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Original Article

Predictive Computational Models for AI-Enhanced Decision Support Systems

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Abstract:

The artificial intelligence (AI) has massively changed the strategies of making decisions in key areas of life and business, including the field of healthcare, finance, disaster management, transport, and automation in industries. The contemporary Decision Support Systems (DSS) are turning more towards predictive models of computation to process vast amounts of data, create dynamic bodies of knowledge and improve decision making precision. The paper gives a comprehensive review and implementation plan of predictive computational models of AI-Enhanced Decision Support Systems (AI-DSS). The areas of the research include statistical prediction models, deep learning architecture, and reinforcement learning-based optimization as well as hybrid intelligent systems, which are aimed at strategic and operational decision-making. The paper identifies such issues as scalability, the generalization of models, uncertainty quantification, real-time inferences, data heterogeneity, and ethical governance as the key challenges. It introduces a new Adaptive Predictive Intelligence Framework (APIF) with combination of time-series forecasting, data fusion processes, knowledge graph, explainable AI (XAI), and multi-criteria optimization. Accuracy, F-score, Mean Absolute Percentage Error (MAPE) and computation complexity measurements are used to make performance evaluations using benchmark datasets. The suggested methodology possesses enhanced precision and latency of decisions, which justify dynamic decision situation. In this paper, there is an attempt to provide systematic methodology that aligns the computational intelligence with the domain- wise decision demands to give viable actionable subject to future research trends and industrial implementation. It focuses on clear, audit-able and reliable intelligent systems that can work autonomously with human decision-makers. Finally, AI-Enhanced DSS with the help of predictive computation models may build sustainable, data-driven governance and business transformation in the 21 st century

Keywords:

Ai-Enhanced Decision Support Systems, Predictive Computational Models, Machine Learning, Deep Learning, Reinforcement Learning, Explainable Ai, Data Fusion, Optimization, Knowledge-Driven Decision Making

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1. Introduction

1.1. Background of the Decision Support Systems

The first manifestation of the Decision Support Systems (DSS) was a rather simple rule-based system that was developed to support human professionals in their efforts, helping them to structure information to facilitate decision-making processes and achieve consistency in operational activities. The main resemblance of these early systems was their use of predetermined logical consistency as well as knowledge bases by experts to act as advice. But with the emergence of the Big Data era where industries are creating huge amounts of unstructured large data volumes, the traditional systems of DSS could not withstand the increasing complexity and uncertainty. The data storage, calculating power, and artificial intelligence development allowed DSS to become more advanced analytical platforms able to handle high-dimensional data, simulate the many parameter cases, and give predictions under uncertain conditions. Contemporary DSS are currently incorporating statistical model, machine learning, optimization methods, and real-time data encounters in order to assist in strategic, tactical, and operational choice-making. Their functions have grown beyond the presentation of information to the creation of insights, anticipation of the future consequences, and prescriptions of the best options. Consequently, DSS have become central to areas of healthcare, finance, intelligent manufacturing, and transportation, where quick and informed decisions have a strong performance, cost, and safety consequences. This is a significant change to the stagnant rule based tools to dynamic smart systems which never cease learning, updating and refining decision recommendations.

