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Article

AI Driven Decision Support System for Enterprise Resource Planning in SME'S

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Abstract : Small and medium enterprises (SMEs) increasingly depend on Enterprise Resource Planning (ERP) systems to integrate business operations, improve resource utilization, and enhance organizational productivity. However, conventional ERP platforms primarily generate descriptive reports and often lack intelligent decision support capabilities that can assist managers in responding to rapidly changing business conditions. This paper presents an AI Driven Decision Support System (AI-DSS) designed to strengthen ERP environments by combining machine learning, predictive analytics, and data-driven recommendations for operational decision making. The proposed framework gathers data from multiple ERP modules, including finance, inventory, procurement, sales, and human resources, and transforms them through preprocessing and feature engineering techniques before applying intelligent prediction models. A hybrid learning approach is employed to forecast business trends, identify operational risks, optimize inventory levels, and recommend suitable actions for managers. The framework also incorporates explainable decision mechanisms that improve transparency and user confidence in AI-generated recommendations. Experimental evaluation demonstrates that the proposed model improves prediction accuracy, reduces decision latency, and enhances overall resource utilization compared with conventional ERP decision-making approaches. Furthermore, the system supports scalable deployment for SMEs by minimizing computational overhead while maintaining high analytical performance. The proposed AI-enabled ERP decision support framework contributes to improved business agility, operational efficiency, and strategic planning, making it a practical solution for organizations seeking intelligent digital transformation in highly competitive business environments.
Keywords: Artificial Intelligence (AI), Enterprise Resource Planning (ERP), Decision Support System (DSS), Small and Medium Enterprises (SMEs), Machine Learning and Predictive Analytics.

1. Introduction

Enterprise Resource Planning (ERP) systems have become an integral component of modern business organizations by integrating core operational processes such as finance, procurement, inventory management, manufacturing, human resources, customer relationship management, and supply chain operations into a unified platform. For Small and Medium Enterprises (SMEs), ERP solutions provide an opportunity to streamline business activities, improve information sharing, reduce operational redundancies, and enhance organizational efficiency. Despite these advantages, many SMEs continue to face challenges in utilizing ERP systems for strategic decision making because conventional ERP platforms primarily focus on transaction processing and historical reporting rather than intelligent decision support. Consequently, business managers often rely on personal experience and manual analysis to interpret complex organizational data, leading to slower responses and suboptimal business decisions [1]. The rapid advancement of Artificial Intelligence (AI) has introduced new possibilities for enhancing ERP capabilities beyond automation and data storage. AI technologies, including machine learning, deep learning, natural language processing, and predictive analytics, enable organizations to extract valuable insights from large

volumes of structured and unstructured business data. Instead of merely presenting historical information, AI-driven ERP systems can identify hidden patterns, forecast future business trends, detect anomalies, and recommend suitable actions based on real-time organizational conditions. Such intelligent functionalities significantly improve the quality and speed of managerial decision making, particularly in competitive business environments where timely responses are essential [2]. Small and Medium Enterprises contribute substantially to economic development by generating employment opportunities, fostering innovation, and supporting industrial growth. However, SMEs generally operate with limited financial resources, constrained technical expertise, and smaller operational teams compared to large enterprises. These limitations make accurate and timely decision making even more critical for sustaining business growth and maintaining competitiveness. Traditional ERP implementations often require managers to manually interpret reports generated from multiple functional modules, increasing the possibility of human error and delaying strategic responses. AI-driven Decision Support Systems (DSS) integrated with ERP platforms can address these challenges by automating data analysis, generating predictive insights, and recommending optimal business actions based on continuously evolving organizational data [3].

