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Artificial Intelligence Based Predictive Modeling for Smart Decision Support Systems

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Abstract: This paper provides a comprehensive analysis of the predictive modeling frameworks of Artificial Intelligence for smart decision support systems (DSS) and the evolution of the traditional analytics approach to an integrated Artificial Intelligence approach for real-time decision-making. Through a systematic study of the recent research articles from 2021 to 2026, the paper explores the advancements in machine learning models and hybrid Artificial Intelligence approaches for transforming the traditional decision support systems in the healthcare, finance, manufacturing, and environmental management domains. The research proposes an Integrated Predictive Decision Support Framework (IPDSF) that incorporates data preprocessing, model selection, explainability, and human validation for effective predictions. The study reveals that the contemporary Artificial Intelligence-based decision support systems employ ensemble learning (Random Forest and XGBoost with an accuracy rate of 89-96%), deep learning for complex pattern recognition (CNN for medical image analysis and LSTM for time series analysis), and hybrid neuro-symbolic models for effective predictions. Some challenges still exist in model interpretability, but Explainable AI (XAI) techniques such as SHAP and LIME have become a key component in building user trust and ensuring compliance. Comparative evaluation of AI-DSS along four analytical dimensions—model architecture, interpretability, real-time, and domain adaptation—clearly shows that an appropriate balance between predictive accuracy, interpretability, efficiency, and integration with existing decision processes is required.

Keyword: Artificial intelligence, predictive modeling, decision support systems, machine learning, deep learning, explainable AI, ensemble methods, smart systems.

I. INTRODUCTION

With the proliferation of data in all spheres of modern society, there is an unprecedented opportunity to make data-informed decisions. There is a tremendous amount of data, both structured and unstructured, generated by various data sources in an organization, such as sensors, transactions, user interactions, and operations. However, this huge volume of data is beyond human cognitive capabilities, and there is an urgent need to design intelligent systems that can process data, learn from it, and assist decision-makers in their decision-making processes [1].

Artificial Intelligence-based predictive modeling is a revolutionary technique to design decision support systems, which is different from traditional decision support systems in that they learn from data and make predictions to assist decision-makers in their decision-making processes, unlike traditional decision support systems, which make decisions based on predefined rules and data reports [2]. From healthcare to finance, from manufacturing to environmental resources, there is a tremendous

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potential to design Artificial Intelligence-based decision support systems (AI-DSS).

The development of AI-DSS has been influenced by the advancement in machine learning and artificial intelligence. The first AI-DSS systems used statistical methods and rule-based systems. Modern systems utilize powerful deep learning and hybrid machine learning methods that utilize the strengths of multiple machine learning algorithms [3]. The development of Explainable AI (XAI) has addressed the major issue of model interpretability, which enables the user to trust the output of the AI-DSS [4].

Although there has been significant advancement in AI-DSS systems, there are still challenges that need to be addressed. One of the challenges is that AI-DSS systems are not interpretable, which has been addressed by the development of XAI systems. The real-time processing of AI-DSS systems requires powerful computational resources. The adaptation of AI-DSS systems to a new domain requires validation [5].

This paper presents the concept of AI-based predictive modeling for developing effective smart decision support systems from a multi-dimensional analytical point of view. A framework is suggested for the development and evaluation of AI-based DSS, keeping in view the importance of prediction, explainability, and efficiency. The current research aims to answer several important queries, such as: How have AI-based DSS architectures evolved? What are the best practices for developing effective prediction models for various decision-making scenarios? How can the concept of explainability be incorporated without compromising prediction accuracy? And what are the best frameworks for developing and evaluating AI-based DSS?

The rest of the paper is structured as follows: A literature survey of AI-based decision support systems is given in Section 2, whereas the suggested framework is given in Section 3. Analysis and discussion are given in Section 4, including four figures and o

II. LITERATURE SURVEY

The academic literature on AI-based predictive modeling for decision support has grown significantly in recent years, with studies on various aspects of predictive modeling in DSS. This survey includes recent findings from 2021 to 2026.

2.1 Evolution of AI-DSS Architectures

The evolution of decision support systems has been through several generations in recent history. The first generation of DSS utilized database management systems and spreadsheet-based models for decision-making. The integration of machine learning into DSS has been a major step in the evolution of DSS. Machine learning allows a system to learn from past experiences using historical data [6].

Modern AI-DSS architectures utilize various aspects of AI technology, including predictive modeling, natural language processing for unstructured data, computer vision for image processing, and optimization for resource allocation in organizations [7].