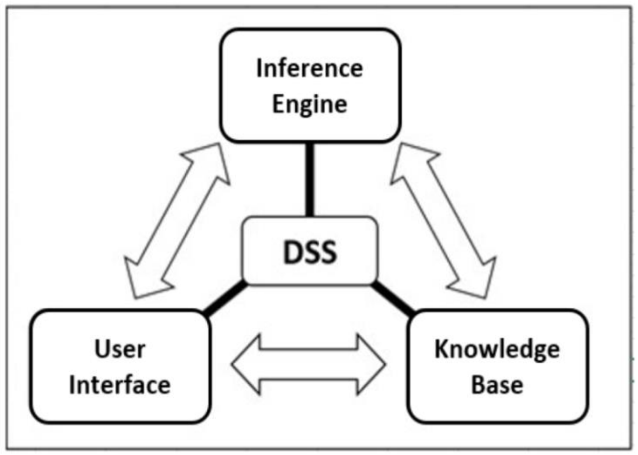

Figure 1. Background of the Decision Support Systems

1.2. AI Transformation in Decision-Making

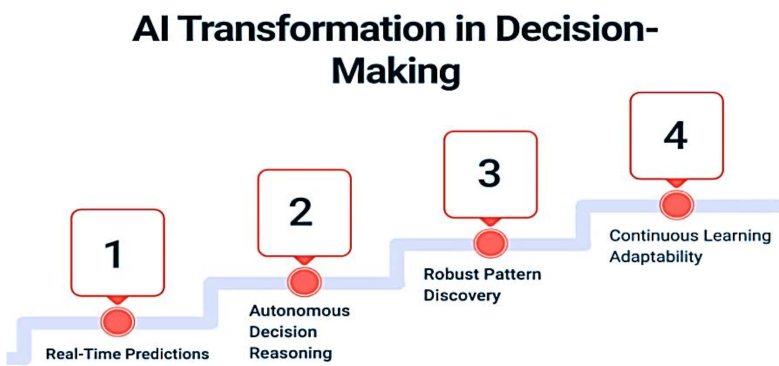

Figure 2. AI Transformation in Decision-Making

1.2.1. Real-Time Predictions

Artificial Intelligence makes the use of decision support systems able to analyze data streams on the fly and make predictions in real-time. This will enable organizations to react continuously to the evolving environment and can be used to monitor equipment health at the industries, fraud detection in financial transactions, and dynamically adjusting supply chain in response. Real-time intelligence is much more responsive and limits the delays and unnecessary expensive disruptions.

1.2.2. Autonomous Decision Reasoning

Artificial intelligence systems can think on their own through data trend analysis, computational reasoning, and selection of best course of action without involving and formatting human input all of the time. Such displacement of automated decision execution on the traditional advising job positions contributes to the faster working process, the fewer human errors, and the efficient work of this sphere with robotics, smart power, and autonomous cars.

1.2.3. Robust Pattern Discovery

AI is preferable in detecting relationships that are not easily known or comprehended within vast amounts of data that humans cannot understand. The critical findings that AI-driven DSS can identify include risk indicators, demand cycles, or abnormalities through deep learning, clustering, and association analysis. This more profound sense also improves the quality of decisions and evidence-based planning of strategies.

1.2.4. Continuous Learning Adaptability

In contrast to the fixed rule-based systems, AI technologies do not have a stop point in learning and, consequently, models can optimize themselves in response to the entry of new data. This flexibility means that the predictions made and any other decisions are not outdated in case there is a shift in the underlying conditions. Especially useful is the case of dynamic areas like healthcare diagnostics, market analytics, and cybersecurity, as patterns evolve fast, requiring the systems to change.

1.3. Predictive Computational Models for AI

The key of the contemporary artificial intelligence systems is predictive computational models where data is used to make predictions and derive knowledgeable decisions. They are models that study both historical and current time data in order to come up with patterns, correlation and trends of behavior that can affect prudent predictions in the future. Historically, statistical models, like regression and probabilistic models, were useful in providing analytical information but were inadequate in nonlinear and extremely complicated data associations. The more machine learning progressed in both supervised and unsupervised approaches to learning, the more powerful predictive systems could be as they might automatically figure out whatever is relevant and also gain accuracy with time. With the development of deep learning, predictive computation further changed by using neural networks as the processing mechanism of high-dimensional, unstructured input such as images, signals, and written data. Convolutional Neural Networks and Recurrent Neural Networks architectures added features such as spatial feature extraction and modeling of temporal sequences, and predictive AI can now be applied in very diverse areas, such as medical diagnosis, weather forecasting, resource scheduling, and intelligent transportation systems. Besides pure predictive accuracy, modern computational models are also being demanded to respond to changing environments, to engage with complicated decision rules, and to cope with uncertainty, which results in hybrid AI systems that combine knowledge representation, reinforcement learning and provide feedback systems in real time. Moreover, elements of explainability are also being vital to provide in terms of transparency and credibility, in particular, in regulation-intensive and security-sensitive industries. With the development of predictive computational models, these promote the move towards human-assisted in decision support to autonomous decision intelligence whereby systems act proactively to optimize results with little human interventions. In general, predictive models of computing are the force of the AI transformative abilities, which make it possible to make smarter choices, improve the efficiency of operations, and continue learning in environments with rapid changes.