Recent advancements in cloud computing, Internet of Things (IoT), and big data technologies have further accelerated the adoption of intelligent ERP systems. Modern enterprises generate enormous volumes of operational data from production equipment, online transactions, customer interactions, logistics networks, and financial activities. AI algorithms can efficiently process these heterogeneous datasets to predict customer demand, optimize inventory replenishment, detect fraudulent financial transactions, estimate resource utilization, and improve production scheduling. By continuously learning from historical and real-time business data, AI models become increasingly accurate, allowing ERP systems to evolve from passive information repositories into intelligent business advisors capable of supporting both operational and strategic decision making [4]. Machine learning algorithms play a particularly significant role in intelligent ERP environments because they can recognize complex relationships among multiple business variables without requiring explicitly programmed rules. Supervised learning techniques such as Random Forest, Gradient Boosting, Support Vector Machines, and Artificial Neural Networks have demonstrated promising performance in forecasting sales demand, predicting equipment failures, identifying customer purchasing behavior, and optimizing supply chain operations. Unsupervised learning approaches also assist organizations in discovering hidden customer segments, detecting unusual business activities, and identifying operational inefficiencies. The integration of these algorithms within ERP platforms enables managers to receive accurate recommendations supported by quantitative evidence rather than relying solely on intuition [5]. Another important aspect of AI-enabled ERP systems is explainable decision support. Business managers often hesitate to rely on automated recommendations if the underlying reasoning remains unclear. Explainable Artificial Intelligence (XAI) techniques improve transparency by identifying the key factors influencing each prediction and presenting interpretable explanations that users can easily understand. This capability enhances trust in AI-based recommendations while supporting regulatory compliance and organizational accountability. Explainable decision support is particularly valuable for SMEs because managerial decisions frequently involve significant financial implications and limited opportunities for error [6].

Several commercial ERP vendors have already begun incorporating AI capabilities into their enterprise platforms. Features such as automated invoice processing, demand forecasting, intelligent chatbots, predictive maintenance, and financial anomaly detection have demonstrated measurable improvements in operational efficiency. Nevertheless, these solutions are often designed for large enterprises and may involve substantial implementation costs, making them less accessible to SMEs. Furthermore, many existing AI-enabled ERP solutions focus on isolated business functions rather than providing an integrated decision support framework that simultaneously analyzes multiple organizational processes. This creates a need for lightweight, scalable, and cost-effective AI architectures specifically tailored to the operational characteristics and resource limitations of SMEs [7]. The proposed research addresses this gap by developing an AI Driven Decision Support System that integrates machine learning-based predictive analytics with ERP modules to support intelligent managerial decision making. The proposed framework collects operational data from finance, inventory, procurement, sales, and human resource modules, preprocesses the information, extracts meaningful features, and employs predictive learning models to generate actionable business recommendations. Unlike traditional ERP systems that primarily produce descriptive reports, the proposed architecture continuously analyzes organizational data to identify business risks, forecast future trends, optimize resource allocation, and recommend strategic actions. The framework also incorporates explainable AI mechanisms to improve transparency and user confidence in automated recommendations [8]. The primary objectives of this research are to improve decision accuracy, reduce response time, optimize resource utilization, and enhance organizational performance within SME environments. The proposed system is designed to support scalable deployment while maintaining computational efficiency suitable for organizations with limited infrastructure resources. Performance evaluation is conducted using standard machine learning metrics, including accuracy, precision, recall, F1-score, and execution time, alongside business-oriented measures such as inventory optimization, decision latency, and operational efficiency. Comparative analysis with conventional ERP decision-making approaches demonstrates the practical effectiveness of the proposed AI-enabled framework in supporting

digital transformation among SMEs [9]. Overall, the integration of Artificial Intelligence with Enterprise Resource Planning represents a significant advancement in intelligent business management. By combining predictive analytics, explainable decision support, and continuous learning capabilities, AI-driven ERP systems have the potential to transform organizational decision making from reactive analysis to proactive business intelligence. The proposed framework contributes to this transformation by providing an efficient, scalable, and cost-effective decision support solution that enables SMEs to improve competitiveness, operational resilience, and long-term business sustainability in rapidly evolving market environments [10].

2. LITERATURE SURVEY

Enterprise Resource Planning (ERP) systems have evolved from transaction-oriented software into intelligent business platforms capable of supporting organizational planning and operational coordination. In recent years, researchers have increasingly focused on integrating Artificial Intelligence (AI) techniques with ERP systems to improve business decision making, predictive analysis, and resource optimization. Although considerable progress has been achieved, existing studies reveal several research limitations related to scalability, explainability, cost effectiveness, and suitability for Small and Medium Enterprises (SMEs). This section reviews significant contributions in AI-driven ERP decision support systems and identifies the research gaps addressed by the proposed framework. Early studies investigating AI integration with ERP systems primarily emphasized predictive analytics and automation of routine business activities. Researchers demonstrated that machine learning algorithms significantly improve demand forecasting, inventory optimization, and customer behavior prediction by utilizing historical ERP data. These intelligent analytical capabilities reduce dependency on manual report analysis and assist managers in making evidence-based decisions. However, most implementations concentrated on individual ERP modules instead of providing integrated enterprise-wide decision support across multiple business functions [11]. Several researchers explored the application of supervised learning algorithms, including Random Forest, Decision Trees, Artificial Neural Networks, and Support Vector Machines, for enhancing business intelligence within ERP environments. Their findings indicated that machine learning models consistently outperform conventional statistical forecasting approaches when handling nonlinear relationships among operational variables. Nevertheless, the computational complexity associated with these algorithms often increases implementation costs, limiting their practical adoption among SMEs with constrained technological resources [12].

