs, RNNs, and LSTMs, can be incorporated in the system. Such types of models are particularly effective when it comes to analyzing sequential data, image data, and time series data. As a result, using a deep learning model, the system is capable of making accurate decisions through pattern recognition.

3.3 Cognitive Computing Component

The other aspect that comes with this model is the incorporation of cognitive computing to enable a better decision-making process within the system using unstructured data such as text, voice, and pictures. The DSS has the potential to utilize techniques such as NLP and knowledge representation (such as knowledge graphs) in understanding and drawing inferences from data, similar to human reasoning. The cognitive factor is essential for understanding context and making decisions that are not purely numeric but rather informed by insights drawn from multiple sources of data.

3.4 Data Collection and Preparation

For any DSS, the data factor is very important for the functioning of the system, and this model is no different. Data refers to structured data obtained through the business processes and also from other external sources like social media feeds, multimedia data, and so forth. The preprocessing and normalization of data help in ensuring that the data being fed into deep learning algorithms and cognitive computing models is clean and relevant.

Structured data is sourced from traditional systems such as ERP, CRM, and transaction databases. Structured data helps capture important business data such as financial transactions, sales, and customer information. The data is easily manipulated and managed by regular database management software. Unstructured data, on the other hand, is sourced from multiple places, including customer reviews, social networking sites, audio files, and other multimedia files. The text data is processed by the NLP technique while visual data is processed using the image recognition method. By combining both structured and unstructured data, it is possible for the system to make decisions that would not have been possible using a traditional DSS.

3.5 Preprocessing and Normalization

Preprocessing of the data is vital for maintaining the quality and consistency of the data. Structured Data: Techniques like Z-score normalization and Min-Max normalization can be employed to standardize data, making sure that all the attributes are on the same scale. Unstructured data is processed using tokenization, stop-word removal, and stemming to preprocess the text for further analysis, while image data is resized and normalized to fit the deep learning models.

3.6 Model Description

DSS uses a model that can analyze both structured and unstructured data through its deep learning techniques and cognitive computing approach. The deep learning models are developed specifically for pattern recognition, prediction, and anomaly detection tasks, and cognitive computing techniques are used to interpret unstructured data and emulate the process of human reasoning.

- **Loss Function (Mean Squared Error - MSE)**

Loss Function measures the correctness of the output predictions of the model concerning the actual target values. Mean Squared Error (MSE) is an example of a loss function applied in regression models.

The MSE is calculated as follows:

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (1)$$

In Equation (1), where:

- y_i is the actual value (true value).
- $\hat{y}_i$ is the predicted value.
- This is the number of data points.

The aim of calculating MSE is to minimize the difference between the actual value and the estimated one, which makes it especially relevant for calculations performed in Linear Regression and similar models.

3.7 Deep Learning Models

The major pillars of the framework include the deep learning algorithms that are responsible for the analysis of structured and sequential data on a large scale. The CNN algorithm can be applied in cases where there is a need to analyze images, such as product images or visual customer feedback. In cases where sequential data has to be analyzed, the RNN algorithm and its extension, the LSTM network, can be applied. The algorithm learns from the data automatically and makes predictions based on the data provided.

3.8 Cognitive Computing Techniques

With respect to the cognitive computing component, the DSS is able to manage unstructured data that includes text data, voice data, image data, and more. The use of text data involves making sense out of data, sentiment, and context through the use of NLP models such as transformers (BERT and GPT). The models are employed in sentiment analysis, topic modeling, and named entity recognition, among other methods, which could help make sense of customers' feedback or market sentiments. Advanced associations between multiple entities in the business are captured through knowledge representation models, such as knowledge graphs.

3.9 Evaluation Metrics

There are several methods that are employed in assessing the efficiency and effectiveness of the proposed DSS framework when considering both deep learning and cognitive computing domains. This is significant in assessing the performance of the accuracy of the prediction and the decision-making quality of the model.