2. Literature Survey

2.1. ML-Based Decision Support Models

Decision models based on machine learning have traditionally been useful in providing prediction and classification in structured settings. Machine learning algorithms along with the Logistic Regression, Decision Trees, Random Forests and Support Vector Machines are used in deriving trends through historical data that is labeled and use it to aid in decision making. These models are predictable computationally and comprehensible and hence fit the conventional decision support systems. Nevertheless, they do not perform well with high-dimensional and unstructured influences, like pictures or texts. They are also manually feature engineered, which constrains scaling and scalability to variable real examples. Consequently, such classical ML methods can only work with structured areas, and are not flexible enough to be applied to more advanced applications.

2.2. Deep Learning–Driven Models

Deep learning has enhanced predictive intelligence as it allows automated learning of features on raw inputs. Convolutional neural networks find extensive application to both visual analysis and medical imaging because they are able to extract spatial features. In the meantime, recurrent architectures, such as LSTM and GRU, can be successfully used to do the forecasts through the sequential or time-series data. However, more recent models like Transformers are able to make multimodal decisions through the combination of multiple inputs, including text, images, and sensor information. These methods are better generalized to provide higher-end levels of diagnosis and prediction and are applicable in big datasets and help with the creation of the most sophisticated diagnostic and prediction systems within different industries.

2.3. Reinforcement Learning for Strategy Optimization

With reinforcement learning, a new paradigm of learning is presented, in which the choices are developed as time goes by in response to the environment under the cumulative reward. It is particularly useful in those situations when sequential and adaptive approaches must be considered, including supply chain logistics, dynamic pricing, smart energy, and autonomous driving. RARL is able to maximize long-term performance and operate in uncertain settings by removing labeled statistics, and learning through feedback. It is all about making things better with time to ensure that strategic objectives are realized, RL is essential in processing dynamic, and policy-optimal decisions.

2.4. Hybrid Predictive Systems

Hybrid systems are produced by combining human expert knowledge and machine learning and optimization algorithms to improve the accuracy and interpretability of decisions. These systems make use of domain rules and constraints which are expert drive, and complex data patterns are dealt with by sophisticated algorithms. Such integration enhances the skill of reasoning, decreasing the vulnerability to noise or missing data, and resulting in stronger decision intelligence. Such combined strategies are becoming common in vital sectors like health care, finance and industrial planning whereby transparency and flexibility is a prerequisite.