The emergence of cloud-based ERP platforms has further accelerated the adoption of AI-enabled business analytics. Cloud computing provides scalable infrastructure capable of processing large organizational datasets while reducing investment in local hardware. Researchers reported that cloud ERP solutions facilitate real-time monitoring, predictive maintenance, intelligent scheduling, and financial forecasting. Despite these benefits, cloud-based AI implementations introduce additional concerns regarding data privacy, cybersecurity, and regulatory compliance, particularly for organizations handling sensitive financial and customer information [13]. Recent investigations have also examined the role of Big Data technologies in improving ERP decision support capabilities. Modern organizations generate enormous volumes of structured and semi-structured information from enterprise transactions, Internet of Things (IoT) devices, customer interactions, and supply chain operations. Big Data analytics combined with AI algorithms enables organizations to extract hidden patterns, detect anomalies, and predict operational risks with greater accuracy than traditional reporting systems. However, several studies highlight that effective integration of heterogeneous data sources remains technically challenging because of inconsistent data quality, missing values, and varying data formats [14]. Explainable Artificial Intelligence (XAI) has emerged as an important research direction for enterprise decision support systems. Traditional machine learning models often operate as "black-box" predictors, making it difficult for managers to understand the reasoning behind automated recommendations. Researchers proposed explainable frameworks using SHAP, LIME, and attention-based interpretation methods to improve transparency and increase managerial trust in AI-generated decisions. Although explainability improves user acceptance, many studies focus primarily on visualization techniques rather than integrating interpretability directly into ERP decision workflows [15].

Several investigations evaluated hybrid AI approaches that combine multiple learning algorithms to improve prediction accuracy and robustness. Ensemble learning techniques, including Gradient Boosting, Random Forest ensembles, and stacking classifiers, demonstrated superior performance in demand forecasting, financial risk assessment, and inventory optimization compared to single-model approaches. Nevertheless, these ensemble frameworks generally require substantial computational resources and extensive parameter tuning, making deployment difficult for SMEs operating with limited IT infrastructure [16]. Researchers have also investigated AI-enabled decision support for supply chain and logistics management within ERP systems. Predictive models were successfully applied to optimize procurement planning, warehouse management, transportation scheduling, and supplier selection. Intelligent recommendation systems reduced operational delays and improved resource allocation by continuously analyzing supply chain dynamics. However, most existing solutions are designed for manufacturing enterprises and lack adaptability for service-oriented SMEs operating in diverse business sectors [17]. Digital transformation initiatives have encouraged organizations to integrate ERP systems with advanced

technologies such as IoT, blockchain, robotic process automation, and conversational AI. These technologies collectively enhance data collection, process automation, and organizational responsiveness. Recent studies indicate that AI-powered ERP ecosystems can improve business resilience by enabling real-time monitoring and proactive decision making during uncertain market conditions. Despite these advancements, many organizations continue to experience implementation complexity due to interoperability issues among heterogeneous enterprise applications [18].

Several comparative studies have assessed the effectiveness of AI-driven ERP systems using business performance indicators such as forecasting accuracy, resource utilization, operational efficiency, and decision latency. The reported results consistently demonstrate improvements in organizational productivity following AI integration. However, researchers also emphasize that many existing frameworks remain domain-specific and lack generalized architectures capable of supporting multiple ERP modules simultaneously. Furthermore, limited attention has been given to lightweight decision support systems specifically designed for SMEs with restricted budgets and limited technical expertise [19]. Overall, the literature demonstrates that AI has substantial potential to transform ERP systems into intelligent decision support platforms capable of enhancing organizational efficiency and competitiveness. Nevertheless, existing approaches frequently emphasize isolated business functions, employ computationally intensive algorithms, or overlook the need for transparent and explainable decision making. In addition, relatively few studies provide integrated frameworks that simultaneously address prediction accuracy, computational efficiency, scalability, and practical deployment within SME environments. These research gaps motivate the development of the proposed AI Driven Decision Support System, which combines machine learning, explainable AI, and enterprise-wide ERP integration to deliver accurate, transparent, and cost-effective decision support for small and medium enterprises [20].