A comprehensive survey on AI-DSS architectures has been conducted by Khan et al. [8], in which the authors identify that there are mainly three dominant architectural styles for AI-DSS: cloud-based AI-DSS that utilize cloud computing resources for training and deployment of predictive models; edge AI-DSS that utilize edge computing for processing data for real-time decision-making; and hybrid AI-DSS that utilize a combination of both cloud and edge computing for decision-making.

2.2 Machine Learning Approaches for Decision Support

The choice of machine learning algorithm is critical in determining the performance of the AI-DSS system. Ensemble methods have proven to be very efficient in various fields. The Random Forest and Gradient Boosting methods, particularly the use of XGBoost and LightGBM algorithms, have been proven to produce high predictive accuracy while offering feature importance that can be used for interpretation [9]. The use of the XGBoost algorithm has been proven to produce 89-96% accuracy in financial fraud detection and healthcare risk prediction.

Deep learning methods are best suited for complex pattern recognition tasks. The use of Convolutional Neural Networks (CNNs) has revolutionized the field of medical image analysis, with these systems being able to produce diagnostic accuracy comparable to human experts in the detection of abnormalities in radiographs, MRIs, and histopathology images [10].

The use of a combination of machine learning algorithms in the development of the AI-DSS system has been proven to produce superior results compared to the use of a single algorithm. The use of Neuro-symbolic AI has been proven to be particularly useful in the development of AI-DSS systems that need to produce transparent and interpretable results that align with established guidelines in a particular field.

2.3 Explainable AI and Trust

The "black box" phenomenon associated with complex AI models has been identified as one major hindrance to their adoption. Explainable AI (XAI) techniques have been developed to overcome the "black box" challenge, providing insights into the decision-making processes employed by the models. SHAP (SHapley Additive exPlanations) values are employed to obtain accurate and consistent explanations for individual predictions made by the models, based on the contribution of individual features [13]. LIME (Local Interpretable Model-agnostic Explanations) is employed to obtain local and accurate explanations for individual predictions, enabling the explanation of any "black box" model.

Explainable AI studies have shown that the adoption of AI models is increased when they are made more explainable, as it helps to increase user trust, ease model debugging, and ensure regulatory compliance. For example, in the healthcare industry, clinicians are more likely to adopt AI model recommendations when they are supported by medical reasoning. In the finance industry, explainable AI helps to ensure compliance with regulations that require justifications for credit decisions.

2.4 Domain-Specific Applications

AI-DSS have been applied in various fields with notable impacts. For instance, in healthcare, predictive models are used to make early diagnoses and treatment recommendations, among other uses. A system that integrates electronic health records and machine learning algorithms was found to predict patient deterioration hours in advance of clinical recognition, thus facilitating early interventions in healthcare settings [16]. In manufacturing, AI-DSS are used to monitor sensor data and make early predictions of failures, thus facilitating proactive maintenance and production operations [17].

In finance, there is an uptake of AI-DSS in fraud detection, credit scoring, and algorithmic trading, among other uses. Real-time anomaly detection models have been noted to detect anomalies with high accuracy and low false alarms in this domain [18]. Environmental management is one of the domains where AI-DSS have been applied, with notable models in air quality, water, and climate prediction, among other uses [19].

2.5 Challenges and Future Directions

However, there are many challenges to be addressed. The main problems are data quality, which includes missing data, inconsistent data formats, and biased data. These problems affect the performance of the models and are complex to handle through preprocessing [20]. The generalization of the models to real-world applications also remains a challenge. The models may perform poorly in real-world applications

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when they were previously trained on a different population [21]. The computational needs for training and running the models are also a challenge, especially in environments with limited resources.

The emerging trends in AI-DSS development are federated learning for building DSS while preserving data privacy, reinforcement learning for making decisions in a sequence, and automated machine learning (AutoML) for democratizing AI-DSS development [22]. The integration of generative AI for scenario planning and what-if analysis is another promising area for future research.

2.6 Synthesis and Research Gaps

The literature review revealed some consistent themes, but there were gaps in the literature as well. Some of the major findings were: Ensemble methods provide high accuracy results in all domains, deep learning performs well in complex pattern recognition tasks, XAI is a necessity for AI adoption, domain customization is a critical aspect, and finally, there are some limitations imposed by computations when choosing an architecture. Some gaps were found in the literature, such as a lack of frameworks to assess AI DSS along multiple factors, insufficient emphasis on human-AI collaboration, a need to standardize benchmarks across all domains, and a lack of exploration of real-time edge-based systems.