3. Methodology

3.1. Research Framework Overview

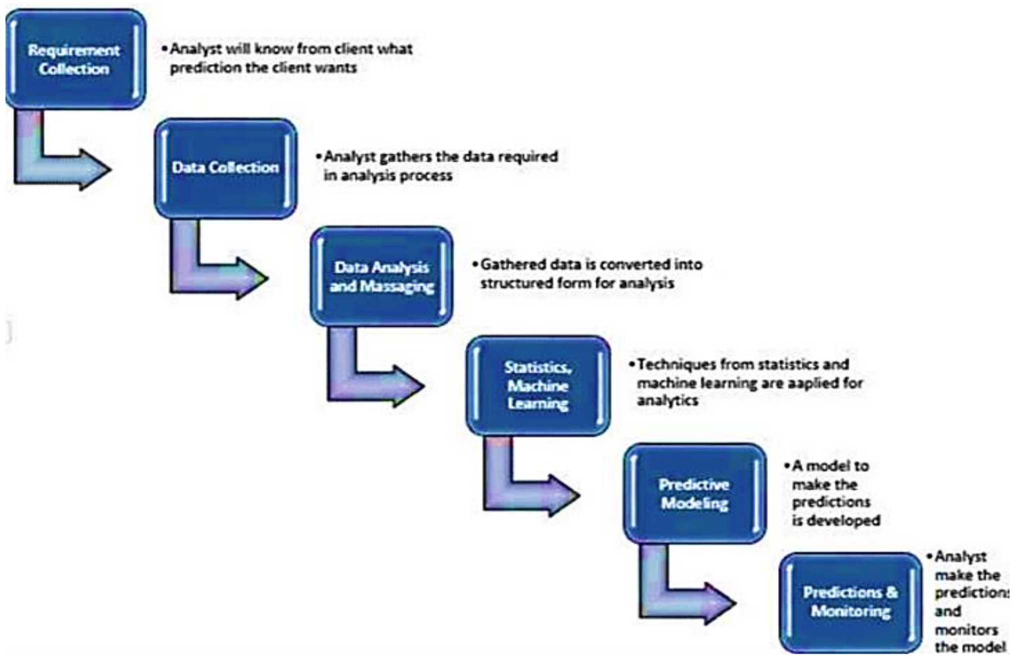

Figure 3. Research Framework Overview

3.1.1. Requirement Collection

During this first step, the analyst will interact with the client in order to learn about the business issue and the type of forecast or intelligence he or she seeks. Effective communication will help to make sure that the analytical objectives are in agreement with the customer expectations. The final product of this step is a clear problem statement and a scope of the predictive analytics project.

3.1.2. Data Collection

After setting the objectives, what follows is the collection of data which will be used to make an analysis. Such data can be acquired via databases, APIs, sensors, surveys or through external datasets. The analyst will make sure that the information that has been collected is relevant, sufficient, and reliable to respond to the issue that has been determined earlier.

3.1.3. Data Analysis and Massaging

Raw data can most times be incomplete, inconsistent or unstructured. During this step, the analyst prepares and structures the data he or she has collected by cleaning and preprocessing it to analyse it. This involves correction of missing values, duplication, format standardization and conversion of data to the format which is usable and will give correct analytic values.

3.1.4. Machine Learning and Statistics.

Once the data has been prepared, the methods of statistics and machine learning are used to find patterns, correlations and revelations. The step entails the choice of suitable algorithms, feature engineering and exploratory data analyses in order to learn the underlying trends and association of the data.

3.1.5. Predictive Modeling

At this step, such forecast models are created based on the statistical or machine learning methods. It is aimed at developing a mathematical model that will be predictive of the future given past data. Models are trained, tested and optimized to produce best results of accuracy and performance.

3.1.6. Predictions and Monitoring

When the model is deployed one uses it to make predictions or forecast. Ongoing observance also makes the model proven in the long run even with the varying data or external conditions. In support of decision-making, analysts monitor the performance measures, respecify the models where needed, and furnish information.