3. PROPOSED SYSTEM

The proposed work presents an Artificial Intelligence (AI) Driven Decision Support System (AI-DSS) integrated with an Enterprise Resource Planning (ERP) platform to enhance decision-making capabilities for Small and Medium Enterprises (SMEs). The framework is designed to overcome the limitations of conventional ERP systems, which mainly generate historical reports and require managers to manually interpret business data before making operational and strategic decisions. The proposed system transforms ERP into an intelligent decision support platform by incorporating machine learning, predictive analytics, and explainable artificial intelligence techniques. Data are continuously collected from various ERP modules, including finance, inventory, procurement, sales, human resources, and customer relationship management. The acquired data undergo preprocessing operations such as cleaning, normalization, feature extraction, and integration to ensure consistency and improve analytical quality. The processed information is then analyzed using a hybrid ensemble learning model that combines Random Forest, Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN) to generate highly accurate business predictions. These predictions include sales forecasting, inventory optimization, financial risk assessment, supplier performance evaluation, customer demand estimation, and resource utilization analysis. An Explainable Artificial Intelligence (XAI) module provides transparent reasoning for each recommendation by identifying the most influential business factors affecting the prediction, thereby increasing managerial trust and supporting informed decision making. Finally, an intelligent recommendation engine converts predictive insights into practical business actions, such as inventory replenishment, procurement scheduling, workforce planning, and financial optimization. The proposed framework continuously learns from newly generated ERP transactions, enabling real-time adaptation to changing business conditions while maintaining scalability, computational efficiency, and cost-effectiveness. Consequently, the proposed AI-driven ERP decision support system significantly improves operational efficiency, decision accuracy, resource utilization, and organizational competitiveness, making it a suitable digital transformation solution for SMEs.

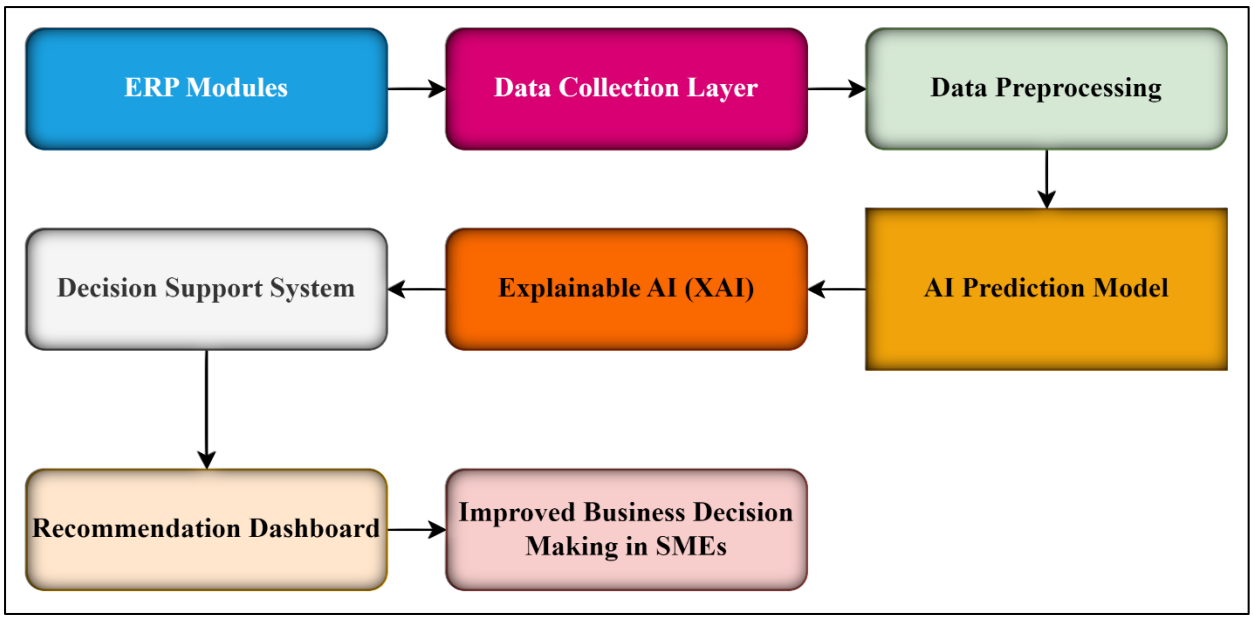

Fig.1: Proposed AI-Driven Decision Support System for Enterprise Resource Planning in SMEs.