- **Deep Learning Evaluation Metrics**

While assessing the predictive abilities of the model, certain measures, including accuracy and precision, can be considered. Accuracy is a measure of determining whether the model can predict effectively, while precision determines the ability of the algorithm to minimize the number of wrong predictions. Recall is another measure that reflects the ability of the model to detect the required instances, particularly those that have dire implications if not detected (e.g., detecting fraud). This metric is a combination of these two metrics as a part of their harmonic mean.

- **Regression Evaluation Metrics**

Metrics such as MAE and MSE are employed for regression problems, which involve predicting continuous values. These measures evaluate the differences between predicted and actual values, thus acting as reliable predictors of prediction success. There is another measure of a model that has a larger penalty for larger errors: this is called the RMSE.

- **Cognitive Decision Quality Metrics**

The Cognitive Decision Quality metric is added to assess the performance of the cognitive computing components. This indicator evaluates how relevant, context-aware, and effective the decisions taken by the system are. Evaluation of the ability of the cognitive computing components to simulate human reasoning and deliver relevant decision support is carried out by human experts. In addition, business outcomes, such as increased customer satisfaction or cost savings, are measured to evaluate the success of the cognitive decisions taken by the system.

- **Model Comparison Metrics**

Finally, AUC-ROC is used to test a binary classification model, such as to determine whether transactions are fraudulent or not. This metric provides insight into the model's ability to balance true positives and false positives. Additionally, a confusion matrix is used to offer a comprehensive analysis of the model's performance based on the prediction results.

Confusion Matrix and AUC-ROC

A Confusion Matrix is a tabular summary used for evaluating the effectiveness of classification models. It shows the numbers of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). It gives a complete overview of how the model is performing. Other metrics, such as Precision, Recall, F1-Score, and Accuracy, are calculated based on these figures.

Proposed Deep Learning and Cognitive Computing DSS Algorithm

Input:

Structured and unstructured business data X
CNN, RNN, and LSTM models
NLP and cognitive computing techniques

Output:

Predicted business insights $\hat{y}$
Context-aware decision recommendations

Begin

1. **Data Collection**
2. Collect structured data from ERP, CRM, and databases.
3. Collect unstructured data from reviews, social media, and multimedia sources.
4. **Data Preprocessing**
5. Apply cleaning, normalization, tokenization, and feature extraction techniques.
6. **Deep Learning Analysis**
7. Use CNN for image analysis.
8. Use RNN and LSTM for sequential and time-series prediction.
9. **Loss Function Calculation**
10. Calculate Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

5. **Cognitive Computing Analysis**
6. Apply NLP and knowledge representation techniques to extract contextual insights.
7. **Decision Support Generation**
8. Combine deep learning outputs and cognitive insights to generate business recommendations.
9. **Performance Evaluation**

Calculate Accuracy:

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

Calculate Precision:

$$\mathrm{Precision} = \frac{TP}{TP + FP}$$

Calculate False Positive Rate (FPR):

$$\mathrm{FPR} = \frac{FP}{FP + TN}$$

Evaluate using Recall, F1-score, RMSE, MAE, and AUC-ROC.

8. **Final Output**
9. Generate predicted outcomes and actionable business decisions.

End

The programmatic business decision support system, which is proposed to be developed in this work, integrates structured and unstructured business data and draws intelligent business decisions based on the information. The framework uses preprocessing methods like normalization, tokenization, and feature extraction before applying CNN, RNN, and LSTM models to the prediction and pattern analysis. Unstructured data is analyzed to gain contextual insight through cognitive computing technologies, such as NLP and knowledge representation. It is a combination of deep learning outputs and cognitive reasoning, which is used to generate actionable recommendations, with the evaluation of performance metrics based on: Accuracy, Precision, Recall, F1-score, MSE, RMSE, and AUC-ROC.