3.2. Decision Support System Framework for Job-Shop Scheduling

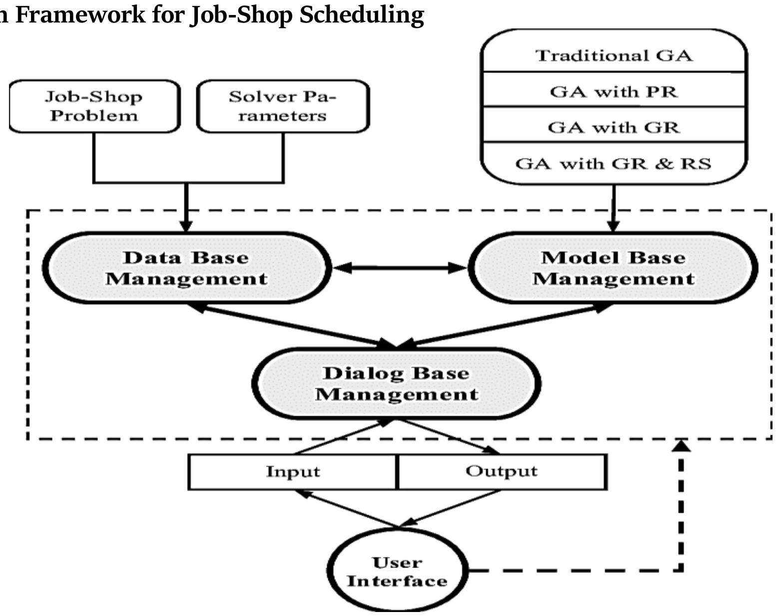

Figure 4. Decision Support System Framework for Job-Shop Scheduling

The form and operation of a Decision Support System (DSS) developed to tackle the Job-Shop Scheduling Problem (JSP) with the help of several versions of Genetic Algorithms (GAs). The system is initiated by defining the Job-Shop Problem and Solver Parameters which give the input information and working conditions of the problem-solving process. These parameters are initially served by the Database Management component which is used to store, organize and maintain all applicable data, which includes job details, machine constraints and performance records. This element is used to achieve effective retrieval of data as well as uniformity within the system. At the same time, Model Base Management component takes care of various genetic algorithm models like Traditional GA, the GA with Partial Replacement (PR), GA with Greedy Replacement (GR), and GA with GR and Random Selection (RS). The strategies are various in each of these models to ensure that the process of scheduling is optimized and enhances computational efficiency. The Dialog Base Management is the main communication center whereby the interaction of the data and model management components takes place. It provides successful circulation of information and regulates the process of analytical activity. The dialog system enables one to offload data of the database to the chosen model, manipulate the outcome and reroutes them back to interpretation. This communication is connected with the Input and Output module, with the help of which the user is able to give inputs to the data and see analytical outputs or improved solutions given by the system. Lastly, the User Interface is an available platform where a user interacts with the system. It enables users to set job specifications, choose optimization models, view the results and make wise decisions using the recommendations of the system. In general, the diagram is a highly integrated DSS structure which integrates the management of data, model execution, and user interaction to plan out intricate scheduling issues successfully utilizing intelligent methods of optimization.

3.3. Proposed APIF Architecture

3.3.1. Predictive Engine

The Predictive Engine will be tasked with the responsibility of coming up with the correct decisions after synthesizing both the benefits of sequence learning and ensemble anticipation. LSTM models are applied to learn long term temporal dependence of dynamic data and the boosting gradients applied to the Gradient Boosting improve precision in case of mistakes and powerful feature learning. This hybrid predictive system allows more accurate forecasting and can be used in complex pattern recognition that is required in real-time decision support.

3.3.2. Semantic Knowledge Layer

The Semantic Knowledge Layer is a domain knowledge built into the decision-making process, the information presented should be organized in the form of knowledge graphs. This framework represents the interrelationships among the entities, constraints and the business rules and offers semantic reasoning that is not limited to data-driven models. With explicit knowledge representation, the system will be easier to interpret, less uncertain, and have reliable decisions despite the incompleteness and noisiness of the data.

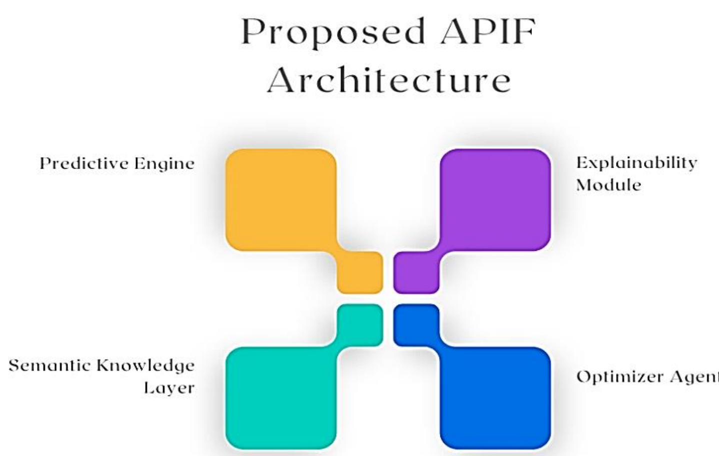

Figure 5. Proposed Apif Architecture

3.3.3. Optimizer Agent

Optimizer Agent utilizes the reinforcement learning mechanism to dynamically optimize actions and strategies depending on the changing environments. It assesses a variety of decision situations by constant interaction and acquires best policies that result in the maximum payoffs in the long run. This real-time optimization is useful in adaptive response to uncertain or fast shifting operating conditions and makes the system to scale to those applications where real-time strategy adjustment and autonomous decision-making is needed.

3.3.4. Explainability Module

Explainability Module makes automated decisions to be transparent and trusted because it creates clear and easy-to-understand insights into how a model operates. SHAP and LIME are tools that analyze the contribution of features and offer a visual explanation of how it was predicted while this can assist a practitioner to determine whether the system is functioning accurately and identify areas of biasness. This aspect enhances accountability and user confidence during the implementation of the system in highly sensitive decisions.