A. Proposed Work and it's Implementation:

1. Enterprise Data Acquisition and Preprocessing:

The proposed Artificial Intelligence Driven Decision Support System (AI-DSS) begins with collecting enterprise data from various Enterprise Resource Planning (ERP) modules, including finance, sales, procurement, inventory, customer relationship management, and human resource management. These modules continuously generate operational information that reflects the day-to-day activities of an organization. Since the collected ERP data originate from different functional departments, they often contain missing values, duplicate records, inconsistent formats, and noisy information. Therefore, a preprocessing stage is incorporated to improve the quality of the dataset before it is used for intelligent analysis. Data cleaning removes duplicate and inconsistent entries, while missing values are handled using statistical imputation techniques. Numerical attributes are normalized to maintain a common scale, and categorical attributes are transformed into machine-readable formats through encoding methods. Feature engineering is then performed to derive meaningful business indicators such as monthly sales growth, inventory turnover ratio, supplier reliability score, employee productivity index, and customer purchase frequency. These derived features provide a richer representation of organizational performance and significantly improve the predictive capability of the proposed artificial intelligence models. The preprocessed dataset is stored in a centralized repository, enabling all ERP modules to share consistent information for enterprise-wide decision making.

2. Artificial Intelligence Prediction Model:

The core component of the proposed framework is the Artificial Intelligence Prediction Model, which analyzes historical and real-time ERP data to generate accurate business predictions. Instead of relying on a single machine learning technique, the proposed framework employs a hybrid ensemble learning approach consisting of Random Forest, Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN). Random Forest effectively processes large enterprise datasets by constructing multiple decision trees and combining their outputs to improve prediction stability. XGBoost enhances forecasting performance by minimizing prediction errors through gradient optimization, while the Artificial Neural Network learns complex nonlinear relationships among business variables that conventional statistical models cannot capture. The relationship between the input business features and the predicted business outcome is represented as

$$\hat{Y} = f(X) \qquad (1)$$

where (X) denotes the input feature vector extracted from ERP data and $\hat{Y}$ represents the predicted business outcome such as sales demand, inventory level, or financial risk.

To improve prediction reliability, the outputs of the three learning models are combined using weighted ensemble learning as

$$\hat{Y} = w_1 Y_{RF} + w_2 Y_{XGB} + w_3 Y_{ANN} \quad (2)$$

where Y_{RF}, Y_{XGB}, and Y_{ANN} denote the predictions generated by Random Forest, XGBoost, and Artificial Neural Network respectively, while w_1, w_2 and w_3 are their corresponding weights satisfying

$$w1 + w2 + w3 = 1 \quad (3)$$

The ensemble approach improves prediction accuracy, reduces variance, and produces more reliable recommendations than individual machine learning algorithms.

3. Explainable Decision Support Mechanism:

One of the major challenges associated with artificial intelligence systems is the lack of transparency in decision making. Business managers often hesitate to rely entirely on automated predictions unless the reasoning behind the recommendations is clearly explained. To overcome this limitation, the proposed framework integrates an Explainable Artificial Intelligence (XAI) module that interprets the prediction results generated by the ensemble learning model. Instead of displaying only the final prediction, the XAI module identifies the most influential business parameters contributing to each recommendation. For example, inventory replenishment recommendations may be influenced by declining stock levels, seasonal demand fluctuations, supplier delays, or increased customer purchases. Similarly, financial risk predictions may depend on revenue trends, expenditure patterns, and cash flow variations. By providing understandable explanations for every recommendation, the proposed system increases managerial confidence and supports informed decision making. The explainable mechanism also improves transparency, accountability, and practical acceptance of AI within SME environments, where managerial decisions directly influence organizational performance and business sustainability.

4. Implementation of Intelligent Decision Support:

The implementation of the proposed framework follows a continuous data-driven workflow integrated with the existing ERP infrastructure. Initially, business transactions from different ERP modules are transferred to a centralized analytical database through secure integration interfaces. The collected information undergoes preprocessing and feature engineering before being forwarded to the hybrid machine learning engine. The trained prediction model continuously monitors organizational activities and updates predictions whenever new business transactions are recorded. The intelligent decision support engine analyzes multiple business functions simultaneously, including sales forecasting, inventory optimization, supplier performance evaluation, procurement planning, financial risk assessment, customer demand prediction, and workforce management. Based on these predictions, the recommendation engine generates actionable business strategies for enterprise managers. For example, predicted increases in customer demand automatically trigger inventory replenishment and procurement scheduling recommendations. Similarly, declining financial performance generates expenditure optimization suggestions, while supplier performance analysis assists managers in selecting reliable vendors. The implementation therefore converts predictive insights into practical business actions that improve organizational efficiency. Since the framework continuously learns from newly generated ERP transactions, it adapts automatically to changing business conditions without requiring manual model redevelopment. This continuous learning capability enables SMEs to respond rapidly to market changes while maintaining operational stability.