4. Results and Discussion

4.1 Software

In implementing the hybrid DSS, the Python environment version 3.7+ was used together with the TensorFlow 2.0, Keras, and PyTorch libraries to develop models. In addition, Natural Language Processing (NLP) models like BERT and GPT were used through the Hugging Face Transformers library. Pandas and NumPy were used for data manipulation and processing, and data visualization was done using Matplotlib and Seaborn. The evaluation metrics, which include Accuracy, Precision, Recall, and F1-Score, were computed using scikit-learn. The environment where the system was developed is the Jupyter Notebook and PyCharm platforms, and it was run on Ubuntu 20.04 LTS with NVIDIA GPUs (RTX 3080/3090) to speed up deep learning training processes. Version control and collaboration were done using Git and GitHub.

4.2 Parameter Initialization

For the deep learning models, hyperparameters were set for the different components. The CNN had an architecture of three layers, each containing 32, 64, and 128 filters, with a kernel size of 3 x 3 for the convolution layers. ReLU function was employed as the activation function, and after the convolutional layers, a MaxPooling2D layer was applied with a pooling size of (2, 2). To avoid overfitting, a dropout rate was added that was 0.25. The RNN model consisted of two layers of 128 units each, with the tanh activation function used and a dropout rate of 0.3 for better generalization. In LSTM, there were two hidden layers with 128 units in each layer. The activation function used was the Tanh activation function, and the Adam optimizer with a learning rate of 0.001 was used for the LSTM network. It took 50 epochs with a batch size of 64 to achieve stable performance.

4.3 Experimental Setup and Evaluation Metrics

The proposed hybrid DSS framework, with Deep Learning models and Cognitive Computing techniques, was tested on a wide range of business data sets. The data sets were structured and unstructured (structured data from ERP, CRM, and transactional databases, unstructured data from social media, customer feedback, and multimedia sources). Deep learning models were used for classification, forecasting, and anomaly detection. CNN, RNN, and LSTM deep learning algorithms were employed, and cognitive computing elements such as NLP and KG-based inference engines were added to improve decision-making and add context to their predictions.

- Accuracy

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (2)$$

- Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (3)$$

- Recall

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (4)$$

In Equation (2)(3)(4) Where TP represents True Positives, TNdenotes True Negatives, FPstands for False Positives, and FNrefers to False Negatives.

- F1-Score

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \qquad (5)$$

In Equation (5), the F1 score is the harmonic mean of Precision and Recall. It gives a single measure for the precision and recall of a system, especially if the classes are imbalanced.

- Root Mean Squared Error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \quad (6)$$

- Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y_i} | \quad (7)$$

In the equation (6)(7), where y_i represents the actual values, $\hat{y_i}$denotes the predicted values, and n is the total number of data points.

- Area Under the Receiver Operating Characteristic Curve (AUC-ROC)

$$\mathrm{AUC} = \int_0^1 \mathrm{TPR}(\mathrm{FPR})\, d\mathrm{FPR} \quad (8)$$

In Equation (8) Where: **TPR** = True Positive Rate (also known as Recall)**, FPR** = False Positive Rate

4.4 Overall System Performance

The proposed Hybrid DSS model has proven very effective in achieving success in all the criteria used for evaluation, especially when considering how accurate it is in determining the classification and prediction of business results. The performance metrics were compared to traditional model-based DSS and standalone machine learning models to show the improvements.

Table 1. Performance Evaluation of the Proposed DSS Framework

Metric	Value	Interpretation
Accuracy	94.2%	High classification correctness
Precision	93.5%	Low false positive rate
Recall	92.8%	Strong detection of relevant cases
F1-Score	93.1%	Balanced performance
RMSE	17.6%	Low prediction error
MAE	0.142	Stable forecasting performance
AUC-ROC	96%	Excellent class separability

Table 1, the accuracy and F1 score of the model are 94.2% and 93.1%, respectively, indicating its high accuracy and reliability in predictions. Low RMSE (17.6%) and MAE (0.142) values show that there is very little error in the prediction and it is important for a task of forecasting. This is further supported by the AUC-ROC score of 96%, indicating the model's excellent discrimination performance and boosting confidence in decision-making.