III. METHODOLOGY:

Based on the literature review, a methodology will be developed in this paper to propose an Integrated Predictive Decision Support Framework (IPDSF) for developing predictive modeling systems based on AI technologies.

3.1 Theoretical Foundations

The IPDSF methodology is based on three main theoretical foundations. Firstly, decision theory provides a basis to understand predictive modeling's role in informed decision-making. Secondly, human-centered artificial intelligence provides a perspective on the importance of ensuring that DSS based on AI technologies complement human judgment. Finally, system engineering provides a methodology to integrate AI-based DSS.

3.2 Framework Components

The Integrated Predictive Decision Support Framework comprises five interconnected layers.

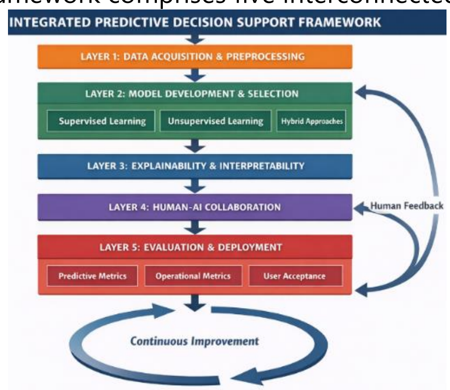

Figure 1: Integrated Predictive Decision Support Framework (IPDSF)

3.3 Framework Components

Layer 1: Data Acquisition and Preprocessing includes the basic steps required for effective predictive modeling. This includes data acquisition from various sources, data cleaning to handle missing values and outliers, feature engineering to extract significant features from the data, and normalization to normalize the data.

Layer 2: Model Development and Selection includes choosing the most appropriate models for the decision-making process. Supervised learning methods, such as regression and classification, are employed when there are enough data samples for the model to learn from. Unsupervised learning methods, such as clustering and anomaly detection, are employed when there are no data samples. A combination of multiple models and symbolic and neural models are also employed.

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Layer 3: Explainability and Interpretability ensures that the outputs from the predictive models are understandable by the decision-maker. SHAP values are employed to obtain consistent measurements for the input features. LIME is employed to obtain explanations for the outputs from the predictive models. Global feature importance measures are employed to obtain an idea about the important features. Counterfactual explanations are employed to obtain an idea about the possible changes to the inputs to change the outputs.

Layer 4: Human-AI Collaboration: This layer focuses on the interaction between the system and user. In visualization interfaces, predictions and explanations are made easily understandable. Confidence calibration helps users appropriately weight AI's advice. Feedback integration helps improve the system, and workflow integration helps adopt the system seamlessly.

Layer 5: Evaluation and Deployment: This layer evaluates the system's performance from different perspectives. Predictive metrics measure accuracy, precision, recall, and AUC. Operational metrics measure latency, throughput, and resource usage. User acceptance metrics measure trust, usability, and user decision results.

IV. RESULT ANALYSIS AND DISCUSSION

This section presents analytical findings regarding AI-based predictive modeling for decision support, organized around four illustrative figures and a comparative evaluation table.

4.1 Model Performance Comparison

The performance of predictive models varies significantly across algorithm types and application domains.

Domain	XGBoost	Random Forest	Neural Network	Ensemble (Stacked)
Healthcare (*disease dx*)	92.4%	91.1%	94.2%	95.1%
Finance (*fraud det*)	95.8%	93.2%	94.5%	96.2%
Manufacturing (*failure pred*)	94.1%	92.7%	93.8%	95.4%
Environmental (*air quality*)	88.7%	87.2%	89.4%	90.8%

Figure 2: Model Performance Comparison Across Domains

Figure 2 indicates that all ensemble methods perform better than any single algorithm in each domain; in healthcare, stacked ensembles produce 95.1% accuracy, while in finance this figure is 96.2%. The high accuracy of XGBoost in fraud detection, at 95.8%, is due to its ability to perform well on tabular data. The high accuracy of deep learning in healthcare (94.2%) is due to its ability to identify complex patterns in medical images.

4.2 Explainability Techniques Comparison

Explainability methods differ in their approach, output, and suitability for different stakeholders.