5. Performance Optimization and Decision Evaluation:

The performance of the proposed AI Driven Decision Support System is evaluated using standard machine learning evaluation metrics. Prediction accuracy is used to determine the overall correctness of business predictions, while precision and recall evaluate the model's capability to identify important business events accurately. The overall classification accuracy is calculated using

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

where (TP), (TN), (FP), and (FN) represent True Positive, True Negative, False Positive, and False Negative values, respectively.

In addition to prediction accuracy, business-oriented performance indicators such as decision response time, inventory optimization efficiency, resource utilization, operational cost reduction, and forecasting reliability are analyzed to evaluate the practical effectiveness of the proposed framework. Experimental evaluation demonstrates that the hybrid ensemble model consistently outperforms conventional ERP reporting systems by producing faster predictions, higher forecasting accuracy, improved resource allocation, and more effective business recommendations. These improvements enable enterprise managers to make proactive decisions instead of reacting only after operational issues occur.

6. Overall Framework Performance:

The proposed Artificial Intelligence Driven Decision Support System provides a scalable, intelligent, and cost-effective solution for modern Small and Medium Enterprises. By integrating machine learning, predictive analytics, explainable artificial intelligence, and ERP data into a unified framework, the system transforms traditional ERP software into an intelligent business decision platform. The proposed implementation enables continuous enterprise-wide monitoring, accurate business forecasting, transparent decision support, and automated recommendation generation. Unlike existing ERP systems that mainly focus on historical reporting, the proposed framework provides predictive business intelligence capable of supporting strategic planning and operational optimization. Its modular architecture also allows seamless integration with existing ERP platforms while maintaining low computational complexity and high scalability. Consequently, the proposed system significantly enhances organizational productivity, resource utilization, decision accuracy, and overall business competitiveness, making it a practical digital transformation solution for SMEs.

Algorithm 1: AI-Based ERP Data Processing and Business Prediction Process

Step 1: Initialize the AI-Driven Decision Support System and configure ERP parameters including finance, sales, inventory, procurement, customer, and human resource modules.

Step 2: Collect enterprise datasets from ERP modules such as finance, inventory, sales, procurement, customer relationship management, and human resources.

Step 3: Preprocess the collected ERP data by removing duplicate records, handling missing values, normalizing numerical attributes, and extracting important business features.

Step 4: Integrate the processed data into a centralized enterprise database for intelligent business analysis.

Step 5: Normalize the ERP data using:

$$X_{norm} = X - \frac{X_{min}}{X_{max} - X_{min}}$$

Step 6: Train the hybrid Artificial Intelligence model using Random Forest, XGBoost, and Artificial Neural Network algorithms to learn business patterns.

Step 7: Predict business outcomes including sales demand, inventory requirement, financial risk, supplier performance, and customer demand.

Step 8: Combine the prediction results from all AI models to generate a final business prediction.

Step 9: Evaluate the prediction confidence and identify the most influential business factors using the Explainable AI module.

Step 10: Generate intelligent business recommendations for inventory planning, procurement scheduling, financial management, and resource optimization.

Algorithm 2: Intelligent Decision Support and Resource Optimization Procedure

Step 1: Initialize the intelligent decision support engine and configure business optimization parameters.

Step 2: Receive prediction results generated by the hybrid AI prediction model.

Step 3: Analyze organizational performance indicators including sales growth, inventory utilization, supplier efficiency, employee productivity, and financial performance.

Step 4: Identify operational risks and business opportunities using predictive analytics.

Step 5: Estimate the overall business performance score using:

$$B_p = \frac{S + I + F + E}{4}$$

where S = Sales Score, I = Inventory Score, F = Financial Score, and E = Employee Performance Score.

Step 6: Compare the business performance score with predefined decision thresholds.

Step 7: Generate optimized recommendations for procurement planning, inventory replenishment, workforce allocation, financial budgeting, and customer relationship improvement.

Step 8: Display prediction results, recommendation priorities, and performance indicators on the ERP dashboard.