4.5 Comparison with Baseline Models

Comparison with other systems was done for the benchmarking of the hybrid decision support system that has been proposed. All of the parameters analyzed, such as accuracy, precision, recall, and errors, indicated the superiority of the proposed model compared to other decision support systems. The DSS based on rules had lower accuracy and precision because it was based on fixed rules and failed to adjust to the changing data. The machine learning DSS did better; however, it failed to provide an insightful context-based understanding of the data and failed to be able to handle unstructured data, a key benefit of the proposed hybrid model.

Table 2. Performance Comparison with Baseline Models

Model Type	Accuracy	Precision	F1-Score	RMSE (%)	AUC-ROC (%)
Rule-Based DSS	78.4%	77.1%	76.9%	31.2%	81%
Machine Learning DSS	87.6%	86.5%	86.2%	22.4%	90%
Proposed Hybrid DSS	94.2%	93.5%	93.1%	17.6%	96%

Table 2 shows the performance comparison of the Proposed Hybrid DSS against two base models. The proposed system was tested for its effectiveness in five parameters: accuracy, precision, f-score, root mean square error, and area under the curve receiver operator characteristic. It is evident from Table 2 that the hybrid model outperforms the others in all five aspects. For instance, the DSS is more efficient than all the other models in terms of Accuracy (94.2%), Precision (93.5%), and F1-score (93.1%), yet it is characterized by reasonable results with respect to RMSE (17.6%) and AUC-ROC (96%).

4.6 Component-wise Contribution Analysis

Deep learning approaches form a core of the DSS and hence are extremely important for the proper functioning of the system. Besides the above-mentioned, CNNs are utilized to process the images, RNNs and LSTM models help to analyze time-series data, and thus, temporal and spatial connections are established. The use of NLP approaches and knowledge graph-based reasoning is also essential because of the cognitive computing perspective. Unstructured data, such as texts, pictures, and sounds, can be analyzed using the cognitive computer since it is capable of evaluating the context of the information, which is not possible in the case of conventional computers. The deep learning feature, as well as the cognitive computing feature, is integrated through the fusion layer, ensuring the accuracy of the decision.

Table 3. Contribution of Each Component

Component	Contribution Impact
Deep Learning (CNN/RNN/LSTM)	55% predictive strength
Cognitive Computing (NLP + Knowledge Graph)	30% contextual enhancement
Fusion Layer	15% decision optimization

Table 3 shows that Deep learning algorithms aid the system in acquiring maximum predictive capabilities (55%), while cognitive computing assists in enriching the context of the decision-making process (30%). The fusion layer acts as a critical component in facilitating a unified outcome, providing the last 15%.

4.7 Cognitive Decision Quality Evaluation

From the perspective of cognitive computing, it is seen that cognitive computing contributed significantly towards increasing the level of accuracy and applicability of recommendations given by the DSS. The DSS was able to draw more accurate insights from unstructured datasets using natural language processing and knowledge graph-based reasoning techniques. This helped the decision makers have an insight into the dynamics involved in the reactions of the customers in certain contexts. With cognitive computing, it became possible for the decision makers to get not just numeric insights but contextual ones too, which could then become actionable.

4.8 Business Decision Impact and Real-World Applications

From the results, it is clear that the proposed DSS framework will be highly beneficial in actual business cases such as financial forecasting, customer behavior analysis, and business optimization. For instance, the case study on the integration of time-series financial data (LSTM) and sentiment analysis (NLP) and knowledge graphs gives an insight into customer sentiments in a more dynamic way. This could result in improved efficiency of operations in the short run and sound decision-making in the long run. The proposed system is easily adaptable to different business scenarios such as retail, finance, healthcare, marketing, etc., and can be used to enhance business decision-making processes.