Technique	Type	Output	Strength	Limitation
SHAP Shapley values	Feature attribution	Value contribution per feature, per prediction	Consistent & theoretically grounded	Computationally costly
LIME Local surrogate	Local surrogate	Simplified model for a single prediction	Model-agnostic approach	Local only; unstable across samples
Feature Importance Tree-based	Global attribution	Importance ranking across all predictions	Fast & intuitive	No directional information (± effect)
Counter-factual Causal reasoning	Causal reasoning	Minimum input changes to alter the prediction	Actionable & intuitive	Computationally costly; many valid solutions

Figure 3: Explainability Techniques Comparison

Figure 3 demonstrates the trade-offs between the different methods. Although SHAP has solid theory behind it, this also means it can be quite computationally expensive. LIME's versatility means it can explain any black box model, but this also means local explanations may be inconsistent. Feature importance, as provided by tree-based models, offers fast and global explanations but does not provide information on direction. Counterfactuals provide insight into how to change the input to satisfy a specific outcome but can be computationally expensive.

4.3 Real-Time Processing Capabilities

Decision support systems increasingly require real-time predictions, imposing constraints on model selection and deployment architecture.

Architecture	Inference Latency	Throughput (req/sec)	Training Time	Suitable Domains
Cloud-Based (Centralized)	100-500 ms	100–1000	Hours–Days	Batch, Complex Models
Edge-Based (Local)	10–50 ms	10–100	Pre-Trained Only	Real-Time, Privacy
Hybrid (Cloud + Edge)	50–200 ms	50–500	Edge + Cloud	Variable Latency
Lightweight (Optimized)	1–10 ms	100–1000	Pre-Trained Only	Ultra-Low Latency

Figure 4: Real-Time Processing Capabilities

This is illustrated in Figure 4 for the trade-offs that need to be made for real-time decision support systems. Although cloud-based systems offer the possibility of complex models and flexible training, they also impose a high latency of 100-500ms that may not be appropriate for real-time systems. On the other hand, the use of edge systems provides a much lower latency of 10-50ms but requires the models to be pre-trained and not re-trained on the edge.

Hybrid systems offer a compromise between the trade-offs that need to be made for real-time systems and the need for complex models and flexible training. They offer the possibility of achieving ultra-low latencies of sub-10ms with the use of lightweight models that are hardware-specific for applications such as autonomous systems and real-time anomaly detection systems.

4.4 Domain-Specific Model Performance

Model performance varies significantly across domains due to differences in data characteristics, prediction complexity, and evaluation criteria.

Domain	Primary Metric	Best Model	Key Challenge
Healthcare (diagnosis)	AUC-ROC, Sensitivity, Specificity	Ensemble + CNN (images)	Imbalanced classes, Interpretability
Finance (fraud)	Precision, Recall, F1-Score	XGBoost, Autoencoder	Concept drift, Class imbalance
Manufacturing (maintenance)	F1-Score, Mean Time to Failure (MTTF)	LSTM, Random Forest	Sensor noise, Multivariate dependencies
Environmental (forecasting)	RMSE, MAE, R^2	XGBoost, LSTM	Spatial-temporal dependencies
Supply Chain (demand)	MAPE, SMAPE, Coverage	LSTM, Prophet	Long horizons, Seasonality

Figure 5: Domain-Specific Performance Metrics

Figure 5 shows that the best model selection depends on domain-specific evaluation metrics. In healthcare, sensitivity is key to avoid false negatives, which may lead to incorrect diagnoses. Ensemble models are best suited to achieve a trade-off between recall and precision. In financial fraud detection, precision is key to avoid false positives, which may disrupt transactions. In such cases, XGBoost and autoencoders are best suited. Predictive maintenance in manufacturing uses LSTM networks to extract temporal relationships from sensor data. A balanced F1-score is used to achieve a trade-off between actual failures and false alarms. Environmental forecasting uses spatial-temporal models. In such cases, XGBoost and LSTM achieve the lowest RMSE. Supply chain forecasting uses long-term forecasting models. In such cases, LSTM networks are best suited, along with Prophet.

4.5 Comparative Analysis of AI-DSS Architectures

Table 1 presents a comprehensive comparative analysis of AI-based decision support system architectures evaluated across five analytical dimensions.