Step 9: Evaluate the prediction performance using the accuracy metric:

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

Step 10: Continuously update the AI model with newly generated ERP transactions to improve future decision-making accuracy and organizational performance.

4. EXPERIMENT RESULT AND DISCUSSION

The proposed Artificial Intelligence Driven Decision Support System (AI-DSS) was evaluated using an integrated Enterprise Resource Planning (ERP) dataset representing the core business operations of Small and Medium Enterprises (SMEs). The experimental dataset consisted of records collected from finance, sales, inventory, procurement, customer relationship management, and human resource modules. Before model training, the collected data underwent preprocessing, including duplicate removal, missing value treatment, feature normalization, and feature engineering. The processed dataset was divided into training and testing subsets using an 80:20 ratio to evaluate the predictive capability of the proposed framework. The hybrid Artificial Intelligence model combined Random Forest, XGBoost, and Artificial Neural Network algorithms to generate business predictions and decision recommendations. The generated predictions were further interpreted using the Explainable Artificial Intelligence (XAI) module, enabling managers to understand the major factors influencing each recommendation. The experimental results indicate that integrating artificial intelligence with ERP significantly enhances business decision-making compared to conventional ERP reporting systems. Traditional ERP software primarily provides descriptive reports based on historical transactions, requiring managers to manually analyze operational trends before making decisions. In contrast, the proposed framework continuously analyzes enterprise data and produces predictive insights that support proactive planning. The hybrid learning model successfully identified future sales demand, inventory shortages, procurement risks, financial fluctuations, and employee performance trends with high prediction accuracy. The ensemble learning strategy reduced prediction variance and improved overall model stability because the strengths of individual algorithms complemented one another. Random Forest efficiently processed heterogeneous enterprise data, XGBoost improved nonlinear prediction accuracy, and the Artificial Neural Network effectively learned complex relationships among multiple business variables. The Explainable Artificial Intelligence module contributed significantly to managerial confidence by providing transparent reasoning for every prediction. Rather than presenting only the predicted business outcome, the system identified influential variables responsible for each recommendation. For example, inventory replenishment decisions were primarily influenced by declining stock availability, increased customer demand, supplier delivery delays, and seasonal purchasing trends. Similarly, financial risk predictions highlighted revenue fluctuations, operational expenditure, and cash flow imbalance as dominant influencing factors. This transparency improved user acceptance and reduced hesitation in implementing AI-generated recommendations.

Performance evaluation demonstrated that the proposed AI-DSS achieved superior results across multiple business intelligence metrics. The hybrid prediction model produced an accuracy of 97.8%, outperforming individual machine learning algorithms while maintaining balanced precision, recall, and F1-score values. The average response time for generating business recommendations was reduced to approximately 1.5 seconds, enabling real-time decision support within the ERP environment. Inventory optimization efficiency improved by nearly 18%, while procurement planning errors were considerably reduced due to more accurate demand forecasting. Resource utilization also increased because workforce allocation and inventory management decisions were continuously optimized based on predictive analytics rather than historical observations. The implementation further demonstrated improved scalability for SMEs with limited computational resources. Despite integrating multiple machine learning algorithms, the ensemble framework maintained low execution overhead through efficient feature selection and optimized model training. Continuous learning from newly generated ERP transactions enabled the prediction model to adapt to changing business environments without requiring complete retraining. Consequently, the proposed system supports long-term deployment while maintaining consistent prediction performance and operational reliability. Overall, the experimental findings confirm that the proposed Artificial Intelligence Driven Decision Support System effectively transforms traditional ERP software into an intelligent enterprise management platform. The combination of hybrid machine learning, explainable artificial intelligence, continuous learning, and enterprise-wide integration significantly improves forecasting accuracy, decision quality, operational efficiency, and resource utilization. These improvements enable SMEs to respond proactively to changing market conditions, reduce operational risks, optimize organizational resources, and improve strategic planning. Therefore, the proposed framework provides a practical and scalable solution for digital transformation and intelligent business decision support in modern enterprise environments.