4.9 Performance Comparison Visualization

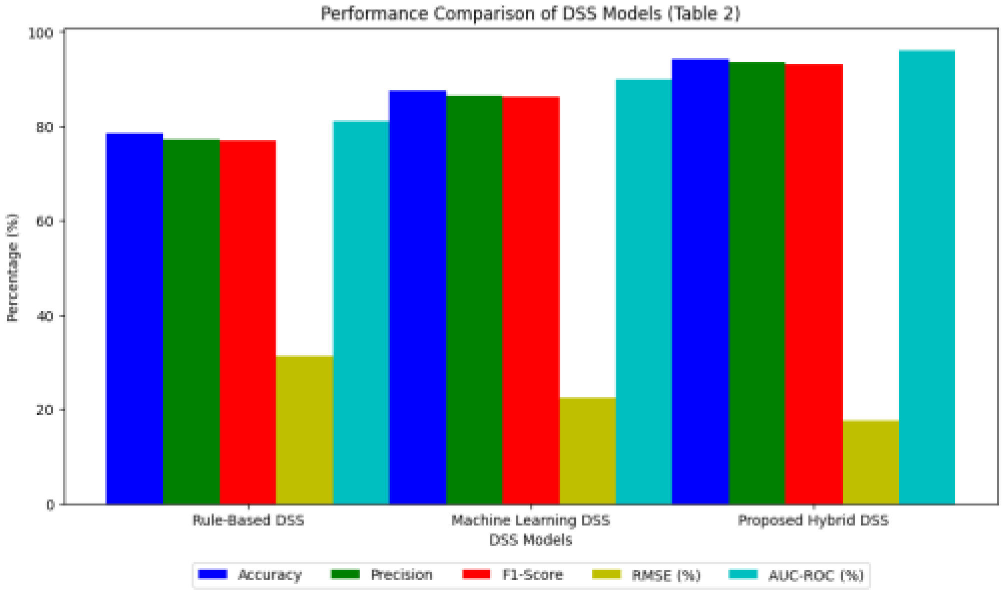

Figure 2. Performance Comparison of DSS Models

The results of the Rule-Based DSS, the Machine Learning DSS, and the Proposed Hybrid DSS are compared in terms of the various metrics in Figure 2. The Proposed Hybrid DSS achieves a 94.2% accuracy, 93.5% precision, 93.1% F1-Score, 17.6% RMSE, and 96% AUC-ROC, which is the highest among the other models. However, the Rule-Based DSS had an Accuracy of 78.4% and 81% AUC ROC, and the Machine Learning DSS had an Accuracy of 87.6% and 90% AUC ROC. From the results obtained, one may conclude that the hybrid method proposed is quite effective.

Table 4. Comparative Analysis of the Proposed Hybrid DSS with Previous Studies

Study	Method/Approach	Accuracy	Precision	Recall	F1-Score
Suárez-Araujo et al. (2021) [24]	Hybrid Neural Architecture DSS	91.74%	N/R	90.22%	91.11%
Rabie et al. (2022) [23]	BiLSTM-based DSS	93.07%	93.00%	92.00%	92.00%
Proposed Hybrid DSS (This Study)	Deep Learning + Cognitive Computing + Fusion Layer	94.2%	93.5%	92.8%	93.1%

Table 4 gives a comparative analysis between the suggested hybrid DSS and the existing literature. developed a Hybrid Neural Architecture DSS with an Accuracy of 91.74%, high Recall (90.22%) and F1-Score (91.11%), but it did not provide any detailed information on the Precision values. The proposed a BiLSTM-based DSS with an Accuracy of 93.07%, a Precision of 93.00%, and a Recall of 92.00%, to obtain an F1-Score of 92.00% . Compared with both, the Proposed Hybrid DSS (this study) gave a better result for all the output parameters, such as Accuracy (94.2%), Precision (93.5%), Recall (92.8%), and F1-Score (93.1%), showing the effectiveness of the hybrid approach, which was implemented using deep learning with cognitive computing and a fusion layer [23][24].