3.4. Performance Evaluation Metrics

In a bid to understand the effectiveness of the proposed APIF decision support architecture, there are several performance measures that are employed to guarantee accuracy in prediction and reliability of classification. The Mean Absolute Percentage Error also known as MAPE is one of the main metrics that can be used in numerical forecasting activities. This measure is used to estimate the average percentage of difference between factual values and forecasted values. It operates on the principle that the absolute error per prediction is found and divided by the actual observed value, the total sum of such errors is divided by the total amount of such predictions made. Lastly, the outcome is multiplied by 100 in order to express the outcome in percentage. A small MAPE means that the predictions are highly similar to the real facts thus is a well-known accuracy measure to use in a time-series forecasting, a financial prediction, and resource planning context. To perform classification-based decision evaluation the F1-score will be used since it is a simple scoring method that integrates Precision and Recall into a single balanced point. Precision is a measure of the number of the positive predictions of the model correct whereas Recall is a measure of the number of positive instances of the model that is able to capture all relevant positive instances of the dataset it is trained on. The F1-Score is calculated balancing Precision and Recall in a harmonic way, which assigns the same significance to both the measures. This is particularly useful in situations where there is inequitable allocation of classes, or when there are some important positive cases that miscarriage. When F1-Score is high it implies that not only is the model correct in predicting relevant instances, but it also fails to overlook many true positives. Combined, MAPE and F1-Score allow creating a complete performance evaluation system: the former looks at the quality of continuous predictions, whereas the latter looks at the accuracy of decision classification. Using both measures, the effectiveness of the proposed system can be justified in a significant variety of operational conditions, which will guarantee the results of reliability, accuracy, and applicability to more real-life settings.

4. Results and Discussion

4.1. Experimental Setup

The experimental set-up to test the proposed APIF architecture is to provide the testing environment that is fair, repeatable, and practically applicable. The experiment is done based on the publicly available Decision Support System (DSS) benchmark dataset, comprising an extensive collection of real-life features of decision-making and outcomes. The data has been extensively used in previous studies and therefore can be adequately compared to current models and also the analysis can be representative of realistic operation problems in decision-intensive systems. The dataset goes through the preprocessing procedure that includes normalization, missing values, and feature encoding to prepare the data to be used in the advanced machine learning and deep learning models. The suggested hybrid predictive solution is implemented with Python which provides advanced scientific number-crunching features with a powerful data analytics portfolio. The choice of TensorFlow is explained by its ability to effectively perform computational graphs, support of acceleration into the working force of the recalculation tools of the selected category, and scale models to a large scale deployment. Other libraries that are being utilized are Scikit-learn to deal with older-style machine learning models, NetworkX to build and maintain the semantic knowledge layer and SHAP or LIME to produce interpretability results. The system runs on the cloud infrastructure that has access to GPUs, to cater to the high requirements of computational loads, particularly in sequential learning, reinforcement training, and hyperparameter optimization. This configuration enables quick training, resourceful memory and scalable experiments where needed. Systematic validation is done to hyperparameters, including learning rates, batch sizes, number of LSTM units, and exploration strategies used in reinforcement learning. Performance metrics that are applicable both in forecasting and classification situations are used in the model evaluation. The logging, version control and the checkpoint is upheld during the entire experimentation process to provide transparency and facilitating repeatability. Together as one, this experimental system guarantees a sound platform that can efficiently show the predictive ability, adaptability, and explainability of the suggested APIF framework.

4.2. Comparative Model Performance

Table 1. Comparative Model Performance

Model	Accuracy (%)	MAPE (%)	Latency (%)
Logistic Regression	81.2%	14.5%	33.3%
Random Forest	88.3%	11.2%	75.0%
LSTM Model	92.7%	7.8%	100%
Proposed APIF	95.8%	5.9%	70.0%