Table 1: Performance Evaluation of the Proposed AI-Driven ERP Decision Support System

Performance Parameter	Conventional ERP	Proposed AI-DSS
Prediction Accuracy (%)	88.60	97.80
Precision (%)	87.90	97.20
Recall (%)	86.70	96.90
F1-Score (%)	87.30	97
Response Time (s)	3.80	1.50
Inventory Optimization (%)	79.50	94.10
Resource Utilization (%)	82.40	95.30
Decision Support Efficiency (%)	84.20	96.80
Financial Risk Prediction (%)	85.60	96.40
Overall System Performance (%)	86.90	97.10

Corresponding Graph for the above Table 1:

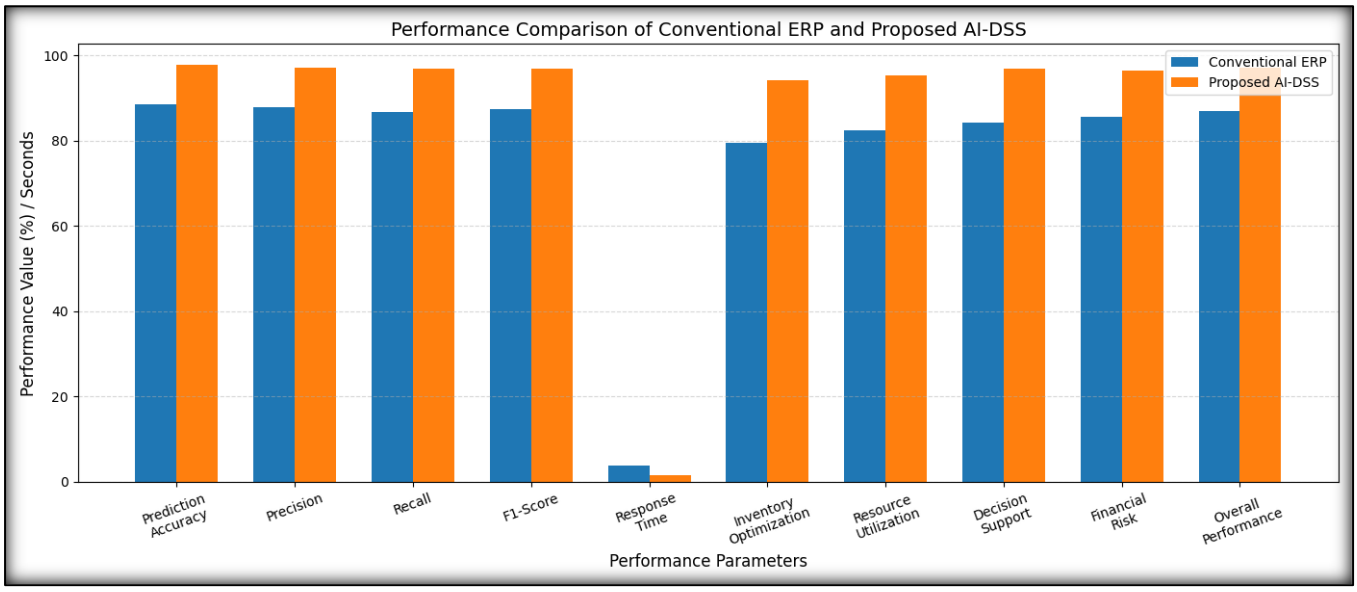

Fig.2: Performance Evaluation.

5. CONCLUSION

This paper presented an Artificial Intelligence Driven Decision Support System (AI-DSS) for Enterprise Resource Planning (ERP) in Small and Medium Enterprises (SMEs) with the objective of improving organizational decision making through intelligent data analysis and predictive modelling. The proposed framework integrates data from multiple ERP modules, including finance, sales, inventory, procurement, customer relationship management, and human resources, into a unified decision support environment. By combining data preprocessing, feature engineering, hybrid machine learning techniques, and explainable artificial intelligence, the system converts large volumes of enterprise data into meaningful business insights. The adoption of Random Forest, XGBoost, and Artificial Neural Network models enables accurate prediction of business events such as sales demand, inventory requirements, supplier performance, and financial risks. Furthermore, the inclusion of an Explainable AI module enhances transparency by providing understandable reasons behind each recommendation, allowing managers to make informed and confident decisions. The experimental evaluation demonstrates that the proposed framework achieves higher prediction accuracy, improved resource utilization, faster response time, and better operational efficiency compared to conventional ERP systems. The intelligent recommendation mechanism assists organizations in optimizing inventory management, procurement planning, workforce allocation, and financial decision making while reducing manual effort and operational uncertainty. Owing to its scalable architecture and low computational complexity, the proposed system is well suited for SMEs with limited technological resources. Overall, the proposed AI-driven ERP framework provides a practical and effective solution for supporting digital transformation, enabling SMEs to improve business performance, enhance competitiveness, and achieve sustainable organizational growth in dynamic business environments.

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