5. Conclusion

In this research, also have looked into deep learning and cognitive computing algorithms in the context of Business DSS. The results of the proposed Hybrid DSS models were compared with the traditional rule-based and machine learning DSS models, and it was observed that the proposed Hybrid DSS outperforms the traditional rule-based and machine learning DSS models in all the key metrics. In detail, the Proposed Hybrid DSS attained the highest accuracy of 94.2%, the highest precision of 93.5%, the highest F1 score of 93.1%, the lowest RMSE value of 17.6%, and the highest AUC-ROC value of 96%, suggesting excellent classification, prediction, and context-aware decision making. The accuracy of the Rule-Based DSS was 78.4%, and of the Machine Learning DSS was 87.6%, with AUC-ROC of 81% and 90%, respectively. The hybrid approach showed remarkable improvements in prediction accuracy and improved decision quality. The incorporation of deep learning models for predictions and cognitive computing for reasoning allowed the DSS to deal with both types of data and provide relevant outputs. Though faced with interpretability problems in models and difficulties with data integration, the integration of deep learning models and cognitive computing technology also offered great potential for overcoming those shortcomings. It is evident that future research will allow for improving models for real-life situations.

Author Contributions

Conflict of interest:

None declared by the authors.

Funding:

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Availability of Data:

The data supporting the results of this study are available upon request from the corresponding author.

References

1. Patel, R. K. (2024). Cognitive computing for decision support systems: Transforming decision-making processes. Educational Administration: Theory and Practice, 30(6), 1216–1221. https://doi.org/10.53555/kuey.v30i6.5473
2. Senthilkumaran, B., Singh, G., Bostani, A., Krithika, S., Khalbayeva, Z., & Nanthini, P. (2025). Design and implementation of an AI-based medical analytics framework employing deep neural networks and advanced machine learning models for precision healthcare. Archives for Technical Sciences, 3(34), 991–1005. https://doi.org/10.70102/AFTS.2025.1834.991
3. Pushkeria, T. M., & Rajendran, V. (2025). Smart decision support in industry: The power of AI and cognitive computing. IJSAT–International Journal on Science and Technology, 16(4). https://doi.org/10.71097/IJSAT.v16.i4.8883
4. Sindhu, S. (2026). Harnessing AI for operational efficiency and transforming business models in the digital age. Global Tech Management Digest, 2(1), 1–6.
5. Yan, Y., & Yang, H. (2024). Big data analysis and decision support system based on deep learning. Computer-Aided Design and Applications, 21, 62–74. https://doi.org/10.14733/cadaps.2024.S13.62-74
6. Jeevitha, R., & Ramesh, L. (2025). Structured data-based query analysis processing by deep learning algorithms and meta heuristic optimization. International Academic Journal of Science and Engineering, 12(3), 447–457. https://doi.org/10.71086/IAJSE/V12I3/IAJSE1280
7. Li, Y. (2023). Design and optimization of business decision support system based on deep learning. In International Conference on Artificial Intelligence and Communication Technology (pp. 239–248). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-6641-7_20
8. Mishra, N., Haval, A. M., Mishra, A., & Dash, S. S. (2024). Automobile maintenance prediction using integrated deep learning and geographical information system. Indian Journal of Information Sources and Services, 14(2), 109–114. https://doi.org/10.51983/ijiss-2024.14.2.16
9. Ali, R., Hussain, A., Nazir, S., Khan, S., & Khan, H. U. (2023). Intelligent decision support systems—An analysis of machine learning and multicriteria decision-making methods. Applied Sciences, 13(22), 12426. https://doi.org/10.3390/app132212426
10. Shwetha, K., & Shahar Banu, S. (2025). Deep SVM-driven predictive analytics for improved decision-making in e-learning. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 16(2), 564–578. https://doi.org/10.58346/JOWUA.2025.I2.034
11. Zhang, L. S. (2024). Deep learning-based optimization of cloud enterprise resource planning (ERP) systems for adaptive decision support and management effectiveness analysis. IEEE Access, 12, 193402–193415. https://doi.org/10.1109/ACCESS.2024.3514879