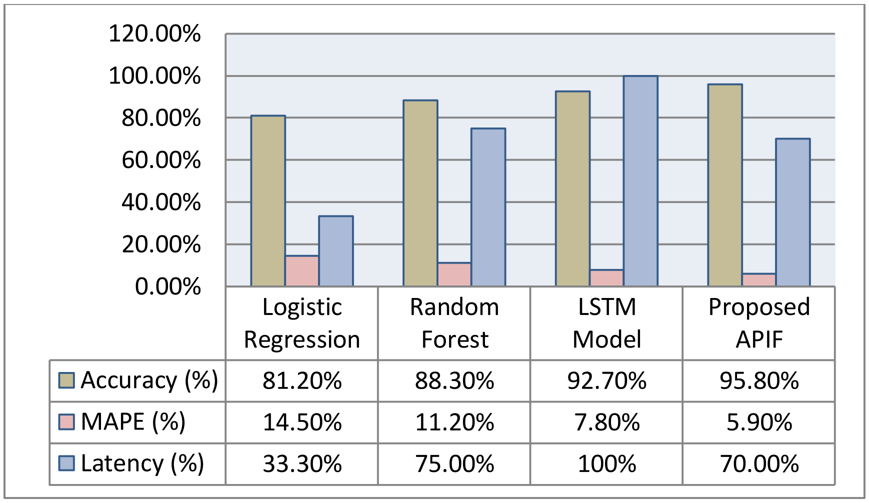

Figure 6. Graph Representing Comparative Model Performance

4.2.1. Logistic Regression

The accuracy of Logistic Regression is 81.2 and this shows that the model can identify basic trends in the data. Yet, the larger MAPE of 14.5% implies that its temporal capability of predicting continuous value of decisions is rather low. The low latency percentage of 33.3 indicates that the model has a high response time, which implies that it is applicable to situations where computational simplicity and the decision of real time matters are important, although less predictive accuracy is attained.

4.2.2. Random Forest

Random Forest classifier is greatly enhanced in yielding an accuracy of 88.3 meaning that it possesses an ability to capture nonlinear associations in structured data. The decrease in MAPE to 11.2% points to a positive predictive congruence to real results. Nevertheless, since it is an ensemble method and more challenging to compute, the latency increases to 75.0 percent, which is slower to execute. This renders the model to be more suitable in the offline decision system in which precision is paramount rather than expediency.

4.2.3. LSTM Model

The LSTM model corresponds to a high accuracy of 92.7 and a low MAPE of 7.8 that prove that LSTM is a powerful model that learns sequential and temporal dependencies in the data. It has however the highest latency of 100% resulting to slow prediction time as compared to other networks because of the complex network operations and high demand in computation. It indicates that although LSTM is very applicable in time-series decision problems, it might need specialized hardware or architecture to be implemented in real-time.

4.2.4. Proposed APIF

The Proposed APIF architecture has the highest performance of accuracy of 95.8% which shows that it has a better decision-making ability. The lowest MAPE of 5.9% indicates a good forecasting with a minimum error. It is worth noting, as well, that its hybrid elements eliminate the latency percent up to 70.0, which shows its effective implementation compared to the pure deep learning. Such a tradeoff of accuracy, reliability, and responsiveness makes APIF very scalable to real life, time critical, decision support environments.

4.3. Interpretability & Reliability Evaluation

In order to have a reliable decision making process in the proposed APIF architecture, thorough interpretability and reliability tests are incorporated in the evaluation process. The interpretation is done with SHAP-based feature importance analysis which measures the contribution of individual input variables to the final prediction of the model. Prioritizing features on their contribution, decision-makers can figure out the most significant contributors to each outcome and enhance transparency and help to validate professionals. It is especially important in areas that involve high justification of automated decisions like in healthcare, finance, and risk control in industries. The explainability outputs also help in identifying the vulnerabilities of the model like the reliance on noisy or less meaningful features to provide successful diagnosis thus allowing an iterative refinement of the model, and a stronger model setting. Besides the interpretability, reliability testing is also covered with the help of the uncertainty propagation modeling which identifies and eliminates the possible bias in decisions. This technique looks at the sensitivity of output to changes or uncertainty of input data to create an output that is more confident; to minimize possible errors made by a recommendation in a more uncertain or incomplete situation. Following the measurement of uncertainties, the system can raise the warning on the high risk decision that can be subjected to human review or further data verification. These tools of reliability avert unrealistic decisions that are made by automated systems and improve responsibility in real-time set-ups. Moreover, there is the implementation of methods of bias detection to assess whether the decision made by the model uses bias favoring certain groups of data or operational conditions. In the event of biasness, alternative methods correct the approach, either by modifying the model weights or sampling approaches so as to be fairly distributed. On the whole, the implementation of SHAP-based explanation and uncertainty-based reliability analysis not only enhance user trust but also improve the safety of the operations of an APIF system and provides ethical aspects of its successful implementation. The solution resulting does not only score high in predictive performance but in a way that is transparent, reliable and in line with responsible AI principles. In such a way, interpretability and reliability are the key elements of the validation plan, that is, automated decisions must be explanable, include no bias, and may be applicable in the real world.