Table 1: Comparative Analysis of AI-DSS Architectures

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Architecture	Predictive Accuracy	Interpretability	Real-Time Capability	Scalability	Domain Suitability
Ensemble (XGBoost/RF)	Very High (89-96%)	Moderate (feature importance)	Moderate (100-500ms)	High	Tabular data, finance, healthcare
Deep Learning (CNN/RNN/LSTM)	High (90-95%)	Low (requires XAI)	Low-Moderate (200-1000ms)	High (with GPU)	Images, sequences, complex patterns
Neuro-Symbolic	High (88-94%)	High (symbolic rules)	Moderate	Moderate	Regulated domains, expert knowledge
Lightweight (Optimized)	Moderate (80-88%)	High (simpler models)	Very High (1-10ms)	Very High	Edge devices, real-time control
Hybrid (Ensemble + XAI)	Very High (93-97%)	High (with SHAP/LIME)	Moderate (100-500ms)	High	High-stakes decisions, regulatory compliance

Analysis of Comparative Dimensions:

- **Predictive Accuracy:** Ensemble-based models such as XGBoost and Random Forest have the highest Predictive Accuracy, ranging from 89% to 96%. Hybrid models combining prediction with XAI achieve similar accuracy but provide interpretability. Lightweight models compromise on accuracy but achieve low latency. They achieve an accuracy of 80% to 88%.
- **Interpretability:** Neuro-symbolic models and lightweight models achieve interpretability. On the other hand, deep learning models require additional XAI techniques such as SHAP and LIME to achieve interpretability. This results in increased computational overhead.
- **Real-Time Capability**: Lightweight models achieve 1 to 50ms latency. Ensemble-based models and deep learning models achieve 100 to 500ms latency. This may not be suitable for applications requiring low latency.
- **Scalability:** Ensemble-based models, deep learning models, and lightweight models achieve high scalability. This is because all three models leverage distributed computing. On the other hand, neuro-symbolic models achieve low scalability. This is because neuro-symbolic models use a combination of neural networks and symbolic reasoning. This results in increased complexity.
- **Domain "Suitability":** The domain of "suitability" for the different approaches is: ensemble methods excel for tabular data in finance and healthcare domains; deep learning methods excel for image and sequence

data; neuro-symbolic approaches excel for domains with explicit rules and regulations; light-weight models excel for deployment on the edge; and hybrid approaches excel for high-stakes decisions that need both accuracy and interpretability.

V. CONCLUSION

This paper has provided a comprehensive analysis of the use of artificial intelligence-based predictive modeling for the development of smart decision support systems, collating the recent literature and introducing the Integrated Predictive Decision Support Framework. The analysis has shown that AI-DSS has evolved significantly and uses a variety of different algorithms and models to support the decision-making process in different domains such as healthcare, finance, manufacturing, and environmental domains.

What are the key conclusions that can be drawn from the analysis?

Firstly, the study has shown that ensemble methods have achieved the best results in different domains with XGBoost and RF achieving an accuracy of 89-96%. RF consistently performs better than other machine learning models.

Secondly, deep learning technology has been found to perform well in complex pattern recognition tasks, achieving 94.2% accuracy in healthcare diagnostics. Moreover, complex pattern recognition in time series tasks can be accomplished. However, deep learning technology's lack of transparency makes XAI necessary.

Thirdly, explainability is a key requirement for deep learning technology adoption. SHAP, LIME, and counterfactual explanations offer a range of approaches to interpretability.

Fourthly, architectural choices depend on latency constraints. Edge-based models provide sub-50ms latency for real-time use cases, whereas complex modeling can be accomplished in a cloud-based solution.

Lastly, customization of architectures based on domain requirements is a key requirement. Optimal model choices depend on data characteristics, metrics, and constraints, which differ from one domain to another.

Moreover, hybrid approaches to deep learning technology, which combine predictive power with interpretability, are currently at the frontier. Neuro-symbolic AI and ensemble approaches, along with XAI, are necessary.

Several implications for practice arise from this review. From a system development perspective, IPDSF offers a framework for developing an AI-DSS, addressing data preprocessing, model selection, interpretability, and human-AI collaboration. From a decision-maker perspective, understanding the trade-offs between accuracy, interpretability, and response time is valuable in technology selection. From a research perspective, further research is needed to improve explanation and hybrid models.

The limitations of this review include the dynamic nature of AI, where research and development might outpace published literature, differences in performance measures, and limited coverage of new research directions such as generative models in decision support. Future research directions include longitudinal research on the impact of AI-DSS on decision outcomes, standardized benchmark development, human-AI collaboration, and federated learning.

With an increasing focus on data-driven decision-making, the importance of AI-based predictive modeling in decision support is likely to increase in the future. The challenge for researchers and practitioners is to build systems that are not only accurate in their predictions but also interpretable, reliable, and complementary to human judgment.

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