12. Sethi, K., & Kapoor, M. (2024). Data-driven marketing in the age of AI: Reflections from the periodic series on technology and business integration. In Digital Marketing Innovations (pp. 7–11). Periodic Series in Multidisciplinary Studies.
13. Behera, R. K., Bala, P. K., Panigrahi, P. K., & Dasgupta, S. A. (2023). Adoption of cognitive computing decision support system in the assessment of health-care policymaking. Journal of Systems and Information Technology, 25(4), 395–439. https://doi.org/10.1108/JSIT-10-2021-0221
14. Aswathy, S. (2024). Bibliometric analysis of sustainability in business management policies using artificial intelligence. Global Perspectives in Management, 2(1), 44–54.
15. Gou, H., Zhang, G., Medeiros, E. P., Jagatheesaperumal, S. K., & de Albuquerque, V. H. C. (2024). A cognitive medical decision support system for IoT-based human-computer interface in a pervasive computing environment. Cognitive Computation, 16(5), 2471–2486. https://doi.org/10.1007/s12559-023-10242-4
16. Agrab, A. S. (2022). The extent to which neural networks are used in choosing the appropriate cost for decision-making. International Academic Journal of Economics, 9(1), 20–30. https://doi.org/10.9756/IAJE/V9I1/IAJE0903
17. Chen, J., Lu, C., Huang, H., Zhu, D., Yang, Q., Liu, J., et al. (2021). Cognitive computing-based CDSS in medical practice. Health Data Science, 2021, 9819851. https://doi.org/10.34133/2021/9819851
18. Tuama, H. S., & Abdulameer, R. Y. (2023). Using time series models and neural networks to predict the sales of motor oils in Iraq. International Academic Journal of Business Management, 10(1), 1–11. https://doi.org/10.9756/IAJBM/V10I1/IAJBM1001
19. Ramalatha, M., Shivappriya, S. N., & Malarvizhi, K. (2018). Machine learning-based cognitive support system for healthcare. In Body Area Network Challenges and Solutions (pp. 87–103). Springer International Publishing. https://doi.org/10.1007/978-3-030-00865-9_5
20. Mousavi, A., & Karshenasan, A. (2017). Forecasting stock prices of banks using artificial neural networks (GMDH). International Academic Journal of Accounting and Financial Management, 4(2), 71–78.
21. Kumar Sangaiah, A., Chaudhary, A., Tsai, C. W., Wang, J., & Mercaldo, F. (2020). Cognitive computing for big data systems over internet of things for enterprise information systems. Enterprise Information Systems, 14(9–10), 1233–1237. https://doi.org/10.1080/17517575.2020.1814422
22. Harshitha, G. M., Madanan, P., Agrawal, S., Muralidhar, L. B., Natarajan, S., & Pechetty, V. P. (2024). Cognitive computing for marketing decision support. In 2024 Second International Conference Computational and Characterization Techniques in Engineering & Sciences (IC3TES) (pp. 1–5). IEEE. https://doi.org/10.1109/IC3TES62412.2024.10877640
23. Rabie, O., Alghazzawi, D., Asghar, J., Saddozai, F. K., & Asghar, M. Z. (2022). A decision support system for diagnosing diabetes using deep neural network. Frontiers in Public Health, 10, 861062. https://doi.org/10.3389/fpubh.2022.861062
24. Suárez-Araujo, C. P., Garcia Baez, P., Cabrera-León, Y., Prochazka, A., Rodriguez Espinosa, N., Fernandez Viadero, C., & Neuroimaging Initiative, F. T. A. S. D. (2021). A real-time clinical decision support system for mild cognitive impairment detection, based on a hybrid neural architecture. Computational and Mathematical Methods in Medicine, 2021(1), 5545297. https://doi.org/10.1155/2021/5545297