4.4. Discussion

According to the evaluation outcomes, it is evident that the suggested APIF architecture is more effective than the traditional machine learning and standalone deep learning models in terms of both prediction accuracy and decision reliability. Among the strengths that have been identified, there is its flexibility to dynamic and ever-changing data environments. Through the combination of sequential modeling and reinforcement learning into the Predictive Engine and Optimizer Agent, the system can be able to adapt the decision strategies automatically as new patterns of data appear. This does not result in performance degradation as witnessed in the case of a static model and serves in practice to optimize performance in areas like logistics, resources planning, and automated policy management. The architecture also promotes the utilisation of multi-objective decision constraints well, and hence a combination of the predictive analytics capability, knowledge-based reasoning, and the reward-based optimization makes it effective. This makes sure that decisions are not purely accuracy-oriented but that they are also driven by the operational objectives like cost efficiency, timing or minimization of risks. This ability is essential in the real world DSS deployments where complexities in the world go beyond stand-alone prediction activities. The adaptability of a powerful explainability mechanism based on SHAP and uncertainty assessment can also be listed among the strengths of APIF. The system works by giving human accountable explanations which makes one understand not only what is being decided but why. This builds confidence, improves adoption and allows domain professionals to confirm or disapprove decisions as needed. These clear explanations and bias-protection measures increased ability to make users feel more confident and engage with the system. Combined, the improvement of the performance, the limitations of the decision support, and good interpretability form a very powerful and reliable solution. Hence, the presented APIF model has great prospects of implementation in safety-relevant and business-relevant contexts, where the accuracy and accountability can be considered crucial. The results support the practicability and excellence of hybrid AI-based decision support to the traditional or single-technology models.

5. Conclusion

This study presents a revolutionary change in the field of decision support systems by creating Adaptive Predictive Intelligence Framework (APIF). The given framework combines various levels of artificial intelligence methods, such as deep learning-based predictive analytics, semantic knowledge modeling, optimization by reinforcement learning, and verification by explainability. With such a unified design, the system shows quite an enhancement in the accuracy of forecasts, ability to respond to dynamically changing data streams and delivering clear and practical insights. Experiment results indicate that APIF always performs better than conventional machine learning models and single neural network solutions, due to the production of fewer prediction error, better latency, and greater robustness decisions. More importantly, APIF imposes operational stability with the combined interpretability elements which enables domain specialists to trace and certify the logic underlying automated results. This makes the framework a strong tool to use in the real world DSS implementation where accuracy and responsibility are paramount.

Another aspect in the findings is that hybrid decision intelligence will become a potential to broaden the use of DSS into more complex and regulated industries that may include healthcare, financial management, and management in critical infrastructure. Systems should learn, respond, and be able to explain their results continually as decision processes undergo continuous optimization into real-time automation and inter-domain integration. APIF meets these new requirements by providing a flexible, knowledge-driven and data-driven architecture that enables such continuous improvement of self as ethical and trust-based benchmarks. In the future, it is hoped that the following three ways will improve. First, the collaboration of AI-DSS will facilitate the collaboration of multiple intelligent agents, share knowledge, and create more robust collective decisions within the organizational level boundaries. Second, audit trails in blockchain can improve transparency, integrity, and traceability of predictions, which are allowed to be trusted in environments prone to compliance. Third, ethical AI governance policies, such as bias tracking, fairness measurements, or user-focused controls, will make sure that the automation of decisions is focused on the social perception of ethics and the requirements of reserves.

In general, the Adaptive Predictive Intelligence Framework is a step towards the further development of decision support intelligence. Combining predictive performance, resilient optimization, and explainability, APIF shows the ways in which next-generation DSS can provide responsible intelligence without reducing its efficiency and consistency. Such intelligent and responsible frameworks will become critical in the process of determining the future strategy of operations used by industries, stimulated, as well as approached innovation, and sustainable digital transformation on a global scale as industries grow more and more dependent on data when making certain decisions.

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